Efficiency Analysis of the Australian Mining Firms

A thesis submitted by

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Abstract

The mining industry is one of the main pillars of the Australian economy and it is usually given credit for preventing Australia from slipping into recession during, and after, the global financial crisis of 2008-2009. Over the past decade, improving Australian living standards has been largely attributable to the mining boom. 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.

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, Zheng and Bloch 2014; Syed et al. 2015). Due to significant differences between individual companies in this sector, efficiency studies at the firm level are essential to complement industry-level analysis. The aim of this study is to shed light on firm-level efficiency, and its determinants, in the Australian mining sector. We apply a two-stage bootstrap data envelopment analysis (DEA), proposed by Simar and Wilson (1998, 2007, 2011), using a panel of 34 companies over the period 2010 to 2014.

To develop the model of technical efficiency estimation, we take into account the common approach of inputs and outputs selection in the production function theory as well as a natural resource-based approach which reflects the specifications of inputs and outputs selection in the non-renewable resource sector of mining. Therefore, we develop two technical efficiency models: Model I, constructed using one output, namely total production, and three inputs including labour, capital and intermediate inputs; and Model II which contains natural resource input in addition to the existing variables in Model I.

Stage-one analysis involves the application of data envelopment analysis (DEA) to estimate the technical efficiency of Australian mining firms. The main advantage of non-parametric DEA, comparing to parametric methods such as stochastic frontier analysis (SFA), is that it does not require any pre-defined functional form; though, it does not take into account statistical noise resulting from measurement errors. To overcome the shortcoming associated with the lack of statistical noise in DEA, we use a bootstrap procedure proposed by Simar and Wilson (1998) to obtain bias-corrected DEA estimates. Both constant returns to scale (CRS)

and variable returns to scale (VRS) assumptions are considered in formulation of technical efficiency models.

In the stage-two analysis, we examine the effects of firm-specific factors on the technical efficiency of mining firms in Australia. The econometric model of stage-two is constructed using 11 variables including ownership, firm size, firm age, capacity utilisation, financial risk, product type, product portfolio diversification, growth factors (including production progress pace as well as growth/decline status), location of operations, and time. To do the second-stage analysis, we apply the bootstrap truncated regression method proposed by Simar and Wilson (2007). This method overcomes the limitation of commonly used methods, such as Tobit regression and Ordinary Least Square (OLS), to handle the issue arises due to the serial correlation among estimated efficiency scores. In this method, instead of conventional efficiency scores, the bias-corrected technical efficiency scores derived from bootstrap DEA are used as the dependent variable in the second-stage econometric model.

Data was 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. These companies account for more than 90% of total output of listed mining companies. In total, our sample consists of 170 panel observations.

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 62% over the study period 2010-2014 under the CRS assumption and Model I specification. This poor level of efficiency gain across Australian mining firms results from the presence of inefficiency in both components of efficiency performance, namely pure technical efficiency and scale efficiency. Once taking account of natural resource input in formulation of the efficiency model, the efficiency performance of Australian mining companies improves significantly. Nevertheless, Model II results show on average 41% technical inefficiency exists among mining companies in Australia. This sizable inefficiency performance is mostly attributed to pure technical inefficiency whereas most mining companies operate around their optimal scale. Our results of the first-stage DEA confirmed the findings of Topp et al. (2008), Zheng and Bloch (2014) and Syed et al. (2015), who addressed the issue in conventional productivity measurement of the mining sector and emphasised the role of resource depletion as a major contributor to the poor productivity performance of the Australian mining sector in recent years. However, the results from the first stage show a significant opportunity for improving technical efficiency across mining companies in Australia even if we account for resource depletion.

The outcomes of the second-stage analysis of both Model I and Model II exhibit similarly significant effects for factors including ownership concentration, firm age, product portfolio and change direction. These factors are dominating the efficiency performance of mining firms regardless of consideration for mining characteristics. Ownership concentration and firm age are positively associated with firm performance. Also, mining firms involved in exploration and extraction of iron ore and gold mines are more efficient than other mining companies in the sample. Furthermore, mining firms achieve higher efficiency gains on years with growing production output while their efficiency gains decline when mining companies reduce their production output.

Product diversification is the only factor that turns out to be insignificant when we redefine input variables in Model II from the initial setup of Model I. Unlike the results of Model I, the coefficients of firm size, financial leverage, location of operations and change pace are reported to be significant under Model II specifications. The correlation between firm size and firm technical performance is positive. Financial leverage negatively affects technical efficiency. Mining companies with active operations outside Australia outperform those companies that limit their operations to domestic mining fields. Finally, companies with stable or gradual growth experience have higher efficiency gains in comparison with companies with sharp changes in their production output.

This thesis provides four major contributions to the existing literature in mining efficiency and productivity analysis. First, this study contributes to the literature through examining efficiency in the Australian mining sector at the firm level during the period 2010-2014. To this point, no study has examined the efficiency of the Australian mining industry at the individual firm level. Second, this work introduces a firm efficiency model accounting for resource depletion which is specific to the mining industry. Sector-level studies have discussed the resource depletion effects on productivity performance. This study extends this concept to a firm-level analysis. Third, this study contributes to the existing literature through examining the determinants of efficiency using a second-stage regression. Only a few firm-specific factors such as ownership and age have been discussed in the existing literature. For the first time, this research explores the effects of factors such as portfolio diversification, product type, capacity utilisation, operation location, financial risk and business stability in the context of mining firms' efficiency. Finally, from a methodological perspective, 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 non-parametric set up.

Through identifying the 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.

List of the Candidate's Publications

Journal Publications:

Hosseinzadeh, A., Smyth, R., Valadkhani, A. and Moradi, A. (2018). What determines the efficiency of Australian mining companies? *Australian Journal of Agricultural and Resource Economics (ABDC: **A**),* 62(1), 121-138.

Hosseinzadeh, A., Smyth, R., Valadkhani, A. and Le, V. (2016). Analysing the efficiency performance of major Australian mining companies using bootstrap data envelopment analysis. *Economic Modelling (ABDC: **A**)*, 57, 26-35.

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Declaration

I certify that this thesis is my own work and contains no material which has been accepted for previous academic awards, in whole or part. I further declare that except where due reference has been made, this thesis contains no material previously published or written by another person.

Ahmad Hosseinzadeh

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To my loving wife and daughter

Table of Contents

List of Tables

List of Figures

1 Introduction

1.1 Background to the Research

The mining industry has contributed to some major economic and social developments in Australia over the past two centuries. In response to the increasing global demand for mineral and energy commodities since 2003-04, the mining sector has experienced substantial growth in the exploration and extraction of mining commodities. This expansion in mining activities has coincided with significant increases in the sector's contribution to the national income, export, investment and employment. Before the boom, the sector's contribution to the Australian GDP was about 5 per cent, increasing to a peak of 9 per cent in 2010-11 (ABS, 2017a). Its contribution to the total export value also reached above 50 per cent over this period (ABS, 2017d). On average, mining export value grew around 1 per cent per annum between 1990-91 and 2003-04. However, the industry experienced an annual increase of 18 per cent in the export value over the 2004-05 to 2010-11 period (Department of Industry, Innovation and Science, 2017). Similar to its income and export performance, the mining industry also increased its contribution to the labour market. The sector's employment increased from 0.9 per cent of the total employment in Australia in 2003-04 to a peak of 2.4 per cent in 2012-13 (Department of Jobs and Small Business, 2017b). What's more, strong capital investment during the mining boom increased the share of the sector in total capital stock in Australia from 7 per cent in 2004-2005 to 15 per cent in 2013-14 (ABS, 2017c).

Further to the positive effects of the millennium boom on the Australian mining sector, the whole Australian economy also benefited from this expansion. Australia's performance in key economic variables, such as employment and national income, surpassed most OECD economies since the mining boom (Grafton, 2012). The economic and social effects of this boom were more evident in the resource-rich states of Western Australia, Queensland and the Northern Territory. Along with the significant capital investment occurring in these states, their average household income growth outperformed the rest of states in Australia during the mining boom. The majority of these expanding mining activities were located in rural and regional Australia; hence, local and indigenous communities in mining regions benefited from the economic growth resulting from the investment boom.

The Australian mining sector's competitive advantages have aided its success in global markets. As a resource-rich country, Australia holds the top place in the world for economic demonstrated resources (EDR) as well as the production of several minerals such as iron ore, bauxite, black coal, brown coal, copper and gold. Furthermore, the Australian Government provided a favourable investment environment, attracting international and domestic investors to its mining projects. A highly skilled workforce and advanced technology utilised in mining operations are two other advantages of Australia's mining sector against its global competitors. Mining exploration and extraction activities in Australia are highly supported by the mining equipment, technology and services (METS) sector. The METS sector in Australia is characterised as internationally competitive and innovative. Finally, Australia's legal and legislative framework supports its communities as well as the mining industry through addressing the environmental accountability and social responsibility in mining activities (Penny et al., 2012; Geoscience Australia, 2015; Geoscience Australia, 2017).

Despite its existing competitive advantages, the Australian mining sector may not be adequately equipped for success in the future. The sector faces a range of new global and domestic challenges that, if not addressed appropriately, could impose severe risks to the future of the Australian economy and particularly the mining sector. From a market demand point of view, the Australian mining sector has heavily relied on the Chinese market; however, the economic expansion of China and its demand for natural minerals and energy has begun to slow, counter to the growth it has experienced in the past few decades. That is, China's economic growth has gradually decreased in recent years; reaching 6.5 per cent in September 2018, its lowest growth since the global financial crisis of 2008 (Department of Industry Innovation and Science, 2018). On the other hand, other emerging economies in Asia, Africa, South America and the Middle East have significant potential to grow. These growth potentials in emerging economies across the globe offer an unprecedented opportunity to the Australian mining sector to maintain its leading position in the global resource market.

Further to the changes in the market demand, the supply side of the market has also experienced some changes. Latin America and Africa succeeded in attracting a substantial level of new investments in mining projects. Comparing to Australia with a 13 per cent share, Latin American and African regions attracted 28 per cent and 13 per cent of the world's new mining investments in 2016 respectively (S&P Global, 2017). Moreover, the large consumers of mining commodities such as China, India and Brazil have changed their strategy toward a more diversified supply portfolio with emphasis on expansion in domestic supply as well as supply from new foreign mining regions (Penny et al., 2012). The realisation of changes in the global market for resource commodities through the development of adequate policy responses is essential to maintain the Australian mining sector's competitive advantages against its counterparts.

In addition to the market demand and supply forces, domestic levers such as social claims and a rising cost structure also influence the shape of the mining industry. In particular, the mining industry is beholden to address community concerns and obtain a social licence to operate in relation to environmental considerations, health and safety requirements, employment, stakeholder engagement and community benefits. Such intangible licences must be obtained and maintained for the entire life of mining projects, from the initial exploration phase to mine development, operations, closure and post-closure phases. The requirements for a social licence to operate can result in increased costs due to longer lead time to attain exploration and mining approvals and comply with more strict regulations (Penny et al., 2012; Geoscience Australia, 2017). Rising costs are the other challenge facing the Australian mining industry. The associated costs with mining exploration and operations are relatively high in comparison with many other global competitors and the emerging mining regions (Penny et al., 2012).

In the presence of declining and fluctuating commodity prices along with decreasing ore grade and the rising production costs of mining operations, productivity improvements and technological changes could support the mining sector to maintain its competitive advantages in the long term (Penny et al., 2012; CSIRO, 2017). In contrast with the positive trends in the 1990-91 to 2000-01 period, from 2001-02 to 2012-13 the mining multifactor productivity (MFP) experienced downward trends. The sector's recent dip in MFP growth came with adverse effects on the nation's productivity performance. Labour productivity and capital productivity declined by 51 per cent and 42 per cent respectively. As a result, the MFP slumped by 44 per cent in this period. These declining trends were mainly due to the resource depletion and the lag between investment and production in mining activities. Due to the nature and characteristics of capital in the mining sector, surging investment in mining activities does not lead to an immediate increase in the production output. In fact, there is a significant lag between the time that new capital is invested and the time that production takes place from a completed development project. While the relationship between investment and productivity is positive in the long term, the increased investment results in declining productivity in the short term (Topp et al., 2008; Syed et al., 2015).

Further to the investment-production lags, resource depletion contributed significantly to the declining productivity performance in the mining sector during the recent boom. In addition to the common factors of production, mining production depends on the natural resource inputs. Changing the characteristics and quality of natural resources over time can deteriorate the productivity of mining activities. Due to the ongoing extraction, mineral deposits have depleted, resulting in less accessible or lower quality deposits over time. Maintaining the same level of output requires consumption of more labour inputs and capital services to reach less accessible deposits or to extract from lower grade deposits.

In addition to the significant influence of investment-production lags and natural resource inputs, a range of other endogenous and exogenous factors have contributed to the productivity performance of mining activities in Australia over the past few decades. Inefficient production of mining products due to high commodity prices, over or under capacity utilisation, skills shortage, infrastructure constraints and significant climate events are named among the other driving factors of low productivity performance of the mining sector in Australia during the recent boom (Topp et al., 2008; Syed et al., 2013; Mason et al., 2013; Lumley and McKee, 2014).

The transition of mining projects from the capital-intensive phase of mining development to the production phase has led to an increase in the Australian mining MFP growth since 2013-14 (ABS, 2018a). Nonetheless, resource depletion will be a continuing concern affecting the productivity performance of the mining sector in the years to come. The sector furthermore suffers from some operational challenges such as non-optimal utilisation of equipment and insufficiency of operational strategies in boosting productivity (Lumley and McKee, 2014). A long-term approach to productivity improvement is critical for both mining businesses and government policy makers in Australia.

1.2 Statement of the Problem

The mining industry plays an important role in Australia's ongoing prosperity. Its significant role in the nation's GDP growth, new capital investment, export, direct and indirect employment as well as developments in regional and indigenous communities has made this sector beneficial to all Australians. Over the past two decades, the Australian mining industry has expanded substantially to respond to the increasing global demand for minerals and mining commodities. Despite the growing economic trends, the Australian mining sector has faced a considerable challenge in relation to its efficiency and productivity performance. During the mining boom, declining productivity trends were one of the major topics in the nation's economic debates and post-boom, most mining companies in Australia listed it as one of the top priorities on their agenda (see e.g. Connolly and Orsmond, 2011; Eslake, 2011; D'Arcy and Gustafsson, 2012; Mitchell et al., 2014; Lumley and McKee, 2014).

In economics, efficiency and productivity are mostly used as the main measures of a producer's performance. While these two concepts are usually used interchangeably, they are not the same. Productivity is simply the ratio of outputs to inputs. Labour productivity, capital productivity and multifactor productivity (MFP) are the most common measures of productivity (OECD, 2001; Coelli et al., 2005). The productivity of each producer is calculated based on its inputs and outputs; however, efficiency is a relative measure and calculated by comparing the observed values of inputs and outputs of a producer against their optimum values. Thus, to measure the efficiency of a producer one needs to estimate the production technology frontier representing the optimum values and then to calculate the producer's distance from the frontier. Such measure is called technical efficiency. Given the availability of price information, one can also calculate the cost, revenue or profit efficiency measures (Fried et al., 2008).

The efficiency measurement techniques can be classified in two categories: parametric and non-parametric. The parametric techniques in efficiency measurement use econometric modelling to formulate the linkage between outputs and inputs in a production system. Stochastic frontier analysis (SFA) is the most common parametric technique in the literature. Due to their stochastic nature, the statistical properties of model parameters and efficiency estimates are derived from the parametric techniques. Having said this, the main disadvantage of these techniques is that their application requires selection of pre-defined functional forms in the econometric model. On the other hand, non-parametric techniques, such as data envelopment analysis (DEA), are flexible and do not need such requirements in selection of functional forms. The efficiency estimates are derived from solving a mathematical programming problem. Due to the deterministic nature of these non-parametric techniques, the efficiency modelling omits consideration of the measurement and random errors in the calculation of efficiency estimates (Fried et al., 2008).

Both econometric and mathematical programming techniques have been widely used in the efficiency and productivity literature. Fried et al. (2008), Aparicio et al. (2016) and Greene et al. (2016) presented various advancements in theoretical modelling and empirical studies in efficiency and productivity analysis. The existing literature covers a broad range of economic activities such as banking, insurance, agriculture, education, hotels and hospitality services, manufacturing and transportation. However, compared to most other industries, the literature is limited to much less research in the efficiency and productivity analysis of the mining industry using frontier techniques such as DEA and SFA (Hosseinzadeh et al., 2016).

Efficiency and productivity studies into the mining industry have been conducted at mine, firm or sector levels. These studies have pursued different aims, performance modelling, variables of interest, common methodologies and policy implications depending on the scope of the research. Early research on efficiency and productivity analysis are limited to mine-level studies. With the aim of improving mine efficiency, the construction of efficiency models in the mine-level studies includes a set of operational input/output variables such as total working hours, utilised equipment capacity, mine geological characteristics and production volume (see e.g. Byrnes and Färe, 1987; Byrnes et al., 1988). On the other hand, sector-level studies have aimed to analyse and improve the productivity of the mining industry through nation-wide or sector-wide policy recommendations. The sector-level productivity modelling has relied on the macroeconomic trends and the official aggregate data of production factors from the national statistical organisations (see e.g. Asafu-Adjaye and Mahadevan, 2003; Rodríguez and Arias, 2008; Zheng and Bloch, 2014).

Nevertheless, the firm-level studies of mining efficiency and productivity have only received attention in recent years (see e.g. Das, 2012; Sueyoshi and Goto, 2012; Geissler et al., 2015). Few studies have been published in the area of efficiency or productivity growth using both mathematical programming and econometric modelling techniques. While some studies limited their scope to the mining activities in a specific county (Fang et al., 2009; Putuma and Kumo, 2010), other studies took a cross-country approach in evaluation of mining firms' efficiency (Eller et al., 2011; Sueyoshi and Goto, 2012; Geissler et al., 2015). Technical efficiency, revenue efficiency and productivity growth are among the main measures being investigated in the firm-level studies. Even though both mathematical programming and econometric approaches have been improved in recent years to tackle their modelling issues, the existing firm-level literature mostly relies on the application of DEA and SFA that were developed decades ago. Among these studies, only Koop and Tole (2008) and Sueyoshi and Goto (2012) applied more advanced methods in economic and mathematical programming approaches respectively.

In the literature, common efficiency model variables include labour input, capital input, intermediate inputs and production output (Coelli et al., 2005). A major difference between mining and other economic sectors is the role of natural resource inputs in the production process. In addition to the common inputs to the production process, the mineral deposits in their natural state contributes to the production of mineral and energy products (Topp et al., 2008). Mineral production from these non-renewable resources results in resource depletion and consequently productivity decline. The role of natural resource inputs has been discussed in sector-level studies. Kulshreshtha and Parikh (2002) included overburden removal as an undesirable output, which partially reflects the effects of natural resource characteristics. Zheng and Bloch (2014) investigated the effects of natural resource inputs on productivity growth using mineral and petroleum exploration capital stock as a proxy for natural resource inputs. Unlike sector-level studies, none of the firm-level studies have taken into account the role of natural resource inputs in the efficiency performance of mining firms. Changes in the ore quality and accessibility of operating mines directly affects revenue and expenses at the corporate level. Hence, the depletion of a company's mineral deposits results in a decline in its overall efficiency and productivity performance. Thus, it is important to include the natural resource inputs among variables of the mining efficiency model of firm-level studies.

Over the past two decades in Australia, several studies have attempted to investigate the productivity of mining industry. Their main intention has been to explain the poor MFP performance across the industry, particularly during the mining boom of the 2000s. The findings from these studies suggest that the official MFP index published by the ABS is substantially influenced by changes in the natural resource inputs. Using different time periods and methodologies, these studies reported consistently moderate and positive adjusted estimates of MFP growth between 2 per cent to 2.5 per cent per annum over the past three decades (see e.g. Topp et al., 2008; Loughton, 2011; Zheng and Bloch, 2014; Syed et al., 2015).

Hence, the official MFP growth estimates are negatively biased indicators of technological progress of the mining industry in the long run.

Further to resource depletion, other factors including sharp increases in input prices, considerable lags between investment and production phases, scale inefficiency and capacity utilisation have contributed negatively to the productivity of the Australian mining sector since the mining boom (Tilton, 2014; Zheng and Bloch, 2014; Syed et al., 2015). The literature suggests that despite the apparent decline in the productivity of Australian mining since 2003-04, the true MFP growth and technological progress has been consistently positive. Therefore, the mining industry does not need to implement any specific policy beyond general advice in improving productivity such as growth in innovation, a more skilled workforce and faster technological progress (Syed et al., 2013; Syed et al., 2015). This view is not necessarily supported by the operational studies that report a significant productivity and efficiency gap in the mining activities in Australia, particularly in equipment and capacity utilisation (Mitchell et al., 2014; Lumley and McKee, 2014).

While the studies conducted in the Australian mining industry have attempted to evaluate the mining sector's productivity, limited research is available on the efficiency performance of mining activities. An early study by Asafu-Adjaye and Mahadevan (2003) decomposed the productivity growth of mining industry in Australian to investigate the role of efficiency changes in productivity performance. They found that the cost efficiency changes contributed negatively in the TFP growth of the mining sector for the 1968-69 to 1994-95 period. More recently, Syed et al. (2015) examined the productivity growth of the mining sector. Contrary to the findings from Asafu-Adjaye and Mahadevan (2003), they reported the positive role of technical efficiency changes in the sector's productivity changes over the 1990-1991 to 2009-2010 period. Hence, at the sector level, the literature findings in efficiency changes are ambiguous, potentially due to the differences in the study period, methodology and efficiency modelling.

Interestingly, research in conducted efficiency and productivity analysis of the Australian mining industry is limited to sector-level studies. That is, no studies have examined the efficiency of mining firms in Australia. Mining companies form the largest division listed on the Australian Securities Exchange (ASX). A large number of domestic and international investors contribute to and benefit from these mining businesses. Certainly, the economic performance of these companies is the interest of various stakeholders including governments, investors, mining business leadership and regional communities. Hence, given the important role of mining companies in the success of the mining sector and the Australian economy, extending the efficiency and productivity analysis to firm-level studies greatly supports policy makers and mining businesses to explore the economic performance across the industry.

In relation to the efficiency performance of mining companies, it is also important to know how to improve it. The answer to such a critical question relies on a clear knowledge about the factors contributing to the firm's efficiency performance. This knowledge helps governments and mining businesses to develop relevant policy aimed at improving the efficiency of mining companies and the sector's overall performance. Few studies in the literature have examined the determinants of efficiency and productivity in the mining industry. The type of factors examined in the literature depends on the scope of the study. Mine-level studies tend to focus on the role of operational factors and mine characteristics in efficiency performance. Geological characteristics in particular are among the most important factors investigated in mine-level efficiency studies (see e.g. Byrnes and Fare, 1987; Byrnes et al., 1988; Koop and Tole, 2008). Firm-level studies, on the other hand, have investigated the influence of firm-specific factors such as ownership, firm age and firm size on the firm's performance (see e.g. Eller et al., 2011; Das, 2012). Meanwhile, the investigation of macroeconomic contributing factors to the productivity growth has been the agenda of the sector-level studies. Factors such as domestic inflation, export and interest rate have been discussed in the productivity literature of the mining industry (see e.g. Mahadevan and Asafu-Adjaye, 2005; Tilton, 2014).

The existing literature explains some driving factors behind changes in the efficiency and productivity of mining activities; however, it is unable to provide a comprehensive picture describing the causes of economic performance of the mining industry. A broader view is needed to aid business management and policy makers in improving mining industry performance. Further to the literature limitations in terms of the scope and the coverage of the efficiency determinants, the applied methodologies also suffer from some modelling issues. The analysis of efficiency determinants in the mining literature, especially in the non-parametric applications, has relied on simple regression techniques (see e.g. Byrnes et al., 1988; Eller et al., 2011). Simar and Wilson (2007, 2011) discussed in detail the issues surrounding the application of OLS and Tobit regression models in two-stage DEA; namely those due to the serial correlation among the DEA efficiency estimates. Better modelling is required to eliminate such issues in the second stage of DEA. These shortcomings indicate the need for further work in the evaluation of the driving factors of efficiency and productivity in the context of the mining industry.

Overall, there are gaps in the existing literature on the efficiency and productivity analysis of the mining industry which require further work. There is room for improvement in the efficiency modelling and the variable selection, particularly the inclusion of natural resource inputs in the analysis. In addition, the absence of recent methodology advancements in the frontier techniques is an evident gap in the mining efficiency literature. In the Australian mining context, despite the body of knowledge in assessing the productivity of the mining sector, the analysis of efficiency performance – particularly at the firm level – is a significant gap in the literature. Moreover, the available studies do not provide a broad picture of the contributing factors to the efficiency and productivity of the mining industry. Specifically, at firm level, the effects of various firm-specific factors are unknown, and for those investigated in the literature, the available knowledge is limited to one or two studies. Finally, the second-stage analysis of a DEA method has been commonly involved in the application of a regression model based on the OLS or Tobit techniques, which provide inconsistent results.

The limitations of the existing literature on the efficiency and productivity analysis of the mining industry have encouraged this thesis to investigate the efficiency performance of mining companies. Focusing on Australian mining companies, this study utilises a two-stage DEA to firstly estimate the efficiency performance of mining firms, and secondly, to investigate the contributing factors to the efficiency performance. In addition to the mining businesses, this research will benefit the regulatory authorities and (more broadly) society through insight into the efficiency challenges and the potential improvement actions toward optimum utilisation of resources in mining operations.

1.3 Research Objectives

This study aims to conduct an empirical investigation into the efficiency performance of Australian mining companies. The main objectives of the research are:

(i) to evaluate the technical efficiency of Australian mining firms;

(ii) to investigate and identify factors significantly contributing to the efficiency of Australian mining firms; and

(iii) to provide policy recommendations to improve the efficiency of Australian mining firms based on empirical findings.

To achieve the above objectives, this study applies a two-stage bootstrap data envelopment analysis (DEA), proposed by Simar and Wilson (1998, 2007, 2011), using a panel of 34 companies over the 2009-10 to 2013-14 period.

The two-stage approach in this study involves the estimation of efficiency scores in the first stage, and the evaluation of effects from the firm-specific factors on the efficiency in the second stage. Toward achieving the first objective in this study, the non-parametric technique of data envelopment analysis (DEA) is used to estimate the technical efficiency of the Australian mining firms. While this technique does not require any pre-defined functional form, which is the main disadvantage in the application of parametric techniques such as SFA, DEA ignores the presence of statistical noise and measurement errors. Hence, this study uses a bootstrap procedure proposed by Simar and Wilson (1998, 2000a) to derive the bias-corrected DEA estimates. Two efficiency models are proposed in this study; the first model is based on the common approach of input/output selection in the production function theory, whereas the second model is a natural resource-based approach to reflect the input/output specifications in the non-renewable resource sector of mining. Therefore, Model I is constructed using one output, namely total production, and three inputs including labour, capital and intermediate inputs. On the other hand, Model II includes the natural resource inputs in addition to the existing variables in Model I.

Aiming at the second objective, this study uses the efficiency estimates obtained from stage one to examine the effects of firm-specific factors on the technical efficiency of mining firms in Australia. The firm-specific factors examined in stage two include ownership, firm size, firm age, capacity utilisation, financial leverage, product type, portfolio diversification, growth status, location of operations and year-specific variables. To overcome the limitation of commonly used regression techniques in providing consistent parameter estimates in the second-stage analysis, this study applies the bootstrap truncated regression method proposed by Simar and Wilson (2007). Unlike techniques such as Tobit regression and Ordinary Least Square (OLS), their proposed method provides reliable and consistent estimates of the econometric model parameters while the firm-specific factors are regressed against the bias-corrected technical efficiency scores derived from the first-stage bootstrap DEA.

The annual reports of the Australian mining companies listed on the ASX are the primary source of data for variables used in the first and second stages of this study. To improve the homogeneity of the sample, this study includes only minerals and metal ore mining companies that had been fully operational over the period of study. The sample consists of 34 mining firms operating over the period 2010 to 2014, accounting for more than 90% of the total output of the listed mining companies in Australia.

Results from stage one and stage two of this study facilitate the development of appropriate policy recommendations as outlined in the third objective. Mining businesses are the main audience of such policy recommendations at the firm level. Nevertheless, policy makers in the government and regulatory authorities can also benefit from the research findings and its recommendations. Most policy recommendations have multiple dimensions associated with various stakeholders such as mining businesses, investors, federal and state governments, and local communities.

1.4 Contributions and Significance of the Research

This study addresses the gap in the literature on mining efficiency and productivity by providing four major contributions. Firstly, this is the first study to examine the efficiency performance of the Australian mining industry at the firm level. Due to the significant contribution of mining companies to the Australian economy, it is essential to understand how mining companies perform in terms of technical efficiency. Improving mining companies' efficiency benefits a broad range of stakeholders such as investors, governments and regional communities. The conducted research on the efficiency and productivity analysis of the Australian mining industry is limited to few sector-level studies. Unfortunately, research on the aggregate data and trends in the mining sector is not sufficient to develop improving actions at the enterprise level. Hence, this study contributes to the literature by closing the existing gap in firm-level efficiency analysis in Australia.

Secondly, unlike most studies in the efficiency analysis of mining companies, this work introduces an efficiency model accounting for natural resource inputs. Due to the nature of the mining sector, the characteristics of mineral deposits can significantly influence the production output of mining activities. Unlike other inputs in the production system, natural resource inputs are non-renewable and can result in resource depletion, i.e. less accessibility or lower quality of mineral deposits. Hence, over time, a greater amount of labour, capital and intermediate inputs is required to maintain the same level of production output or value with a given technology. As natural resource inputs are specific to resource sectors, such as mining, it is important to account for their effects on the efficiency of mining activities. While few sector-level and mine-level studies have discussed resource depletion effects on productivity performance, no firm-level studies have included natural resource inputs in their efficiency models. This study addresses such gap in the literature by extending the efficiency model to include a proxy for natural resource inputs as the natural resource-based model of technical efficiency.

Thirdly, this study examines the effects of a broad range of firm-specific factors on the efficiency performance of mining companies. Any policy implications rely on understanding the contributing factors of efficiency performance. Despite the important role of firm-specific factors in determining efficiency performance, the existing literature covers only a few contributing factors. Although the existing literature has attempted to explain some driving factors behind changes in the efficiency and productivity of mining activities, it has been unable to provide a comprehensive picture describing the causes of the economic performance across mining companies. The firm-level studies in the literature have only discussed a handful of firm-specific factors such as ownership, size and age; however, a broader view is needed to aid business management and policy makers in improving mining industry performance. While the need for investigation of firm-specific factors have been acknowledged in the literature, for the first time, this study attempts to examine the effects of multiple factors such as portfolio diversification, product type, capacity utilisation, location of operations, financial risks and business stability on mining firm efficiency.

Finally, this study is the first in employing a two-stage bootstrap DEA to investigate efficiency and its determinants among mining companies. No studies in the literature have addressed the issues associated with the deterministic nature of non-parametric techniques in the context of the efficiency analysis of mining companies. Non-parametric methods, such as DEA, ignore the presence of statistical noise and measurement errors. As the frontier is constructed based on the extreme points in the observed data, the estimation of efficiency scores is highly sensitive to outliers. In addressing such methodology issues, this study adopted the bootstrap DEA proposed by Simar and Wilson (1998, 2000a) to derive the error terms and the confidence intervals of the DEA efficiency estimates. Further to the improvement in the employed technique of the first-stage analysis, this study adopted a technique that provides consistent results in the second stage. Simar and Wilson (2007, 2011) discussed that common techniques in the second stage analysis, such as OLS and Tobit regression, are unable to provide reliable and consistent parameter estimates when DEA efficiency estimates are the dependent variables. For the first time in the context of mining efficiency analysis, this study uses a bootstrap truncated regression technique proposed by Simar and Wilson (2007) that provides consistent estimates of second-stage model parameters.

1.5 Organisation of the Thesis

This thesis includes eight chapters. Following this introductory chapter, the remainder of the thesis is organised in the chapters briefly outlined below. Chapter 2 reviews the mining sector in Australia and discusses its main contributions to the Australian economy through value added, investment, export and employment. Furthermore, this chapter outlines the opportunities and challenges facing the mining sector in Australia and discusses the productivity concerns during and after the recent mining boom. The role of factors potentially contributing to the undesirable productivity trends are also explored in this chapter.

Chapter 3 reviews and critically discusses the existing literature on efficiency and productivity analysis in the mining industry. Unlike many other sectors, the efficiency measurement in the mining industry is limited to some narrow research streams, most of which are reviewed in this chapter. This review starts by exploring the existing studies that examine the efficiency and productivity of the mining industry at mine, firm and sector levels. Due to the differences in the research aims, variables of interest, methodologies and policy implications, this chapter discusses the mine-level, firm-level and sector-level studies in three separate sections. This review follows by outlining the available body of knowledge in the context of the Australian mining industry. The last part of the literature review presents the existing studies that examine efficiency and productivity determinants.

Chapter 4 looks at the relevant methodologies and presents the frontier techniques in efficiency measurement. The efficiency modelling is presented in the form of mathematical formulations and graphical illustrations. Also, the related concepts are explained in detail to help audiences with less expertise in mathematical modelling to understand the presented methods. Two prominent frontier approaches in the efficiency measurement, namely econometric and mathematical programming, are discussed in this chapter. Focusing on the mathematical programming approach and the DEA method, this chapter explores the recent developments in the statistical foundations of efficiency estimates from the deterministic techniques and introduces the procedures used in this study to derive the bias-corrected efficiency scores. As the intention of this study is also to examine the efficiency determinants, this chapter discusses the common methods in the second-stage analysis in the investigation of contributing factors to efficiency performance. While the issues of the second-stage regression techniques are discussed, this chapter introduces a procedure used in this study that eliminates the shortcomings of the existing techniques to instead provide the reliable and consistent results in two-stage DEA.

Chapter 5 introduces the scope of the study, the research variables and the empirical models. First, this chapter presents the source of data and 34 ASX listed companies in the sample, studied over the period 2009-10 to 2013-14. It proceeds to introduce the variable used for the efficiency model variables. There are two efficiency models developed in this study; Model I is based on the common approach in input/output selection and Model II is a modified efficiency model for consideration of natural resource inputs which are specific to mining activities. Further to the variables in the efficiency models, this chapter review the variables used in the second-stage analysis. Following this section, the chapter presents the empirical mathematical model of stage one and the empirical econometric model of stage two.

Chapter 6 presents the empirical results from the models developed in Chapter 5. The first stage involves the estimation of efficiency scores based on both efficiency models, i.e. the common model of technical efficiency (Model I) and the natural resource-based model of technical efficiency (Model II). For each model, the efficiency estimates are derived from the original DEA and the bootstrap DEA techniques. The presented results include efficiency scores under both CRS and VRS assumptions. The second stage involves the estimation of parameters in the second-stage regression model. Applying the procedure explained in Chapter 5, the second-stage results for both efficiency models are presented and explained in this chapter.

Chapter 7 reviews the results achieved in this study and discusses the findings of factors contributing to the efficiency performance of mining companies. Each explanatory variable is discussed in detail and the implications of their effects in the mining industry are evaluated. In relation to the significant contributing factors, this chapter provides a set of policy recommendations to aid the mining businesses and the government in addressing the efficiency and productivity challenges facing the mining industry.

Finally, Chapter 8 summarises the findings and outlines the concluding remarks on the efficiency of mining companies. The summary of findings from stage one and stage two is followed by a summary of the relevant recommended policy options. Furthermore, the contribution of this study to the existing literature is presented in this chapter. The chapter ends by addressing the limitations surrounding this study and proposes an agenda for the future studies.

2 Overview of the Australian Mining Industry

2.1 Introduction

Over the past two centuries, the mining sector has played a critical role in the Australian economy. Since the early 2000s, the sector has experienced a significant expansion in exploration and extraction activities in response to the increasing global demand for mineral and energy commodities, particularly from emerging economies such as China and India. With such a significant contribution to the national income, the Australian mining sector has dominated the nation's export earnings and investment. The regional and indigenous communities have also benefited from the investment, employment and economic growth brought by the Australian mining sector. Furthermore, the sector has contributed to the growth in downstream and service industries and the Australian Government has earned substantial revenue from growing activities in this sector.

The prominence of the mining sector in the Australian economy has been supported by the sector's competitive advantages in global resource markets. In addition to the resource endowment, the attractive investment environment and the developed technology and skills in Australia have pioneered this sector among global competitors (Penny et al., 2012). However, the sector is facing some critical challenges that may influence its future success. The productivity of the Australian mining sector is among those challenges that need vital attention from both industry and government. During the recent investment boom in mining activities, the productivity performance declined substantially and, even after its transition to the production phase, the sector still faces some critical productivity challenges. In addition to short-term operational solutions, overcoming these challenges requires a strategic orientation toward long-term success in the global market.

The purpose of this chapter is to provide background knowledge on the mining sector in Australia and its economic performance. Therefore, through the following five sections, this chapter is organised to present the role of mining sector in the Australian economy and its main characteristics of the sector with a specific focus on the productivity performance. Section 2.2 introduces the mineral and mining activities in the Australian context. Section 2.3 discusses the role of mining activities in the Australian economy. This review includes the contribution of the mining sector to the national output, investment, employment and exports in Australia. Section 2.4 reviews the sector's strengths that have enabled its boom over the past two decades, as well as the opportunities and challenges facing the sector which will influence its future success. Section 2.5 elaborates on the productivity performance of the mining sector and the challenge resulting from a poor multifactor productivity (MFP) growth during the recent mining boom. Based on conventional reports, this section explains some major factors that have driven the productivity growth in the Australian mining sector over the past two decades. Finally, Section 2.6 summarises the concluding remarks from the review of the mining sector in Australia.

2.2 Mining Activities in Australia

According to The Australian and New Zealand Standard Industrial Classification (ANZSIC) 2006, the mining division consists of five sub-divisions including coal mining, oil and gas extraction, metal ore mining, non-metallic mineral mining and quarrying, and exploration and other mining support services (ABS, 2006). Table 2.1 presents the mining division classification in ANZSIC 2006. This classification groups mining units based on the natural resource mined.

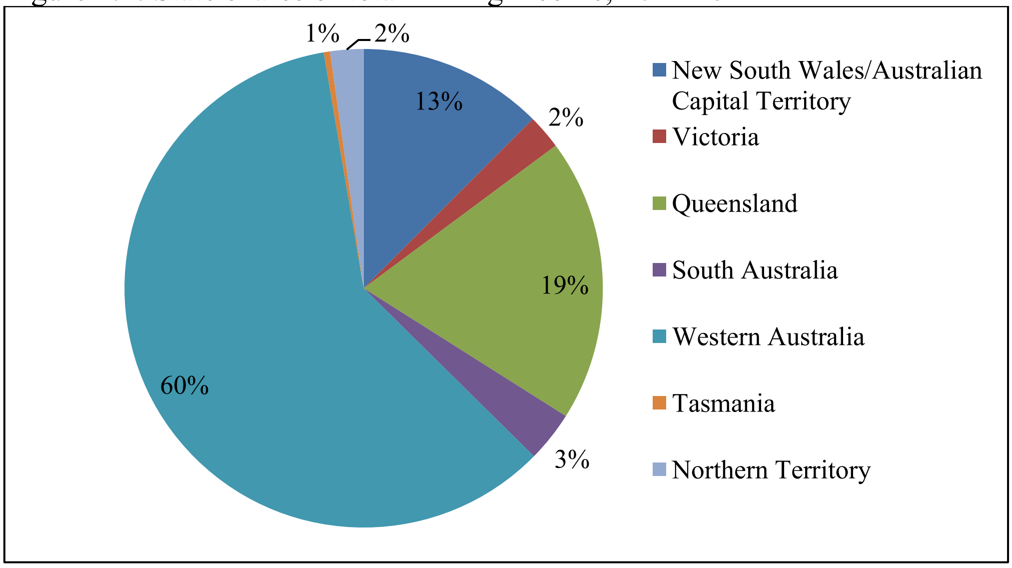
The mining sector covers a diverse range of distinct exploration and extraction activities with a variety of operational techniques in different geographical locations and attributes. A broad range of mineral commodities are produced and exported in Australia. Both open-cut and underground mining methods are utilised in the Australian mining operations. These mining operations are distributed unevenly across Australia. Western Australia has the main contribution to the total mining production in Australia. Almost 60 per cent of total sales and service income from the mining industry in 2014-15 was generated from this state. This was followed by Queensland and New South Wales by contributions of 19 per cent and 13 per cent respectively (Figure 2.1).

Table 2.1: ANZSIC Mining division classification

Sub-division	Group	Class
06 Coal Mining	060 Coal Mining	0600 Coal Mining
07 Oil and Gas Extraction	070 Oil and Gas Extraction	0700 Oil and Gas Extraction
08 Metal Ore Mining	080 Metal Ore Mining	0801 Iron Ore Mining
		0802 Bauxite Mining
		0803 Copper Ore Mining
		0804 Gold Ore Mining
		0805 Mineral Sand Mining
		0806 Nickel Ore Mining
		0807 Silver-Lead-Zinc Ore Mining
		0809 Other Metal Ore Mining
09 Non-Metallic Mineral Mining and Quarrying	091 Construction Material Mining	0911 Gravel and Sand Quarrying
		0919 Other Construction Material Mining
	099 Other Non-Metallic Mineral Mining and Quarrying	0990 Other Non-Metallic Mineral Mining and Quarrying
10 Exploration and Other Mining Support Services	101 Exploration	1011 Petroleum Exploration
		1012 Mineral Exploration
	109 Other Mining Support Services	1090 Other Mining Support Services

Source: ABS (Australian and New Zealand Standard Industrial Classification, 2006, Cat. no. 1292.0)

Figure 2.1: State shares of total mining income, 2014-15



Source: ABS (Mining Operations, Australia, 2014-15, Cat. no. 8415.0 Table 6)

The major activities undertaken in the mining industry include exploration, mine development, extraction, processing, transformation and restoration of land. This range of activities may be undertaken by mining companies or contracted out to specialised contractors (Topp et al., 2008). Table 2.2 presents the details of activities involved in mining operations.

Table 2.2: Mining activities

Activity	Examples
Exploration	Prospecting; Determine characteristics of deposit; Feasibility analysis
Mine development	Acquire mining rights; Construct access roads and infrastructure; Construct mine to access deposit; Install plant and equipment
Extraction	Remove deposit from the ground
Processing	Crushing; Milling; Concentration
Transport	Move extracted material or milled product to transport head
Reclamation	Remove buildings, plant and equipment; Treat waste and tailings; Environmental rehabilitation

Source: Topp et al. (2008)

Table 2.3: Share of Australia in world minerals production in 2009

Commodities	Australian percentage share of world
Crude oil	0.7
Natural gas	1.6
Hard coal	5.7
Iron ore	24.8
Copper	6
Zinc	11.2
Nickel	12.3
Zircon	41
Rutile	48.5
Bauxite	31.3
Uranium	15.7
Gold	9.4

Source: ABS (Year Book Australia, 2012, Catalogue Number 1301.0)

The aim of exploration is to find commercially viable quantities of minerals to mine. This process determines the area to be explored, conducts sampling and geological analysis, and completes comprehensive technical and socio-economic analysis. As a result, a physical location can be transformed into a mineral resource (a significant but imprecisely measured deposit) and subsequently, an ore reserve (a precisely measured deposit that is profitable to mine at current and expected future prices). Once the viability of mineral deposits is proved and the extraction decision is made, the production stages will commence which constitutes the remainder of activities in Table 2.2 (Topp et al., 2008).

At the global scale, Australia is a major producer of several mineral products. Table 2.3 shows the contribution of Australian mining to the total world production in selected products. The significant share of total world mining production in commodities such as iron ore and bauxite has turned Australia into one of the major players in the global natural resource market.

2.3 The Role of Mining Industry in the Australian Economy

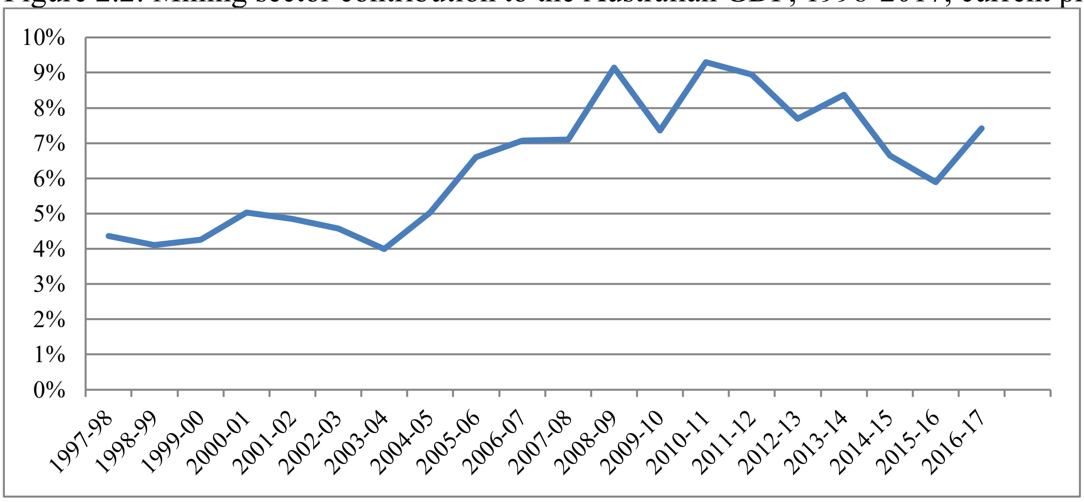
Since the early 2000s, the global mining industry has experienced a rapid growth due to a significant increase in global demand for most mining commodities. This rapid growth was followed by a moderate expansion of mining activities in response to the modest global consumption growth of resource commodities and declining commodity prices in recent years (Department of Industry, Innovation and Science, 2017). The growth in industrial production and urbanisation in developing countries, particularly China and India, resulted in growth in demand for mining products and an extraordinary increase in mining commodity prices. The global exporters of mining commodities, including Australia, enjoyed the benefits from this increased demand; however, the recent slowdown in demand growth has concerned the mining industry and policy makers across the world. Hence, improving the productivity performance of mining activities is a critical solution to the adverse effects of the price decline. The long-term projection of global economic growth shows a need for further demand in mining commodities as the urbanisation and population growth continuous around the world, particularly in India and African countries. As the Australian mining industry is heavily integrated with the global market, such expansions seem to be in favour of mining companies in Australia which have made a significant investment in new exploration and extraction projects over the past decade.

2.3.1 Mining Sector Output and Investment

Historical data from the Australian Bureau of Statistics (ABS) shows the mining sector contributes around 5 per cent to the Australian gross domestic product (GDP). The trend of the mining sector's contribution to the Australian GDP over the past two decades is presented in Figure 2.2. Along with increasing global demand for mineral commodities in the 2000s, the mining sector's GDP share grew and reached above 9 per cent in 2008-09. From 2011-12 onward, the drop in mineral commodity prices resulted in a decrease in GDP share of mining sector, but it has maintained its position above the historical average. The mining commodity price increase in 2016-17 caused the share of mining sector in the Australian GDP reached above 7 per cent after its drop to below 6 per cent in 2015-16.

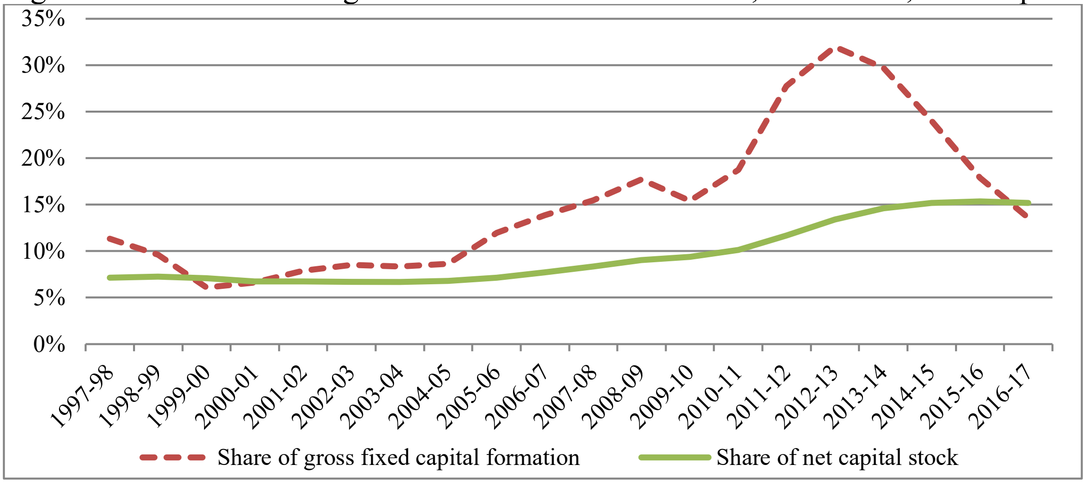
Due to the increased global demand and prices for mining commodities, the increase in mining share in the Australian GDP was accompanied by a significant increase in new investment in the mining sector (Figure 2.3). At current prices, the gross fixed capital formation increased from 9 per cent of total gross capital formation in Australia in 2004-05 to 32 per cent in 2012-13. In response to a slower economic growth in target countries, particularly China, and reduced mining product prices, this trend has been reversed since 2012-13. The share of mining sector investments in the Australia's gross capital formation declined to 14 per cent in 2016-17. Its share in the net capital stock of Australia has been maintained at 15 per cent from 2014-15 to 2016-17.

Figure 2.2: Mining sector contribution to the Australian GDP, 1998-2017, current prices



Source: ABS (Australian System of National Accounts 2016-17, Cat. no. 5204.0 Table 5)

Figure 2.3: Share of mining sector investment in Australia, 1998-2017, current prices

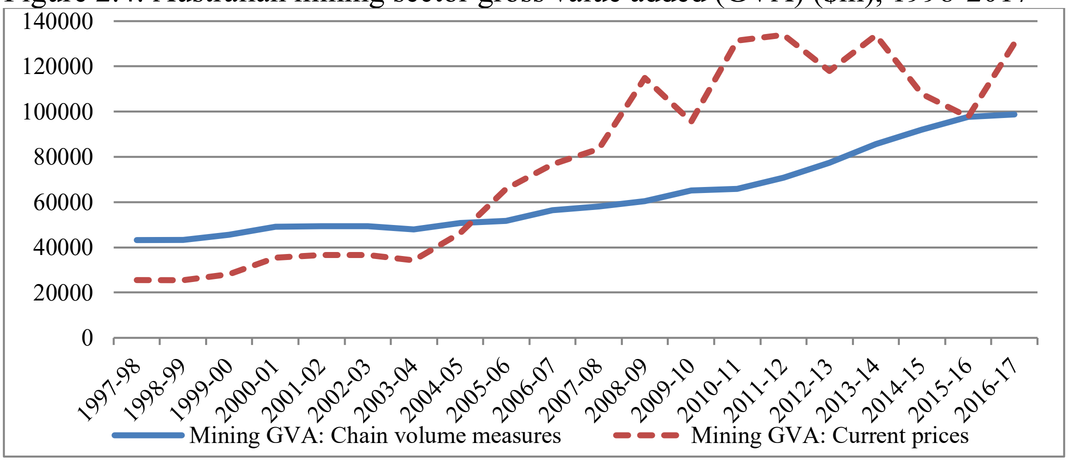


Source: ABS (Australian System of National Accounts 2016-17, Cat. no. 5204.0 Tables 63 & 64)

2.3.2 Volume of Mining Sector Output

The gross value added of mining activities in Australia in current prices has grown fast along with significant fluctuations since the recent boom. The value of mining sector output has increased fivefold over 20 years, from 1997-98 to 2016-17, averagely more than 20 per cent per year. However, in real terms, the total output of the mining sector shows a less steep growth. The chain volume measures of gross value added of the mining sector has increased smoothly by 7 per cent in two decades. Figure 2.4 compares the nominal and real output of the Australian mining sector between 1998 and 2017.

Figure 2.4: Australian mining sector gross value added (GVA) ($m), 1998-2017



Source: ABS (Australian System of National Accounts 2016-17, Cat. no. 5204.0 Table 5)

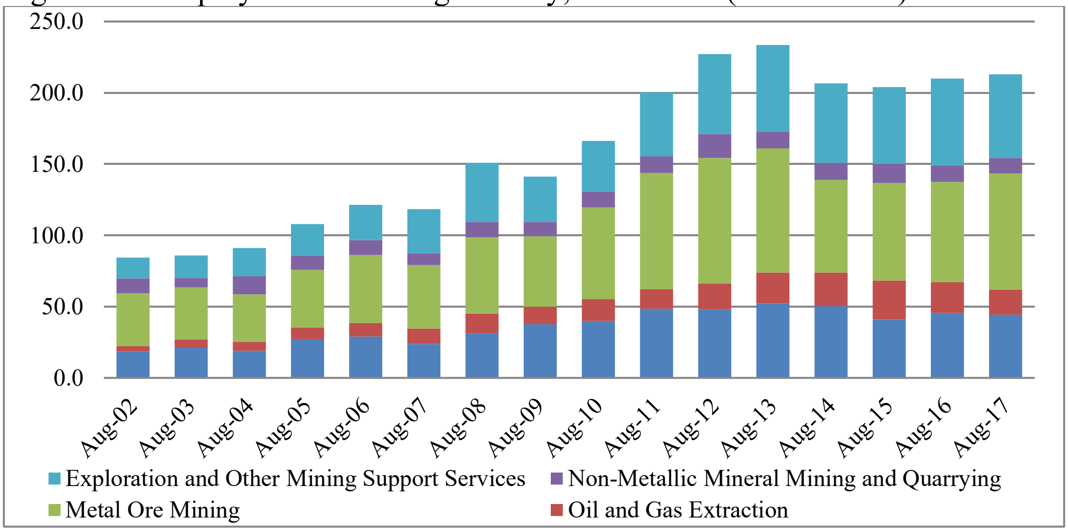
2.3.3 Employment in Mining Sector

Since its early 2000s' boom, the mining sector has experienced a significant increase in new exploration and extraction projects across Australia. Along with this expansion, the labour employed in this sector increased 220 per cent between 2002 and 2013. The sector reached its highest employment in 2013 with almost 270,000 personnel. Employment in the sector declined in 2014 and 2015 (Figure 2.5).

Based on the ABS Labour Force Survey data, the Department of Jobs and Small Business of Australia has projected the employment trends in the mining sector will grow by 2.4 per cent over the next five years (up to May 2022). Based on this estimation, the sector's employment is expected to reach 237,000 workers. The gradual growth of employment in the mining sector is chiefly due to the transition from the investment phase to the production phase. Employment growth is furthermore attributed to new exploration projects, particularly gold, and increased metal ore mine production (Department of Jobs and Small Business, 2017a).

In terms of distribution of employment among mining sub-divisions, metal ore and coal mining activities have the major share of employment in mining operations. The contribution of exploration and mining services are also significant in total mining sector employment.

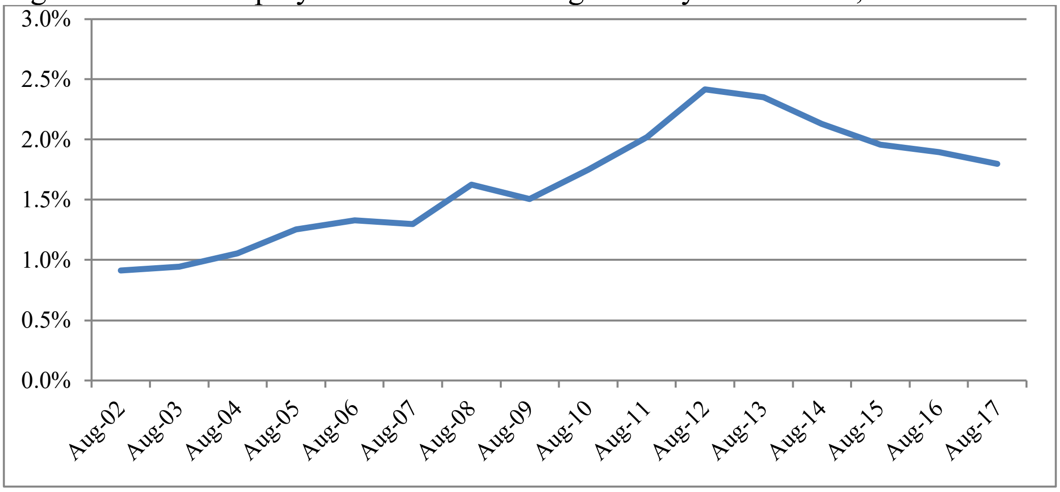
Figure 2.5: Employment in mining industry, 2002-2017 (in thousands)



Source: Labour Market Information Portal at < http://lmip.gov.au>, viewed 10 December 2017

Although it is assigned intensive capital, the mining sector covers a small proportion of total employment in Australia. The quantity of labour employed in the mining sector increased substantially since the boom; however, its share in the Australian workforce remains low. From a low level of 0.9 per cent share in the Australian labour force in 2002, the mining sector reached a peak of 2.4 per cent contribution in total employment in Australia in 2012. Since then, this share has been declining gradually. In 2017, only 1.8 per cent of total employment in Australia was allocated to the mining sector (Figure 2.6).

Figure 2.6: The Employment share of mining industry in Australia, 2002-2017

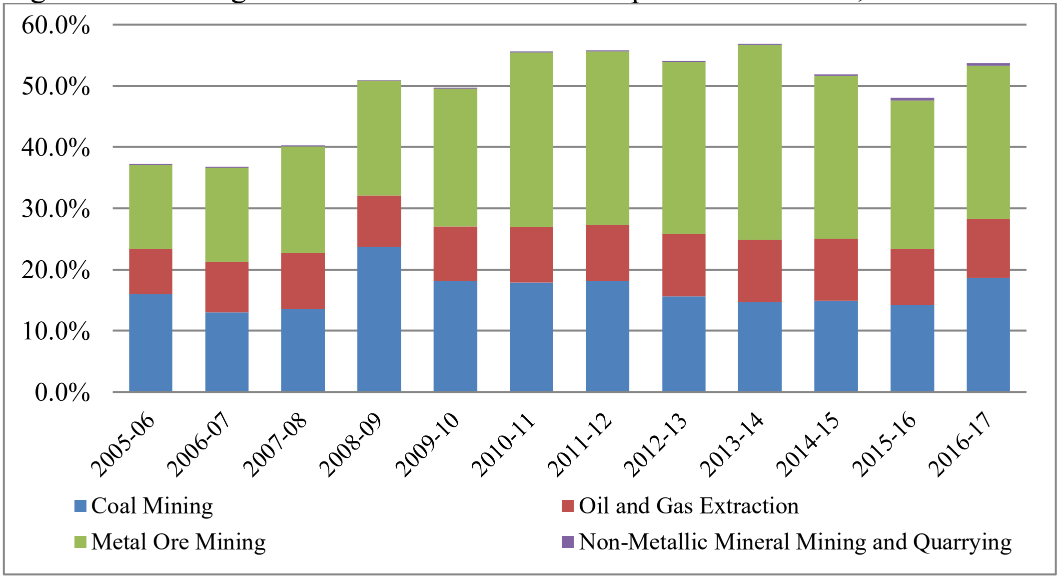


Source: Department of Jobs and Small Business, Labour Market Information Portal at < http://lmip.gov.au>, viewed 10 December 2017

2.3.4 Export Performance of Mining Sector

Similar to the production, investment and employment performance of the mining sector in the recent boom, the exporting of mining commodities significantly increased in the 2000s. That is to say, mining is export-oriented. Three of its main industries – metal ore mining, coal mining, and oil and gas extraction – contributed to over 50 per cent of the total exports in Australia over the past decade (Figure 2.7). In fact, the majority of mining commodities extracted and mined in Australia are exported to foreign destinations, particularly China. In 2016, 73 per cent of minerals exported from Australia had China as their destination (The World Bank, 2017).

Figure 2.7: Mining sector contribution to total export in Australian, 2006-2017



Source: ABS (International Trade in Goods and Services, Australia, Cat. no. 5368.0 Table 32a)

2.3.5 Distribution of Mining Sector Output across Sub-divisions

Among mining sector sub-divisions, coal mining and oil and gas extraction had the main contribution to the mining sector output. ABS data shows around 50 per cent of industry value added by the mining sector had been generated from these two industries over the past 20 years (ABS, 2017a). Since 2008-09, the output of iron ore mining has grown constantly. Although coal mining and oil and gas extraction have been remained as major activities in the Australian mining sector, iron ore mining has been positioned as the largest mining activity in Australia. In 2014-15, iron ore mining comprised 38 per cent of total value added by the mining sector, well above other mining activities in Australia. These three industries account for 78 per cent of the value of mining sector output. Since the more recent move from extensive investment to the production phase, the share of exploration and service to mining activities in total value added of this sector has declined. In 2014-15, only 6 per cent of mining sector value added was assigned to the exploration and other mining support services. Table 2.4 lists the distribution of value added by the mining sector.

Table 2.4: Mining sector value added by sub-division and class in 2014-15

Sub-division/class	Industry value added	
	Value (in millions dollar)	Per cent
06 Coal mining	15,925	13%
07 Oil and gas extraction	31,891	27%
08 Metal ore mining		
0801 Iron ore mining	45,458	38%
0803 Copper ore mining	2,000	2%
0804 Gold ore mining	7,448	6%
0805 Mineral sand mining	1,088	1%
0807 Silver-lead-zinc ore mining	2,140	2%
0802, 0806 and 0809 Bauxite, nickel and other metal ore mining	2,928	2%
09 Non-metallic mineral mining and quarrying	2,352	2%
10 Exploration and other mining support services	7,050	6%
Total Mining	118,281	100%

Source: ABS (Mining Operations, Australia, 2014-15, Cat. no. 8415.0 Table 3)

2.4 Strengths and Challenges in the Australian Mining Industry

The Australian mining sector is globally competitive, with an outstanding position in the global resource market. Major consumers of mineral commodities across the globe rely on the mining activities in Australia, just as the Australian economy has come to rely on this sector for its long-term prosperity. The knowledge of current strengths and future opportunities and challenges can help in developing government and industry policy and programs toward the mining sector's long-term success in Australia.

2.4.1 Strengths of Mining Industry in Australia

The Australian resource sector has been developed with the aid of some critical enablers, facilitating its global competitiveness. Australia stands among the top countries in the world in both economic demonstrated resources (EDR) and mine production of several minerals such as iron ore, bauxite, black coal, brown coal, copper and gold (Table 2.5). The exploration of mineral resources is greatly supported by the Australian Government through providing public access to geoscience information (Geoscience Australia, 2017).

Table 2.5: Australia's global position in economic demonstrated resources (EDR) and production of major minerals in 2015

Mineral Commodities	Australia in world EDR		Australia in world mine production		EDR to production ratio
	Rank (No.)	Share (%)	Rank (No.)	Share (%)	Life (years)
Bauxite	2	22	1	29	75
Black Coal	5	10	4	8	110
Brown Coal	2	24	3	8	1095
Copper	2	12	6	5	90
Gold	1	17	2	9	351
Ilmenite	2	19	2	9	165
Iron Ore	1	28	2	25	65
Lead	1	40	2	14	70
Manganese	2	17	3	16	30
Nickel	1	24	4	9	80
Rutile	1	52	1	47	85
Silver	2	15	6	5	75
Uranium	1	29	3	9	210
Zinc	1	31	2	12	40
Zircon	1	67	1	31	80

Source: Geoscience Australia (2016)

The substantial resource endowment is coupled with encouraging investment environment in Australia. Australia is ranked as a low sovereign-risk country due to its stable social, political and cultural structure with strong regulatory and legal systems and a high degree of openness in trades and investment (Penny et al, 2012). This positive perception of sovereign risk attracts investors to engage in investment projects across Australia. The Fraser Institute ranked Australia as the second most attractive region in the world for investment in 2017. Among Australia's states, Western Australia followed by Queensland, South Australia and Northern Territory have attained high scores in both investment attractiveness and policy perception indices over the past decade (Stedman and Green, 2018). The Australian mining companies are able to attract their required capital through listings and share placements on the Australian Securities Exchange (ASX). The material, including mining companies, is the largest sector on the ASX in terms of number of companies. Domestic and international borrowings and foreign direct investment (FDI) are other main methods to access the intensive capital required for mining development and extraction projects. As Table 2.6 illustrates, mining investment comprises the majority of foreign direct investment in Australia. In line with the capital formation trends, mining FDI reached its peak in 2013 with around $51 billion in investment contributing to 88 per cent of total FDI in Australia.

Table 2.6: Mining foreign direct investment (FDI) in Australia, 2011 – 2016

	2012	2013	2014	2015	2016
Value of mining FDI ($million)	39,353	51,205	35,389	11,550	29,747
Share of total foreign direct investment (%)	68%	88%	79%	45%	46%

Source: ABS (International Investment Position, Australia: Supplementary Statistics, 2016, Cat. no. 5352.0 Table 14a).

The Australian mining sector benefits from a highly experienced and skilled workforce. More than 70 per cent of its workforce have attained a post-secondary qualification which is above the average ratio for the post-secondary qualifications of workforce in Australia (Table 2.7). A number of government and industry initiatives have been introduced to improve the workforce skills in the short term and long term (Penny at al., 2012). Furthermore, Australia's university and research sector is world-leading in mineral geoscience, contributing to the development of new knowledge as well as training highly skilled workforce for mining sector (Geoscience Australia, 2017).

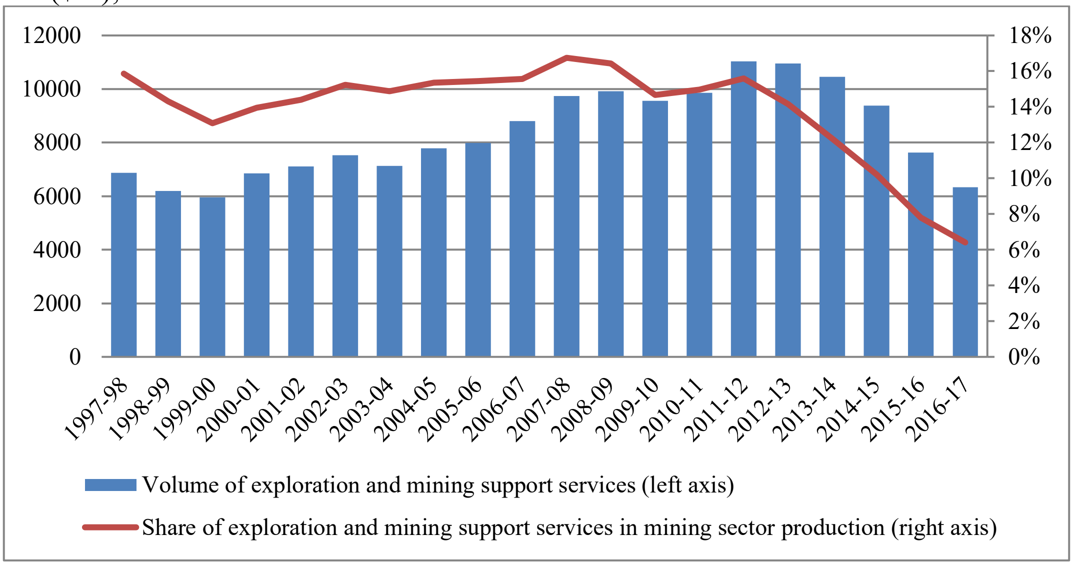
Table 2.7: Mining workforce education in comparison with other industries in 2017

Industries	Higher education degree	Post-secondary qualifications
Agriculture, forestry and fishing	19%	44%
Mining	31%	71%
Manufacturing	28%	59%
Construction	18%	64%
All industries	43%	65%

Source: ABS (Education and Work, Australia, May 2017, Cat. no. 6227.0 Table 14)

Technology advancement is another strength of the Australian mining industry. In addition to the utilisation of advanced technology in the exploration and extraction of mineral products, the mining equipment, technology and services (METS) sector is world-leading in providing specialised products and solutions across the mining value chain, including mineral exploration, development, extraction, processing, transport and remediation (Geoscience Australia, 2015). As it is characterised by being internationally competitive and innovative, the Australian METS sector is set as a benchmark for some global competitors. Almost two thirds of companies in the METS sector are export-oriented. These companies export approximately $15 billion annually. The Australian METS accounts for 76 per cent of patents filed in the mining sector. Furthermore, Australia is in third place, after Japan and Germany, as the top inventor location for Patent Cooperation Treaty (PCT) applications in mining inventions (CSIRO, 2017). Since the recent mining boom, the total output of exploration and mining support services increased significantly. However, following the transition from the mining development phase to the production phase in 2013, both total services volume and its contribution to mining sector production have declined considerably.

Figure 2.8: Exploration and mining support services in Australia: chain volume measures ($m), 1998-2017



Source: ABS (Australian System of National Accounts 2016-17, Cat. no. 5204.0 Table 5)

Further to the resource endowment, the favourable investment environment, workforce capabilities and technology advancement, the environmental accountability and social responsibility are well respected in mining activities and legislative framework in Australia. Both the Commonwealth and states have introduced comprehensive legislation in regard to national and local environmental significance. The environmental impact assessment is a vital part of any commencing projects including mining exploration and extraction activities (Penny at al., 2012).

2.4.2 Opportunities and Challenges facing the Australian Mining Industry

Relying on its strengths, the Australian mining sector has been highly competitive globally in the past. However, increasing global competition in the resource sector of mining has no guarantees for the future success of the Australian mining sector. The mining sector is facing new challenges which must be addressed in government and industry policy and programs. The change in market portfolio of mineral and energy commodities is a main driving factor shaping the future of the resource sector in Australia. In addition to the advanced economies, the emerging economies will have an increasing importance to the global commodity markets (Penny et al., 2012). China's industrial production has grown rapidly over the past few decades and its growth is expected to continue; albeit, at a slower rate. It has already resulted in the expansion of resource-intensive industries such as energy generation and metal production. The Australian economy, in general, and the mining sector, in particular, is highly sensitive to China's economic growth. Other emerging nations in Asia, such as India, Indonesia and the Philippines, have significant potential to grow. The growth potential of Asian countries as well as other emerging economies across the globe offers an unprecedented opportunity to the Australian mining sector to maintain its leading position in the global resource market.

The increasing demand and high commodity prices in the 2000s encouraged the global suppliers of mining products to increase substantially their investment in exploration and development projects. Yet, despite the peak in commodity prices in 2012, the general trends in mining investment have been declining across the globe. As the future growth in production depends on the exploration of new mineral resources, the exploration expenditure is a sound indicator of mineral supply potential in the future. In 2016, the Latin America region (including Chile, Peru, Mexico, Brazil, Argentina and Colombia) attracted 28 per cent of global nonferrous exploration budgets. Canada followed by Australia as the most popular national targets accounted for 14 per cent and 13 per cent of the global budget respectively. In addition, the Africa region could attract 13 percent of the global total (S&P Global, 2017). Although these records show the importance of the Australian mining sector in the global market, significant investment in exploration of mineral resources in other regions can substantially influence its future global position. Over the 2007- 2016 period, no quality Tier 1 discoveries were made in Australia out of a total of 12 Tier 1 discoveries found around the globe. Such exploration outcomes urge the mining exploration firms to move from the well-established regions to remote unexplored or less explored regions in Australia. However, the current trends in exploration activities do not support this urgency (Geoscience Australia, 2017).

Further to the exploration expenditures by suppliers, the large consumers of mining products have diversified their supply strategy to secure their long-term supply. They have introduced this diversification strategy through expansions in supply from domestic deposits as well as new mining regions. For instance, Chinese companies have increased their involvement in the global mineral exploration expenditure while around one third of their budgets were allocated to projects outside China. What's more, China, India and Brazil have increased their direct and indirect foreign investment in the resource sector of a diverse host of countries (Penny et al., 2012).

In addition to fulfilling the formal regulatory conditions and obtaining a licence to mine, the mining companies need to address community concerns and obtain a social licence to operate. The industry faces increasing social claims from the community and governments. The challenge of mining sector's social licence to operate encompasses various aspects including environmental considerations, health and safety requirements, employment, stakeholder engagement and community benefits. Such intangible licence must be obtained and maintained for the entire mining project life, from the initial exploration phase to mine development, operations, closure and post-closure phases. Increasing community concerns and the requirements for a social licence to operate has resulted in increased costs due to longer lead time to attain exploration and mining approvals and complying with more strict regulations (Penny et al., 2012; Geoscience Australia, 2017).

The rising costs are the other challenge facing the Australian mining industry. The associated costs of mining exploration and operations are relatively high in comparison with many other global competitors and emerging mining regions (Penny et al., 2012). Moreover, some global investors believe that most low-cost mining regions in Australia have been discovered many years ago. Due to resource depletion in existing mine sites, further developments require moving from low-cost but exhausted regions to less explored regions where the associated costs of mineral exploration and mining are substantially higher. This perception influences adversely attraction of new exploration investments in an increasing competitive market (Geoscience Australia, 2017).

Finally, the productivity challenge is a significant concern in the Australian mining sector. Similar to some other major players in the global resource market, such as Canada and the US, the multifactor productivity of Australia's mining sector experienced decline in the decade 2000-2010. This significant decline in productivity performance has been explained as a result of the special characteristics of the mining sector, namely the resource depletion and investment-production lags (e.g. see Topp et al., 2008; Zheng and Bloch, 2014; Syed et al., 2015). Since 2013-14, along with a decline in new capital investments and the transition of the industry from the investment-intensive phase to the production phase, the Australian mining

MFP has started to grow (ABS, 2018a). However, the resource depletion will increasingly continue to influence future productivity performance. Moreover, regardless of its investment state, the mining sector faces some fundamental challenges at the operational level. Compared to other countries, Australian mining equipment contributes to lower annual output while the adopted operational strategies by the Australian mining companies have not been changed in response to changing economic circumstances (Lumley and McKee, 2014).

2.5 Productivity Performance of the Australian Mining Industry

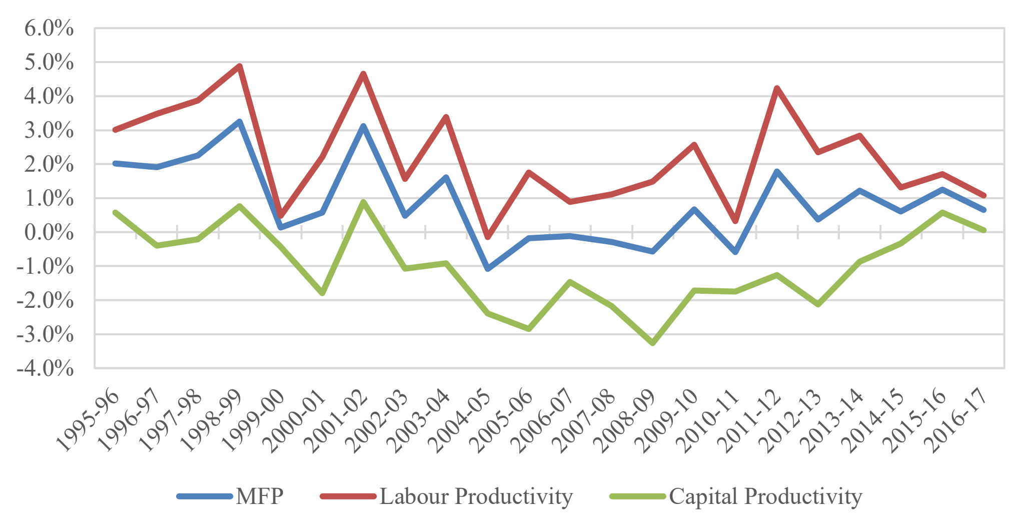
The Australian mining sector continues to contribute significantly to the nation's economy. Contributing up to 7 per cent of the GDP, 15 per cent of capital stock and over 50 per cent of exports, the mining sector is considered a valuable and influential sector in Australia (ABS, 2017a, 2017c, 2017d).

The recent mining boom had a profoundly positive influence on Australian prosperity. Some examples of its positive effects are higher government tax and levy earnings, increased company revenue, increased and sustained real income growth (especially during the great recession of 2008-09 and the years after) increased investment in mining and infrastructure projects, increased employment and wages in the resource sector, as well as stronger exchange rate in favour of Australian consumers of imported goods (Penny et al., 2012). Having said that, the significant growth in mining activities in Australia caused some challenges in the Australian economy including declined productivity performance.

2.5.1 Australia's Productivity and Mining Sector

The adverse effect on the national productivity performance was one of challenges resulting from the rapid expansion of mining sector activities in Australia. Eslake (2011) discussed this issue and showed that the market sector's multifactor productivity (MFP) declined at an annual average rate of -0.7 per cent over 2000-09, while the trend was positive at an annual average rate of 1 per cent a decade before, from 1990 to 2000. This negative MFP growth trend was primarily due to the decline in two specific sectors, namely the mining sector and electricity, gas, water and waste services. The sharp drop in MFP of the mining and utilities sectors was blamed as the main contributor to Australia's MFP decline over 2000s. Figure 2.9 shows trends of MFP based on the hours worked, the capital productivity and the labour productivity since 1995-96. Over this period, labour productivity growth has been almost positive. However, the market sector's MFP performance experienced both positive and negative growth rates. From 2004-05 to 2010-11, the Australian mining sector recorded a poor MFP growth performance. In 2011-12, the market sector MFP growth turned to positive rate, and it was maintained in subsequent years (Figure 2.9).

Figure 2.9: Market sector labour, capital and multifactor productivity growth, 1996-2017



Source: ABS (Estimates of Industry Multifactor Productivity, Australia, Cat. no. 5260.0.55.002)

Table 2.8 presents the average of MFP growth in the past three decades. The mining sector MFP grew by 1.8 per cent annually during the 1990s. However, unlike most industries, its MFP growth was negative by an annual rate of -2.7 per cent in the period of 2000-01 to 2009-10. Over this period, the productivity of Australia's mining sector declined by almost 30 per cent. Although the average annual MFP changes maintained negative from 2010-11 to 2016-17, the mining sector productivity performance has improved over this period.

The high productivity growth in the 1990s was mainly attributed to the economic reforms introduced in 1980s and early 1990s. These reforms included facilitating international trade with the abolition of input quotas and reduction of tariffs, floating of the exchange rate to abolish most restrictions on the international movement of capital, liberalisation of product markets and competition policy, corporatisation and privatisation of government business enterprises, labour market reform and increases in working hours, tax and welfare reforms, and monetary and fiscal policy changes to promote macroeconomic stability (Syed et al., 2013). By contrast, the slowdown of productivity growth of Australian businesses was partially attributed to the fading impact of 1980s and 1990s reforms. The absence of significant economic reforms can explain the gradual productivity growth in the 2000s (Eslake, 2011).

Table 2.8: MFP growth in Australia, selected sectors, average annual growth, 1990-91 to 2016-17

Commodities	**1990-91 to 1999-00**	**2000-01 to 2009-10**	**2010-11 to 2016-17**	**1990-91 to 2016-17**
A Agriculture, Forestry and Fishing	4.3%	3.0%	2.9%	3.5%
B Mining	**1.8%**	**-2.7%**	**-1.4%**	**-0.7%**
C Manufacturing	0.8%	0.5%	-0.4%	0.4%
D Electricity, Gas, Water and Waste Services	2.8%	-3.3%	-1.1%	-0.5%
E Construction	0.7%	0.6%	0.0%	0.5%
F Wholesale Trade	2.9%	1.6%	3.6%	2.6%
G Retail Trade	1.8%	1.7%	1.5%	1.7%
H Accommodation and Food Services	0.6%	0.3%	0.8%	0.5%
I Transport, Postal and Warehousing	2.2%	0.9%	0.2%	1.2%
J Information, Media and Telecommunications	2.3%	0.9%	1.9%	1.7%
K Financial and Insurance Services	3.2%	1.0%	2.2%	2.2%
R Arts and Recreation Services	-0.8%	0.1%	0.2%	-0.2%
12 Selected industries	**1.8%**	**0.5%**	**0.6%**	**1.0%**

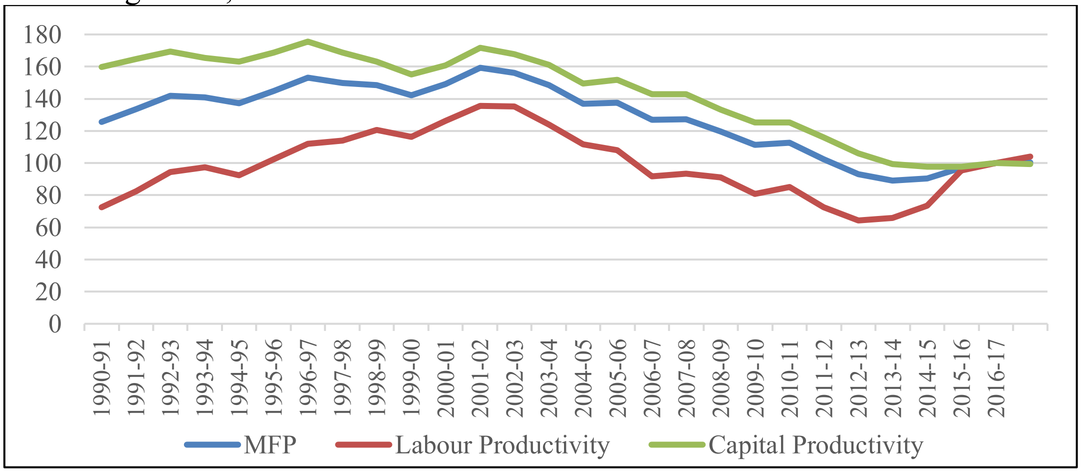
Source: Author's estimation based on ABS (Estimates of Industry Multifactor Productivity 2017, Cat. no. 5260.0.55.002 Table 1)

In the case of the mining sector, the decline in productivity performance in the 2000s was mainly attributed to the increased demand and prices of mining commodities. In response to the increasing market demand, mining companies across Australia were encouraged to increase their production outputs. This increase required a substantial increase in labour and capital inputs. Over this period, the increase in labour and capital inputs exceeded the increase in output resulting in a decline in productivity performance.

2.5.2 Productivity of the Australian Mining Sector

As discussed earlier in this chapter, the productivity performance of the Australian mining sector declined during the recent mining boom, as driven by increased global demand for mining commodities. Figure 2.10 shows different measures of productivity including capital productivity, labour productivity and multifactor productivity.

Figure 2.10: Indexes of labour, capital and multiple factor productivity in the Australian mining sector, 1990–91 to 2016-17



Source: ABS (Estimates of Industry Multifactor Productivity 2017, Cat. no. 5260.0.55.002 Tables 1, 6 & 7)

Note: Reference year for indexes is 2015-16 = 100.0.

Table 2.9: Productivity growth in the Australian mining sector, 1990-91 to 2016-17

Productivity measures	**1990-91 to 2000-01**	**2000-01 to 2012-13**	**2012-13 to 2016-17**	**1990-91 to 2016-17**
Labour productivity	64.1%	-51.4%	58.0%	26.1%
Capital productivity	4.2%	-42.2%	0.0%	-39.8%
Multifactor productivity	19.1%	-44.1%	12.8%	-24.8%

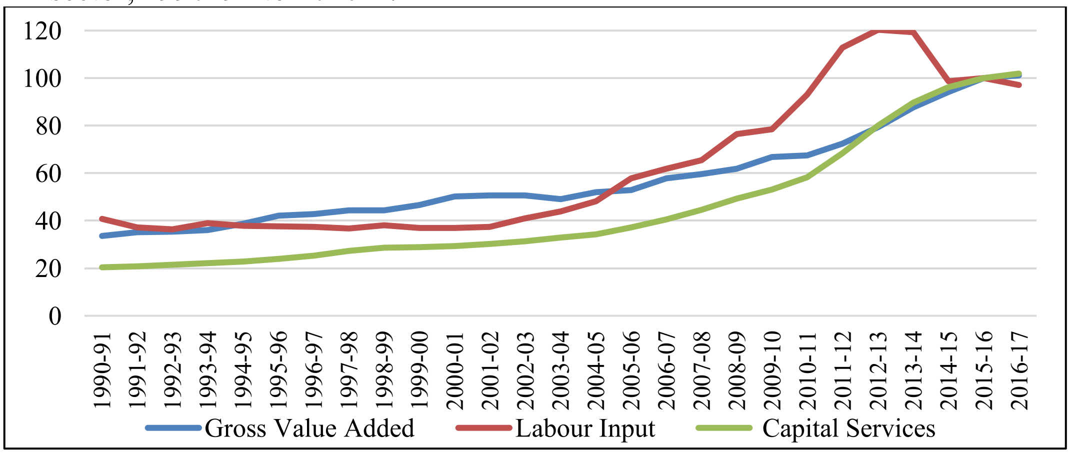
Source: Author's estimation based on ABS (Estimates of Industry Multifactor Productivity 2017, Cat. no. 5260.0.55.002 Tables 1, 6 & 7)

The mining sector productivity trends can be segmented into three periods. From 1990-91 to 2000-01, the measures of productivity indicate a general growth. Labour productivity grew notably by almost 64 per cent while capital productivity experienced low changes by 4 per cent between 1990-91 and 2000-01. Hence, a modest MFP growth of 19 per cent was recorded over this period in the Australian mining sector. In contrast to the 1990-91 to 2000-01 period, from 2001-02 to 2012-13 all three measures show downward trends. Labour productivity and capital productivity declined by 51 per cent and 42 per cent respectively. As a result, the multifactor productivity slumped by 44 per cent from 2000-01 to 2012-13. Since 2012-13, signs of improvement in productivity performance of the Australian mining sector are evident. Labour productivity sharply boosted by 58 per cent over only four years. Capital productivity remained unchanged during this period. Therefore, a limited growth of 13 per cent was achieved in multifactor productivity of the Australian mining sector from 2012-13 to 2016-17. Overall, the labour productivity has grown by 26 per cent since 1990-01; however, the substantial drop in capital productivity by 40 per cent resulted in the declining MFP level of the Australian mining sector by 25 per cent over the past 26 years. Table 2.9 summarises the growth trends in these three distinct periods of productivity growth.

2.5.3 Input and Output Growth in Mining Sector

The decomposition of MFP to labour and capital productivity measures shows the influence of input-output growth in productivity performance. Figure 2.11 presents the trends of labour (hours worked) and capital service levels relative to the volume chain measure of value added index. From 1990-91 to 2000-01, the labour input demonstrated a steady trend, while the capital services gradually increased. The total output of the mining sector, however, showed steeper rise relative to the input changes. Subsequently, the multifactor productivity improved over this period.

Figure 2.11: Indexes of labour, capital and gross value added in the Australian mining sector, 1990–91 to 2016-17



Source: ABS (Estimates of Industry Multifactor Productivity 2017, Cat. no. 5260.0.55.002 Tables 8 to 10); Note: Reference year for indexes is 2015-16 = 100.0.

From 2001-02 to 2012-13, the volume of mining sector output increased by 5 per cent per year, similar to output growth trends in the previous period; however, both labour input and capital services rose strongly by 19 per cent and 14 per cent per year, respectively, over this period. Hence, the input growth exceeded the output growth, resulting in a declined productivity performance. From 2012-13 to 2016-17, the mining sector demonstrated stronger output growth, at around 7 per cent per year. Over this period, capital services grew moderately by almost 7 per cent annually, while labour input to mining activities dropped by 5 per cent annually. Thus, the multifactor productivity slightly grew during these recent years. Table 2.10 shows the growth rates of inputs and output of the Australian mining sector in three distinct periods of productivity performance.

Table 2.10: Inputs and output growth in the Australian mining sector, 1990-91 to 2016-17

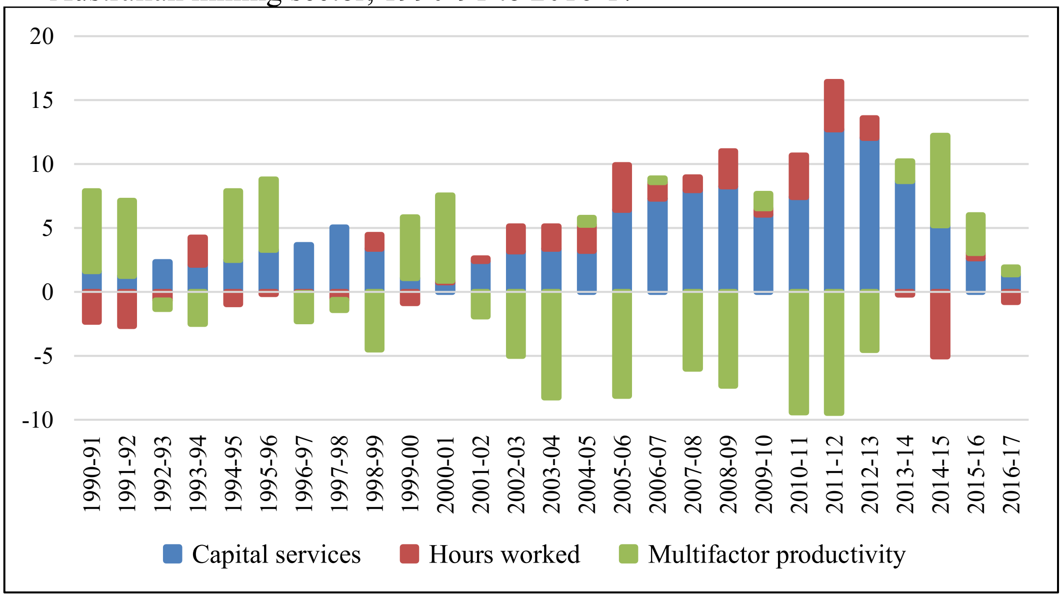
Productivity measures	1990-91 to 2000-01	2000-01 to 2012-13	2012-13 to 2016-17	1990-91 to 2016-17
Labour input	-8.9%	224.8%	-19.3%	138.8%
Capital services	43.5%	173.2%	27.5%	399.8%
Gross value added	49.5%	57.9%	27.5%	201.1%

Source: Author's estimation based on ABS (Estimates of Industry Multifactor Productivity 2017, Cat. no. 5260.0.55.002 Tables 8, 9 & 10)

2.5.4 Explanations for the Productivity Challenges in Mining Sector

In the 1990s, similar to the overall trends across the Australian economy, the mining sector experienced growing productivity performance. The multifactor productivity rose by 1.9 per cent per year in the period 1990-91 to 2000-01. It is plausible that the economic reforms introduced in the 1980s and early 1990s positively influenced the productivity performance of the Australian mining sector, similar to the general pattern in the Australian economy.

Figure 2.12: Contribution of capital, labour and productivity to output growth of the Australian mining sector, 1990-91 to 2016-17



Source: ABS (Estimates of Industry Multifactor Productivity 2017, Cat. no. 5260.0.55.002 Table 25).

In the 2000s, in response to the increasing global demand for energy and minerals, particularly from China and India, the mining activities in Australia expanded rapidly. As shown in Table 2.10, both labour and capital service inputs grew significantly while a moderate increase in production output was recorded for Australia's mining sector. From 2001-02 to 2012-13, the input growth exceeded the output growth, resulting in negative productivity trends over this period. While the contribution of labour input and capital services to gross value added growth remained positive over these years, the multifactor productivity contributed negatively to the mining sector output growth in most years. Figure 2.12 and Table 2.11 illustrate the contribution of labour input, capital services and MFP to value added output growth from 1990-91 to 2016-17.

Over the period of 1990-91 to 2000-01, the value added output grew by 4.16 per cent per year. The capital services and MFP contributed positively to the value added output growth of the mining sector, whereas hours worked shared a negative contribution as a result of declining labour input utilised in the Australian mining activities.

Almost with the same annual growth rate, the value added output grew by 4.09 per cent per year in the period of 2001-02 to 2012-13. However, over this period, the source of production growth was primarily due to increases in capital services and labour input rather than productivity growth. On average, MFP contribution to value added growth was -4 per cent per year. In the 2013-14 to 2016-17 period, the contribution of productivity to value added growth turned to positive records. In this phase, on average, 50 per cent value added growth per year was due to productivity.

Table 2.11: Average contribution to output growth per year in the Australian mining sector, 1990-91 to 2016-17

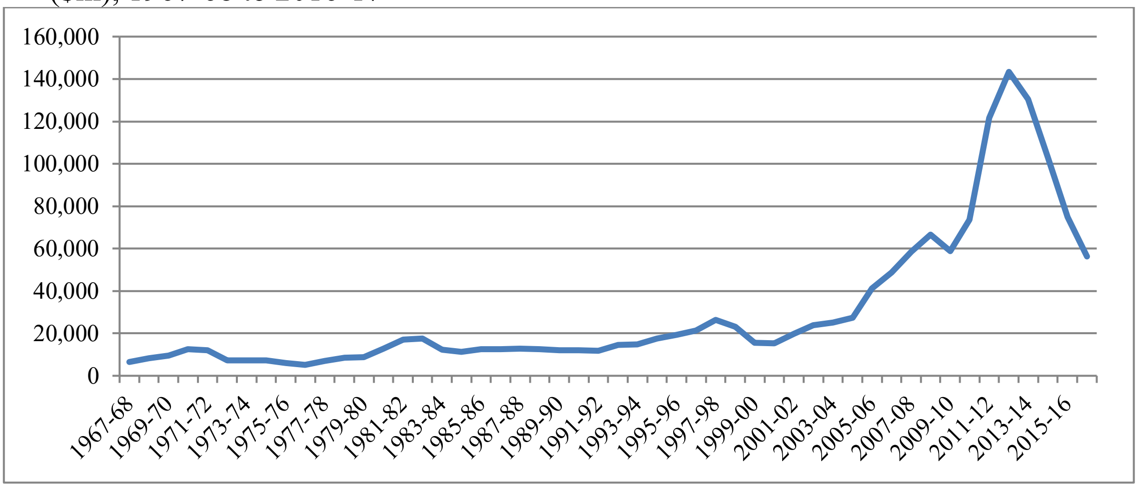
Productivity measures	**1990-91 to 2000-01**	**2001-02 to 2012-13**	**2013-14 to 2016-17**	**1990-91 to 2016-17**
Value added output growth	4.16	4.09	6.08	4.29
Capital services	2.46	6.24	4.47	4.64
Hours worked	-0.46	1.82	-1.41	0.47
Multifactor productivity	2.16	-3.96	3.02	-0.82

Source: Author's estimation based on ABS (Estimates of Industry Multifactor Productivity 2017, Cat. no. 5260.0.55.002 Table 25)

(i) Investment-Production Lags

The growth pattern in inputs, outputs and productivity of mining activities shows some major characteristics contributing to a productivity challenge in this sector. This pattern illustrates the cyclical investment behaviour in the Australian mining sector over time. Figure 2.12 clearly shows two cycles of capital service contribution to the value added output of the mining sector. The first cycle ends in 2000-01 and the second cycle ends in 2016-17. The historical trends of gross capital formation in the Australian mining sector in Figure 2.13 show four cycles of investment in the sector over the past five decades with peaks in 1970-71, 1982-83, 1997-98 and 2012-13. Each peak is followed by a few years of declining investment. Among these four cycles, the magnitude of the recent surge in mining investment is not comparable with the previous cycles.

Figure 2.13: Australia's mining gross fixed capital formation: Chain volume measures ($m), 1967-68 to 2016-17

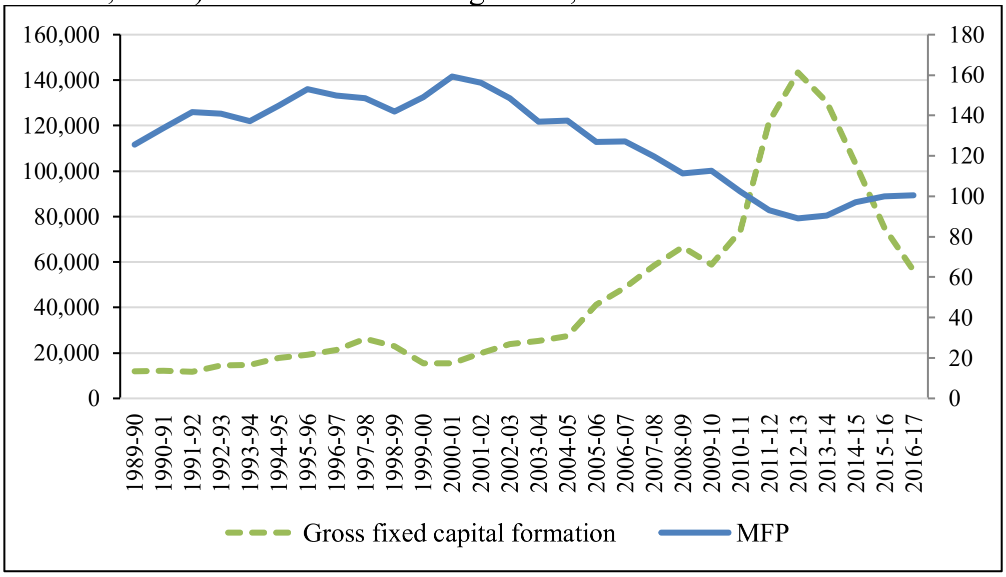


Source: ABS (Australian System of National Accounts 2017, Cat. no. 5204.0 Table 64).

The comparison of investment and productivity trends reveals an inverse relationship between changes in capital investment and changes in multifactor productivity (MFP) of the mining sector. As Figure 2.14 presents, a rapid increase in capital formation is associated with significant decreases in MFP. The productivity growth rates are negative in peaking periods in investment, and vice-versa. This negative association of new investment and MFP is primarily due to the nature and characteristics of capital in the mining sector. Surging investment in mining activities does not lead to an immediate increase in production output. In fact, there is a significant lag between the time that new capital is invested and the time that production takes place from a completed development project. Hence, in the short term, the association of new capital investment and productivity is negative. However, in the long run, there is no such inverse correlation between new investment and productivity. Over the longer term, new investments lead to improvement in technology or management practice; hence, the general long-term trends of new capital investment and productivity are expected to be positively correlated (Topp et al., 2008).

The investment-production lag in the mining sector is the result of the capital-intensive nature of the mining sector. The duration of mine development projects is significantly long. Although in most mine development projects the production can commence a short time after construction starts, reaching the maximum production capacity is generally quite a long process. Furthermore, once a mine development project is complete, there is limited capacity to expand production. Apart from a variety of techniques and processes utilised in mining activities, the invested capital expenditures in most mining projects are sunk costs. That is, there are few opportunities to recover the investment capital through the sale or transfer of assets in the future. Also, the adopted technology is almost fixed; once implemented, the significant upgrade costs make technology improvement infeasible. Hence, due to the capital-intensive nature of the sector, further expansions in production capacity are associated with high cost and long production lag (Topp et al., 2008).

Figure 2.14: Gross fixed capital formation (left axes, \$m) and multifactor productivity (right axes, index) in Australia's mining sector, 1967-68 to 2016-17



Source: ABS (Australian System of National Accounts 2017, Cat. no. 5204.0 Table 64); ABS (Estimates of Industry Multifactor Productivity 2017, Cat. no. 5260.0.55.002 Table 1).

Note: Reference year for MFP index is 2015-16 = 100.0.

Since both expansion of existing mines and new mine development require significant capital expenditures and face risks of significant investment-production lag, productivity performance declines sharply during investment surging periods; a pattern that is evident in the Australian mining sector over the past few decades.

The existing literature in empirical studies emphasises the importance of investment-production lag in the productivity performance of mining activities. However, the suggested approximation of lags is different from one study to another. Topp et al. (2008) discussed the existing lag between capital expenditures and production from a new investment based on empirical studies and government published data. They concluded that, on average, the lag between investment in new productive capacity and its associated production is three years. Based on ABS data, Syed et al. (2013) illustrated that the value added output lags two years from both labour inputs and capital services. Zheng and Bloch (2015) examined the various lags for capital services and suggested that consideration of one year lag between investment in capital goods and their use in production is appropriate.

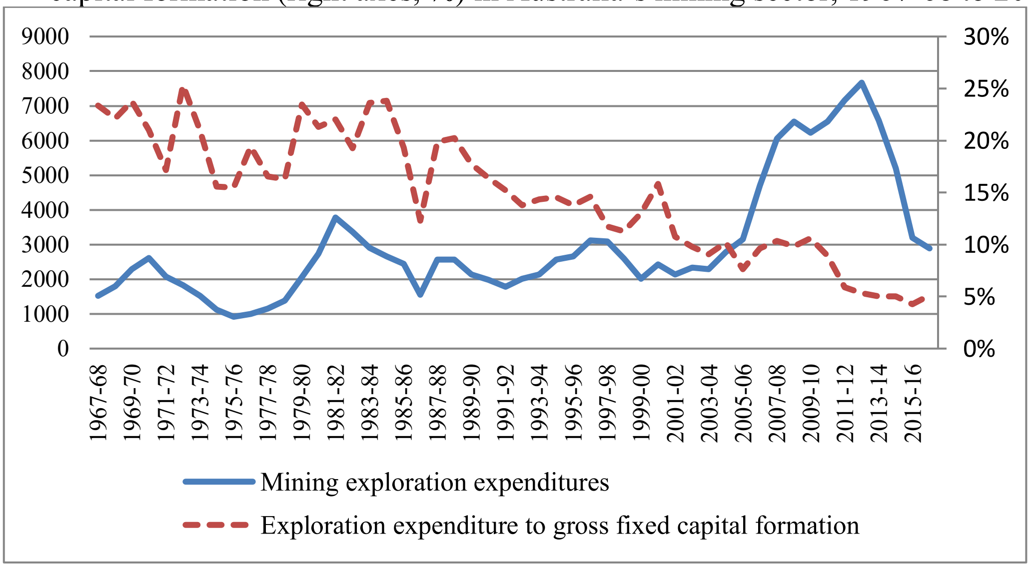
(ii) Natural Resource Inputs

In addition to common factors of production, the mining industry's productivity is influenced by the effects of natural resource inputs. Changing the characteristics and quality of natural resources over time can deteriorate the productivity of mining activities. Unlike most industries, the raw material input to mining production processes is not renewable. Due to ongoing extraction, resource deposits are depleted resulting in less accessible or lower quality deposits over time. Maintaining the same level of output requires consumption of more labour inputs and capital services to reach less accessible deposits or to extract from lower grade deposits. Topp et al. (2008) explained the effects of natural resource depletion on the productivity performance of the Australian mining sector. They argued that the conventional productivity measurement ignores the natural resource inputs; hence, the reported productivity performance is biased.

As a result of such depletion in natural resources, mining companies are required to spend constantly in search and exploration of mineral resources. By definition, exploration and evaluation of mineral resources are expenditures incurred before the technical feasibility and commercial viability of extracting a mineral resource is demonstrable (AASB, 2015). The exploration expenditure is unique to mining activities. The expenditures in exploration and evaluation of mineral resources follow almost the general pattern of capital formation in the Australian mining sector. However, their contribution to the total fixed capital formation has been declining over time. In 2016-17, the exploration and evaluation expenditures consisted of 5 per cent of gross fixed capital formation (Figure 2.15).

In the 2000s, significant increases in exploration and evaluation activities in response to increasing demand for mineral products in the global market contributed negatively to the sector's productivity performance. The lag time between incurring exploration and evaluation expenditures and possible production from the explored resources is much longer than the investment-production lag associated to other capital investments. Also these incurred expenditures may not result in exploration of a feasible mineral deposit. Therefore, exploration expenditures do not contribute to the productivity performance in the short term, and their long-term contribution depends on the success in exploration of feasible and viable deposits.

Figure 2.15: Exploration expenditures (left axes, $m) and their contribution to gross fixed capital formation (right axes, %) in Australia's mining sector, 1967-68 to 2016-17



Source: Author's estimation based on ABS (Australian System of National Accounts 2017, Cat. no. 5204.0 Table 64).

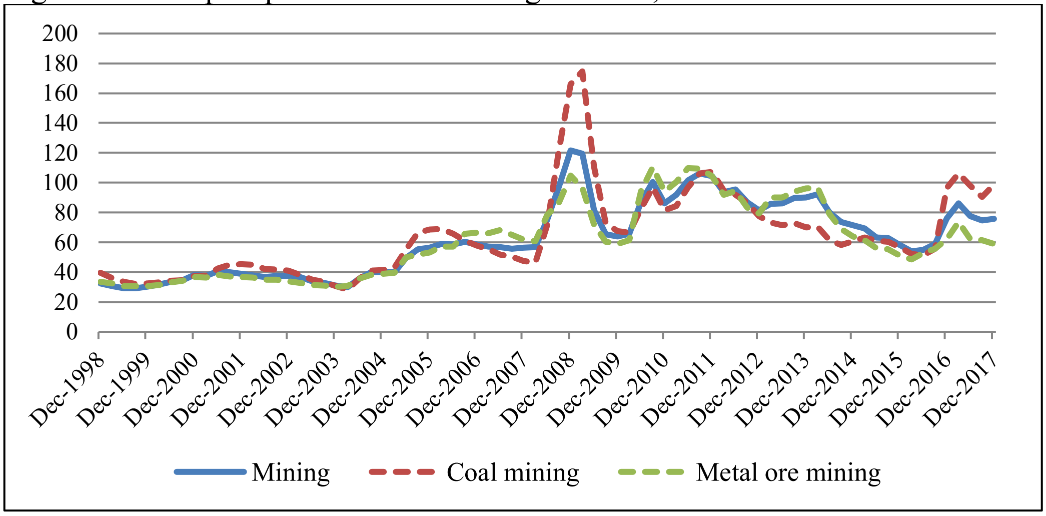
(iii) Other Influencing Factors

In addition to the significant influence of investment-production lags and natural resource inputs, a range of other endogenous and exogenous factors have contributed to the productivity performance of mining activities in Australia over the past few decades. One of the driving factors of mining production output is the commodity price.

As shown in Figure 2.16, from 2003-04 to 2013-14, the Australian mining sector experienced high commodity prices. Over this period, the aggregate export prices increased threefold. The general pattern of commodity price changes is also evident in mining sub-divisions such as coal mining and metal ore mining. Along with higher commodity prices, this period recorded high mining input growth rates and low productivity performance.

Higher commodity prices encourage miners to continue the extraction of mining products from depleted deposits. Higher prices make the extraction of lower grade or less accessible deposits profitable, while productivity declines due to consumption of more inputs per unit of output. Also due to the shortage of required inputs, particularly the specialist equipment and labour, miners may utilise a non-optimal combination of inputs to overcome the imposed constraints. Such non-optimal and mismatched resource allocation results in the productivity decline of mining operations (Topp et al., 2008; Syed et al. 2013).

Figure 2.16: Export price index of mining division, 1998 to 2017



Source: ABS (International Trade Price Indexes, Australia 2018, Cat. no. 6457.0 Table 19).

Another influencing factor of productivity growth in the mining sector is technology. The Australian mining industry has benefited from major technology advancements over the past few decades. Topp et al. (2008) discussed the role of technology changes in the sector's operations and concluded that the technological advances contributed positively to the multifactor productivity in Australian mining. Increases in open-cut operations in coal and metal ore mining, development in drilling technology in oil and gas production, introducing the heap-leaching and hydrometallurgical extraction processes, and increases in information and communications technology (ICT) are some examples of these technological advancements.

On the other hand, mining companies have experienced some difficulties in optimal utilisation of adopted technology. Lumley and McKee (2014) reported a significant decline in mining equipment productivity in all major global mining regions since 2007. Also, most international competitors have outperformed Australia's mining equipment productivity. The Australian annual output from utilised equipment is generally lower relative to other regions including North America, South America, Asia and Africa. Lumley and McKee (2014) expressed that the underperforming equipment productivity in Australia relative to other international competitors is not only associated with poorer equipment of the environment, but it is a function of work practices, culture, leadership and strategy which needs detailed investigation.

Topp et al. (2008) discussed that work practices, poor weather and infrastructure constraints are among other influencing factors of productivity performance of the Australian mining sector. The changes in work arrangement and management practices in 1980s and 1990s, such as increased working hours and 12-hour shifts, contributed positively to increased multifactor productivity in the mining sector. However, the rise of fly-in fly-out work arrangement in 2000s incurred additional costs to mining companies, resulting in a detrimental effect on mining firms' levels of productivity.

Significant climate events have also impacted the productivity performance of mining activities in the short term. The impact of some recent extreme weather events in Australia on mining investment and operations has been enormous. The 2010/2011 Queensland floods caused more than $2 billion loss to coal mining operations through closure or restricted production of 40 out of 50 coal mines in Queensland (Mason et al., 2013). However, in the long term, significant influence from climate events on productivity is not expected.

Finally, the infrastructure constraints in Australia adversely influenced the productivity growth in the mining sector during the early 2000s' production surge. The capacity constraints on the transport supply chain, including rail and port infrastructure, resulted in congested transportation of mined coal and iron ore toward export destinations. Since 2011, the mining commodity prices have generally declined; however, the production output has increased constantly. That is, the sector is in transition from the construction phase to the production phase with expansion in the volume of exports. The existing infrastructure supports current mining operations without significant constraints in the transportation supply chain. However, the growing production and exports of mining commodities require adequate infrastructure planning to ensure growth opportunities are maximised. Infrastructure Australia (2016) addressed the importance of this long-term infrastructure plan in the success of mining operations across growing regions such as the Pilbara.

2.6 Summary

The mining sub-divisions in Australia includes coal mining, oil and gas extraction, metal ore mining, non-metallic mineral mining and quarrying, and exploration and other mining support services (ABS, 2006). Mining companies are mostly involved in a range of activities, from exploration and mine development to mineral extraction, processing, transformation and restoration of land.

This sector plays an important role in the Australian economy. Following the millennium mining boom that commenced in 2002-03 due to a significant increase in global demand and prices for most mining commodities, the Australian mining sector has experienced considerable growth in terms of employment, investment, export and revenue. The average annual growth in export values of the Australian resources between 2004-05 and 2010-11 was 18 per cent, compared with an average annual increase of 1 per cent between 1990-91 and 2003-04 (Department of Industry, Innovation and Science, 2017). Along with increased prices, the total revenue of mining activities across Australia increased substantially. The contribution of the mining sector to the Australian economy increased from a historical level of 5 per cent before 2000 to a peak of above 9 per cent in 2010-11 (ABS, 2017a). The majority of Australia's mined products are exported to foreign destinations. The exporting of mining commodities increased substantially during the mining boom and the sector's contribution to the total export value reached above 50 per cent in 2008-09. This substantial contribution has been maintained in many subsequent years (ABS, 2017d). The expansions in mining activities across Australia has resulted in sharp growth in mining sector employment. The share of mining sector employment reached its peak in 2012-13 by 2.4 per cent contribution to the total employment in Australia, while this share was only 0.9 per cent in 2003-04 (Department of Jobs and Small Business, 2017b). With significant increases in capital investment, the share of the mining sector in total capital stock in Australia increased from 7 per cent in 2004-2005 to 15 per cent in 2013-14 (ABS, 2017c).

The effects of the millennium mining boom were not only limited to the Australian mining sector. The key economic variables such as employment and national income show the superior performance of the Australian economy against most OECD economies (Grafton, 2012). The resource-rich states, including Western Australia, Queensland and Northern Territory, attracted the majority of capital investment. The average household income in these states outperformed the rest of states in Australia. Furthermore, the regional and indigenous communities in mining regions benefited from the economic growth resulted from the investment boom.

The Australian mining success over the recent boom relied on its competitive advantages in global markets. Australia is a resource-rich country, among the top nations in terms of economic demonstrated resources and production of several minerals. Moreover, a favourable investment environment has been provided for international and domestic investors to stimulate capital flow to mining projects. The mining companies benefit from the employment of a highly skilled workforce and the utilisation of advanced technology. The mining equipment, technology and services (METS) sector in Australia is characterised by being internationally competitive and innovative. The legislative framework ensures the environmental accountability and social responsibility of active parties in the mining sector (Penny et al., 2012; Geoscience Australia, 2015; Geoscience Australia, 2017).

However, the future prosperity of the Australian economy, particularly the mining sector, relies on its success to overcome the challenges in increasingly competitive markets. Both the demand side and supply side of the global resource and energy market have undergone significant changes. The growth in demand for mineral commodities is moving from the traditional developed economies to emerging economies in Asia, Africa, South America and the Middle East. In response to the increasing global demand, the major exporters – in addition to some new players in the production of resource and energy commodities – have expanded their efforts in attracting the capital investment for exploration and development of mining projects. The diversification and risk-reducing strategies taken by the main global consumers also influence the resource exporters. The realisation of changes in the global market for resource commodities through the development of adequate policy responses is essential to maintain the Australian mining sector’s competitive advantages against its counterparts.

In addition to the changes in the global market of resource products, the mining sector is under the influence of domestic challenges such as social licence and cost structure. Obtaining and maintaining the social licence to operate is becoming more and more challenging for mining companies, resulting in increases in the associated costs of mining activities. An increased cost structure of mining activities puts further pressure on the sector to maintain its cost-competitive advantage.

In the presence of declining and fluctuating commodity prices, along with decrease in ore grade and rising production costs of mining operation, productivity improvements and technological changes could support the mining sector in maintaining its competitive advantages in the long term (Penny et al. 2012; CSIRO, 2017). However, the multifactor productivity (MFP) growth declined during the recent mining boom with adverse effects on the nation's productivity performance. The productivity downturn during the millennium mining boom was mainly due to the resource depletion and the lag between investment and production in mining activities (Topp et al., 2008; Syed et al., 2015). The transition of the mining sector from the capital-intensive phase of mining development to the production phase since 2013-14 has led to the increase in the Australian mining MFP growth (ABS, 2018a). Nonetheless, resource depletion will be a continuing concern that affects the productivity performance of mining companies for years to come. Furthermore, the sector suffers from some operational challenges such as non-optimal utilisation of equipment and insufficiency of operational strategies in boosting productivity (Lumley and McKee, 2014). A long-term approach to productivity improvement is vitally needed for both private mining businesses and government policy makers in Australia.

3 Literature Review on Efficiency Analysis in Mining Industry

3.1 Introduction

The efficiency and productivity literature has grown extensively over the past four decades. Both mathematical programming and econometric approaches have received wide attention from scholars in the field of economics and management science. Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are among the most popular techniques in efficiency and productivity measurement. These techniques measure the efficiency and productivity of producers or decision-making units by comparing the observed values against their corresponding optimal values on a frontier. These frontier techniques have been used widely in the empirical studies across various economic activities and industries. In the context of the mining industry, a range of research studies have attempted to investigate efficiency and productivity performance. However, unlike some other industries such as banking, insurance, manufacturing and utilities, the application of frontier techniques in the mining industry has been limited to a few studies conducted at sector, firm or mine levels.

This chapter starts with an introduction to some concepts and mythology background. This review is brief, with a more comprehensive discussion on concepts and methodologies presented in Chapter 4. Section 3.2 provides the basic concepts of efficiency and productivity and discusses their differences from the view of economics literature. The section continues by explaining a frontier approach in efficiency and productivity measurement as opposed to a non-frontier approach. Furthermore, focusing on the frontier approach, it introduces the two prominent methodological streams of efficiency and productivity measurement, namely parametric and non-parametric approaches.

Following the initial introduction on the concept and methods, Section 3.3 reviews the major studies conducted in the mining industry. Due to the differences among studies conducted at sector, firm and mine levels in terms of aims, modellings, policy implication and audiences, the review of each study type is presented in a separate sub-section. Because of the importance of the mining industry in Australia and the defined scope of study in this thesis, the relevant literature in the Australian mining context is presented in a separate sub-section at the end of Section 3.3.

Further to the discussion in Section 3.3 on the existing literature in efficiency and productivity measurement, Section 3.4 reviews the literature in its determinants in the mining industry. In regard to identifying what determines efficiency and productivity performance, limited studies have been published in the context of the mining sector. Therefore, to avoid missing any important dimensions covered in this narrow literature, each section unpacks all relevant studies first and then provides an overall critical discussion on the reviewed literature. Finally, Section 3.5 summarises the application of frontier efficiency and productivity measurement in the mining industry.

3.2 Economic Efficiency and Productivity Concepts

Performance measurement is the process of quantifying the efficiency and effectiveness of action; hence, a performance measure is a metric used in this process to quantify such efficiency and/or effectiveness (Bourne et al., 2003). From an organisational perspective, performance measurement is the process of monitoring resources and investments toward reaching desired targets (Thompson et al. 2007). There are various methods in the measurement of firm performance. Using financial indicators, efficiency and productivity measures and market performance metrics are among common methods used to evaluate the performance of economic units. Accounting and finance literature has broadly used financial ratios in profitability, market value, asset management and financial leverage. However, the economics literature has promoted the application of efficiency and productivity. This section introduces the economics view to firm performance measurement. Furthermore, this section briefly discusses the techniques in economic performance measurement while Chapter 4 presents them in detail.

3.2.1 Productivity and Efficiency

In economics literature, productivity is a common performance measure of economic units. A productivity ratio, which is the ratio of outputs to inputs, is a natural measure of performance.

Obviously, a larger value of this ratio represents a better performance. In the case of a multiple input-multiple output production model, a method of aggregation is needed to obtain a single index for inputs and/or outputs to construct the productivity ratio (Coelli et al., 2005). Hence, even in the case of multiple inputs and/or outputs, the productivity remains as a ratio of two scalars. In addition to the measurement of productivity ratio, the productivity growth is an important measure in economics literature. Productivity growth is calculated as the difference between output growth and input growth (Fried et al., 2008).

The OECD productivity manual (OECD, 2001) outlines the productivity measurement objectives as tracing technology progress, identifying efficiency changes, real cost savings, benchmarking production processes and assessing standards of living. While the concept of productivity seems to be straightforward, there is no agreement on a unique measure of productivity. The choice of productivity measure mainly depends on the purpose of measurement and the availability of data. Productivity can be measured at the industry or firm level, can be single-factor (single input) or multifactor (multiple inputs), and can be calculated using gross output or value-added. Single-factor productivity measures of labour productivity and capital productivity as well as multifactor productivity (MFP) measures of capital-labour MFP and capital-labour-energy-materials-service MFP (KLEMS MFP) are among the most common productivity measures in the economics literature (OECD, 2001).

While productivity and efficiency are closely related, they are not precisely the same. Productivity refers to the ratio of outputs to inputs; however, the efficiency of an economic unit refers to comparing its performance against its best practice. In other words, efficiency measurement involves a comparison between the observed and optimal values of output and input of a producer. Toward such measurement, one can compare observed output to maximum potential output given the available input. Alternatively, one can compare observed input to minimum potential input in production of a given output. If the optimum is defined in terms of production possibilities, the efficiency measure is technical. But if the comparison is between observed and optimum cost, revenue or profit, then the efficiency measure is economic (Fried et al., 2008). Further details in efficiency measurement are provided in Chapter 4.

3.2.2 Frontier and Non-Frontier Approaches

In the measurement of productivity growth, two approaches of least-square econometric production models and total factor productivity (TFP) indices are widely used. These methods are mostly applied to measure technical changes and/or TFP on aggregate time-series data. These approaches assume that all firms are technically efficient (Coelli et al., 2005). That is, these methods do not compare the observed and optimal values of inputs and outputs of economic units as it is assumed producers behave efficiently. Hence, these methods do not attempt to construct the production frontier representing optimal values. Such methods are classified as non-frontier approaches to productivity measurement. Coelli et al. (2005) provides a detailed review of non-frontier methods and OECD (2001) presents a comprehensive manual for the application of a growth accounting framework and TFP index numbers.

On the other hand, frontier approaches do not assume that producers are technically efficient. These methods construct a production technology frontier and compare the observed values against the respective optimal values from the frontier. Pioneered by Koopmans (1951), Debreu (1951) and Farrell (1957), the frontier approach in efficiency and productivity measurement has been developed substantially over the past few decades, particularly in two main streams of mathematical programming and econometrics. These methods are most often applied to a cross-section sample of economic units to measure the relative efficiency among observations. Nonetheless, given the availability of panel data, both frontier approaches are capable of measuring productivity growth and its components including technical changes and efficiency changes (Coelli et al., 2005). The following section provides a brief review on the frontier approaches, but the detailed presentation on these methods is provided in the next chapter.

3.2.3 Parametric and Non-Parametric Frontier Approaches

As discussed above, the frontier approaches to efficiency and productivity analysis rely on the concept of efficiency, which measures the performance of producers relative to their corresponding frontier in a production possibility set. However, the true frontier is not known. Thus, the efficiency and productivity measurement in frontier approaches involves an empirical approximation of production frontier. Mathematical programming and econometric approaches are two dominating streams of frontier efficiency measurement in the economics literature.

The econometric approach consists of a set of techniques involving the econometric estimation of parametric functions. The main advantage of parametric techniques is their ability to incorporate random errors and statistical noise. Stochastic frontier analysis (SFA) is one of the main parametric frontier techniques proposed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977). This technique separates the effect of statistical noise from that of technical efficiency. Furthermore, SFA provides the statistical inferences for the efficiency estimates including standard errors and confidence intervals. Hypothesis testing of endogenous and exogenous factors is another advantage of SFA. However, the main drawback of SFA and in general parametric techniques is the need for adopting pre-defined functional forms of technology frontier and error terms (Fried et al., 2008). In addition, most parametric techniques such as SFA are unable to incorporate multiple outputs directly into the efficiency model; and in the case of small samples, these techniques do not provide a reliable estimation of efficiency and model parameters (Coelli et al., 2005).

On the other hand, the mathematical programming approach consists of a set of techniques that are mostly non-parametric (or deterministic). This approach involves construction of a non-parametric piece-wise surface or frontier over the sample data (Coelli et al., 2005). Data envelopment analysis (DEA) is the most frequently used non-parametric frontier technique, first proposed by Charnes et al. (1978). In this technique, the distance from the frontier represents the degree of inefficiency of a producer. Constant returns to scale (CRS) and variable returns to scale (VRS) are the two main DEA models in the frontier literature. The former model assumes that all producers are operating at their optimum scale while the latter considers the possibility of working away from the optimum scale due to exogenous constraints such as imperfect competition, government regulation and finance.

The non-parametric techniques such as DEA do not require any pre-determined functional form. In addition, their flexibility and ability to incorporate multiple outputs into efficiency model as well as their superior performance in efficiency measurement of small samples make them an attractive approach in the frontier literature. Nonetheless, the main shortcoming of a mathematical programming approach in general, and data envelopment analysis (DEA) in particular, is their deterministic nature. There is no room for statistical noise. The frontier is constructed using the observed values; hence, these techniques are highly sensitive to outliers (Fried et al., 2008).

Recent advancements in efficiency and productivity methodology have closed the gap between parametric and non-parametric techniques. From one side, the development of statistical foundations in mathematical programming techniques has provided the basis for statistical inference. From the other side, developments such as flexible functional forms as well as semi-parametric, non-parametric and Bayesian techniques have overcome the parametric rigidity (Fried et al., 2008).

3.3 Efficiency and Productivity in Mining Industry

This section aims to review and discuss the existing literature on the efficiency and productivity analysis in the mining industry. The attention of this section is mainly turned on the application of frontier techniques; in particular, multiple non-frontier productivity studies that contribute substantially to the body of knowledge in the literature. First, the major frontier studies in the mining industry are reviewed. Due to the differences among mine-level, firm-level and sector-level studies in terms of aims, performance modelling, variables of interest, common methodologies and policy implications, a separate sub-section is assigned to each level of study. Next, studies in the context of the Australian mining industry are examined. Due to the importance of non-frontier studies, the review of the Australian mining literature will include both frontier and non-frontier research.

3.3.1 Application of Frontier Approaches in Mining Industry

In the past four decades, the existing literature on frontier approaches of efficiency and productivity analysis has grown rapidly and the developed theoretical models have been applied across a number of sectors. Fried et al. (2008) summarised some examples of frontier approach application in efficiency and productivity analysis across a broad range of industries. More recently, Aparicio et al. (2016) and Greene et al. (2016) presented various advancements in theoretical modelling and empirical studies in efficiency and productivity analysis. Both dominating approaches, namely parametric and non-parametric, have been applied in performance analysis of various industries. A rich body of literature exists in some industries such as banking, insurance, agriculture, education, hotels and hospitality services, manufacturing and transportations. However, unlike most industries, there are only a limited number of studies applying frontier approaches such as data envelopment analysis (DEA) and stochastic frontier analysis (SFA) to measure efficiency and productivity in the mining industry. These studies looked at the mining industry from different angles. Most early studies focused on the efficiency performance among mines. Sector-level analysis also has been a main interest of researchers over the past two decades. However, firm-level studies have become the centre of efficiency and productivity analysis in recent years.

This section reviews the most relevant efficiency and productivity studies conducted in the mining industry. The majority of these presented studies used frontier techniques; however, this section also includes some significant non-frontier studies in the mining literature. As the aims, the modelling and the audiences of efficiency and productivity studies may vary depending on the level of study, i.e. mine-level, firm-level or sector-level, the literature related to each level is reviewed in a separate sub-section. Nonetheless, various study variables, methodologies and findings are consistent among these studies, so much that none of these three levels can be excluded from the scope of this literature review. Table 3.1, Table 3.2 and Table 3.3 present the details of selected studies on efficiency and productivity at mine, sector and firm levels respectively.

(i) Mine-Level Efficiency and Productivity Studies

In one of the earliest studies, Byrnes et al. (1984) used a frontier approach to estimate the efficiency of a sample of 15 coal mines in the U.S in 1978. They decomposed the Farrell technical efficiency measure into measures of purely technical efficiency, input congestion (which reflects the overutilisation of inputs) and scale efficiency using a non-parametric mathematical approach. The importance of this study in the efficiency literature is due to its attempt to introduce inefficiency sources. Such knowledge aids managers in the mining industry in particular, and other industries in general, to focus on areas causing inefficient operations. Their efficiency model was constructed using one output (tons of coal) and eight inputs (e.g. labour in thousand miner-days, three capital variables of bucket capacity of draglines, dipper capacity of power shovels and earth-moving capacity of wheel excavators) as well as four geological variables (e.g. thickness of first (upper) seam mined, depth to first seam mined, thickness of second (lower) seam mined and depth to second seam mined). The geological input variables are specific to the mining industry and reflect the availability and accessibility of utilised natural resources in mining operations. Byrnes et al. (1984) interpreted these geological variables as a proxy for the ore quality. Based on their study, Byrnes et al. (1984) concluded that efficient mines, in comparison with inefficient mines, are characterised by having more seams, lower labour-output ratio, lower stripping ratio (lower overburden to retrieved coal ratio), higher earth-moving capacity, and being newer and safer. Despite the novelty in modelling efficiency measures, the application of the developed model in this study was limited to a small sample of coal mines. Furthermore, the characteristics of efficient versus inefficient mines were not statistically validated and the reported results were only comparisons of arithmetic averages.

Byrnes and Färe (1987) later examined the sources of inefficiency for a larger sample of surface coal mines in the interior U.S for a cross-section sample of 186 observations in 1978. Using a non-parametric linear programming technique, their study analysed the effect of mine characteristics on efficiency. Following Byrnes et al. (1984), this study constructed a technical efficiency measure consisting of three components including pure technical efficiency, input congestion and scale efficiency. One output (total coal production) and nine input variables including a labour input variable, six capital input variables (reflecting surface coal mining equipment capacity) and two variables to measure geological characteristics of mines (coal seam thickness and depth) were used to estimate technical efficiency measures. Also, five mine characteristics were used to analyse the efficiency measure results. These include location of the mine, the age of the mine, union status of employees, the amount of captive production (i.e. production not sold in open market) and the ratio of acres reclaimed to acres stripped. This study reported that more than 90 per cent of coal mines were not fully efficient, mainly due to their operating under the optimum scale. This study showed that location of operation is a determinant of efficiency gains as Texas outperformed the other states in all components of technical efficiency while Arkansas performed poorly, largely due to scale efficiency. Surprisingly, the study revealed that the unionised mines were more efficiency than non-unionised mines. Overall efficiency and all its three components had higher averages in unionised mines compared to non-unionised mines. Next, the study reported that aged mines (more than 28 years in operation) as well as newly opened mines (less than 3 years in operation) performed poorly. The other unanticipated finding in this research was the revelation of significantly higher efficiency gains in captive mines where extracted mining commodities were not sold in the open market.

In another study for U.S mines, Byrnes et al. (1988) compared the efficiency results of a non-parametric mathematical programming method, substantiating the sources of inefficiency, with a parametric econometric method based on the Cobb-Douglas production function. This study investigated the effects of unionisation on the efficiency performance of U.S surface coal mining. The data used in this study were comprised of two data sets: a cross-section sample of 84 observations of coal surface mines from Interior U.S. in 1978; and a sample size of 113 from an unbalanced panel of 64 Western U.S. coal surface mines over 1975-78 period. Due to different geological characteristics and utilised operation technologies, two samples were not pooled but treated separately. In construction of efficiency measures, this study used one output (total production), and nine input variables including a labour input, six capital inputs (e.g. equipment capacity for removal of overburden, coal extraction and land reclamation), and two geological variables (e.g. thickness of coal seams and inverse of overburden thickness or volume). Results from the non-parametric technique in this study revealed the significant level of inefficiency (nearly 40 per cent) among mines in the samples. Also, this study attributed the inefficiency mainly to input congestion in both Interior and Western samples. Furthermore, non-union mines were reported to have lower efficiency performance due to input congestion in Western mines and operating beyond the optimal scale in Interior mines. Similar to the findings from the non-parametric approach, the results of the parametric approach in this study confirmed that union mines are more efficient than non-union mines. However, the econometric approach was unable to provide information on the source of inefficiency.

These three studies for U.S. mines introduced a useful quantitative framework to evaluate the technical efficiency of mining activities. Although these studies looked at mining activities at mine level, their findings from efficiency modelling and analysis can aid decision makers beyond mining operations, such as through corporate leadership in mining firms or government authorities for developing mining sector policy and strategies.

Using an unbalanced data panel of 419 mines over 1996 to 2005, Koop and Tole (2008) conducted a Bayesian econometric frontier technique to evaluate technical and environmental efficiency in the gold mining industry. This research includes the volume of mined ore as the main production output in the econometric model. Gold mining can be involved in the extraction of other metal ores; therefore, in addition to the volume of gold production, this study measured the production volume of copper and silver as two other outputs of mining operations when applicable. Waste, measured as all geological and chemical-geological waste from the processing stage, as well as low-grade ore served as a bad environmental output of mining operations. The set of explanatory variables in this study include the type of mining operation (i.e. open-pit or underground) and the geological characteristics represented by resources (measured by total probable and proven ore reserves), and ore grade (measured using the grade of ore in the ore body). Following the economics literature, labour measured as total full-time employees and capital proxied by project cost were included in the model as conventional inputs; however, due to the unavailability of data for many mines in the sample, these two variables are excluded in the analysis. The effects of ownership (foreign or domestic) as well as location country (rich or poor) on efficiency estimates were also examined in this study.

The findings of the multiple input-multiple output Bayesian frontier model in this study show that there is no systematic difference in technical and environmental efficiency of mines located in rich or poor countries or those that are owned domestically compared to those with foreign ownership. The authors argued that due to the presence of multinational mining firms in operation of these mines, irrespective of the location of operation, a standard of performance defined by rich countries is evident across the operating mines.

In a comparative study, Tsolas (2011) used data from Byrnes et al. (1984) and Thompson et al. (1995) to investigate the variations in efficiency estimates of strip coal mining when taking into consideration undesirable outputs as well as random errors in the sample data. The author developed a bootstrap DEA model including two inputs of labour (in thousand man- days), capital (in million dollars), one desirable output of extracted coal (in thousand tons) and one undesirable output of overburden (thousand tons). The results from the output-oriented DEA model under weak disposability and variable returns to scale (VRS) assumptions did not show the significance of undesirable output in estimation of technical efficiency scores. However, by applying a bootstrap technique, greater inefficiency was detected in coal mining activities.

Except Koop and Tole (2008), the remaining reviewed studies in efficiency and productivity analysis of operating mines applied non-parametric frontier techniques. Largely, the intention of these studies has been the evaluation of technical efficiency which seems to be a more appropriate efficiency measure at an operational level. None of these studies evaluated the economic and allocative efficiency measures due to the lack of financial information and factor prices. Such economic measures can aid leadership teams in mining companies in formulation and evaluation of their strategies at both corporate and operational levels.

From an efficiency modelling point of view, the input/output variables defined in these studies are operational. Labour is measured as total working hours or man-days and capital is measured based on the capacity of extraction equipment utilised in mining activities. Output is measured as the volume of production. Also, mine geological variables, such thickness and depth of seams or volume of overburden and extraction, are a main part of efficiency modelling and analysis for mine-level studies. To maintain homogeneity in the research sample, these studies looked at one specific mining activity. However, the investigated mining activities in these studies are limited to coal and gold.

One other highlight from the review of the existing mine-level efficiency and productivity literature is that these studies have concentrated more on non-parametric techniques. Both frontier approaches have the ability to be used in performance measurement and the benchmarking of operational activities such as mining operations. Perhaps the difference in the origins of parametric and non-parametric techniques can explain why non-parametric techniques, as opposed to not parametric techniques, have been used mostly in mining-level efficiency studies. As explained in the frontier literature (see e.g. Fried et al., 2008), the parametric frontier techniques are based on econometric modelling. These techniques have been developed in economics and they are vastly used in the efficiency and productivity analysis of economic agents at both macroeconomic and microeconomic levels. On the other hand, non-parametric mathematical programming techniques have been developed in management science. Focusing on decision making units (DMUs), these techniques are powerful tools in the benchmarking of operational units and companies in terms of their ability to transform inputs into outputs.

In general, studying the efficiency and productivity of mining operations under the production frontier approach seems to be an underresearched area which could utilise recent methodological developments to investigate efficiency- and performance-driving factors.

Table 3.1: Selected mine-level studies on efficiency and productivity of mining industry

Study	Method	Data	Inputs/Outputs	Indexes	Results
Byrnes et al. (1984)	DEA	15 Illinois strip coal mines in the U.S., 1978	Inputs: Labour, capital variables (capacity of draglines, power shovels, wheel excavators), geological variables (first seam thickness, first mined seam depth, second seam thickness, second mined seam depth) Outputs: Production volume	Overall technical efficiency Pure technical efficiency Input congestion Scale efficiency	Minimum efficiency score was 64%. A major source of inefficiency was identified as the non-optimal scale of production. The pure technical efficiency score of all mines was 100%. Characteristics of efficient mines: higher number of seams, less labour output ratio, less non-fatal accident, less mine opening duration, less stripping ratio and more earth-moving capacity.
Byrnes and Fare (1987)	DEA	186 coal mines in the U.S., 1978	Inputs: Labour, capital variables (number of draglines and power shovels, total loaders and brooms, total of scrapers, dozers and graders), thickness of seams, inverse of thickness of overburden excavated)	Overall technical efficiency Pure technical efficiency Input congestion Scale efficiency	With an average of 46% efficiency, the major source of inefficiency was deviation from the optimal scale. Unionised mines showed better performance than non-unionised mines, and captive mines were more efficient than non-captive mines.
Byrnes et al. (1988)	DEA Econometric Analysis	A: 84 interior surface coal mines in the U.S. in 1978 B: 64 western surface coal mines in the U.S. from 1975 to 1978	Inputs: Labour, capital variables (number of draglines and power shovels, total loaders and brooms, total of scrapers, dozers and graders), thickness of seams, inverse of thickness of overburden excavated) Outputs: Production volume	CRS technical efficiency NIRS technical efficiency VRS technical efficiency Input congestion Scale efficiency	On average, mines were 60% efficient. The overall efficiency of union mines was more than non-union mines. The results for the econometric method were consistent with the DEA results.
Koop and Tole (2008)	Bayesian stochastic production frontier	419 mines over 1996 to 2005	Inputs: Labour, capital, waste, ore grade, ore resources, mine operation type Outputs: production of gold, copper and silver (desirable), waste (undesirable)	Technical efficiency Environmental efficiency	Waste, ore grade and type of mine operation significantly contribute to production output; however, the effect of ore resources on production is not statistically evident. On average, mines in the sample were 68% environmentally efficient, regardless of being located in a rich or a poor county.
Tsolas (2011)	DEA (output oriented VRS DEA) Bootstrap-DEA	15 Illinois strip coal mines in 1978 (using data from Byrnes et al (1984) and Thompson et al. (1995))	Inputs: Labour, capital Outputs: Mixed mine environmental performance indicato r (production volume as desirable output divided by overburden as undesirable output).	Technical efficiency: -Point estimates -Bias-corrected estimates -Confidence intervals	Omitting undesirable output did not cause significantly biased efficiency results. The bootstrapped results showed that mines were less efficient than that achieved by point estimation (with an average of 2.142 in bias-corrected estimates than 1.775 from the original model).

(ii) Firm-Level Efficiency and Productivity Studies

Fang et al. (2009) applied a non-parametric model to compare coal mining companies in China with the U.S. Their sample consisted of 17 Chinese and 8 American coal mining companies. In this paper, Fang et al. (2009) constructed an input-oriented DEA model using operating costs, total assets and number of employees as inputs, and earning per share, operating revenue and net profit before tax as outputs. Their findings revealed that the American coal mining companies outperformed their Chinese counterparts in the overall measure of technical efficiency as well as component measures of pure technical efficiency and scale efficiency. They discussed that state ownership, being in an early development stage, low industry concentration, over-competitiveness and high withdrawal threshold are among main contributors of poor efficiency performance in the coal mining industry in China.

In the investigation of profit efficiency in the mining industry of South Africa, Potuma and Kumo (2010) applied stochastic frontier analysis to estimate the efficiency performance of 14 small and medium-sized mining firms over the 2003-2006 period. With taxable income as a dependent variable, they used data from financial statements to define explanatory variables including wage bill, sales revenue, gross interest income, interest expenses, other income and asset size. Based on the findings from this study, there is a significant degree of inefficiency among the small and medium-sized mining firms in South Africa. With high variation, the average profit efficiency was only 37 per cent among the selected SMEs over the study period. Also, the authors found that the ranking of high-performing companies have been reasonably stable from 2003 to 2006.

Eller et al. (2011) applied data envelopment analysis (DEA) and stochastic frontier analysis (SFA) to compare the efficiency of national oil companies with international private oil companies. Their sample consisted of a panel of 78 oil companies over three years from 2002 to 2004. The set of variables in this study included three inputs including number of employees, volume of oil reserves and volume of natural gas reserves, and one output of revenue. The authors found that the efficiency estimates from the output-oriented CRS DEA and the maximum likelihood SFA models are highly correlated and two orderings are not independent. Hence, the authors concluded as the results from these two different techniques are consistent, the variations observed among efficiency estimates are due to firm-specific characteristics and not due to the applied estimation method. They argued that due to differences in firm structural and institutional features, national oil companies were less efficient than international private oil companies.

To investigate the role of ownership in the efficiency performance of mining companies, Dos (2012) examined the productivity growth of 65 Indian mining firms over the period 1988-89 to 2005-06. Using 872 observations in this sample, they estimated the total factor productivity (TFP) of firms at the first stage and then computed the sector weighted average TFP including mining industry and its four sub-sectors of metallic, non-metallic, coal and petroleum. The Cobb-Douglas production function applied in this study includes deflated production values as a proxy for production output as well as gross fixed assets, estimated labour hours and deflated energy cost as proxies for labour, capital and energy inputs, respectively. From a methodological point of view, the author argued that the estimated coefficients of labour, capital and energy from the OLS method are biased when compared to results derived from a semi-parametric method developed by Levinsohn and Petrin (2003). Also, in the context of mining industry productivity, this research showed that private companies are significantly more efficient than their public sector counterparts in metallic, non-metallic and coal mining. However, the petroleum sector presents a different pattern with a higher but declining TFP index in private companies in the first half of the study period and almost comparable trends in the second half. In general, productivity in both private and public companies improved over the course of study. Further regression analysis in this study revealed that private ownership as well and initial TFP level play a significant and positive role in productivity gains. While age does not significantly contribute to productivity performance in the mining industry and petroleum sub-sector, it positively influences the level of TFP index in metallic, non-metallic and coal sub-sectors.

In development of a DEA model for environmental assessment, Sueyoshi and Goto (2012) applied a non-radial DEA model to investigate the efficiency performance of 19 national and international oil companies over 2005 to 2009 in the presence of undesirable outputs. Their model includes four inputs (oil reserve, gas reserve, operating cost and number of employees), two desirable outputs (oil production and gas production) and one undesirable output (CO2 emissions). This study considered two types of unification for desirable and undesirable outputs in their environmental assessment using DEA; first, decreasing an input vector along with decreasing the undesirable vector (referred as natural disposability), and second, increasing an input vector while decreasing the undesirable output vector (referred to as managerial disposability). The authors argued that under the natural disposability approach, national oil companies gain higher efficiency than those international private companies. However, under a managerial disposability approach, international oil companies outperform the nationally owned companies. Furthermore, while mixed results were observed among national oil companies in terms of their returns to scale (RTS) status, all international oil companies require decreasing the operational scale. Also, both national and international oil companies need to decrease their operational size to improve their environmental performance in CO2 emissions.

Geissler et al. (2015) used DEA to analyse the technical efficiency performance of 24 world-leading state-owed and publicly quoted companies operating in phosphate rock mining in 2012. They considered two model specifications based on the arrangement of output variables. Both models included operating costs, total assets and number of employees as three inputs; however, their first model used turnover and EBIT as two outputs while their second model only used EBIT to improve discrimination power of the model. The results of the input-oriented DEA models in this study showed that model specifications have a negligible effect on efficiency estimates. In both models, it was found that the phosphate rock mining companies are above 90 per cent efficient. Although the findings of this study indicate that scale inefficiency is not a chief concern, most firms can increase their operating scale to improve their efficiency. In terms of input reduction strategy, the first model of this study suggested that employees are the first input to focus on, with an average reduction target of 19.8 per cent followed by total assets and operating costs with an average reduction target of 11.3 per cent and 7.3 per cent respectively. Despite the observed difference between arithmetic averages of the efficiency performance of state-owed and publicly quoted companies, further statistical analysis did not confirm the significance of this difference.

The existing literature in firm-level studies of mining efficiency and productivity shows that this research area has only received attention in recent years. Using both mathematical programming and econometric modelling techniques, few studies have been published regarding the evaluation of efficiency or productivity growth. While some studies limited their scope to mining activities in a specific county, other studies took a cross-country approach in the evaluation of mining firms' efficiency. Technical efficiency, revenue efficiency and productivity growth are among the key measures being investigated in firm-level studies. Despite recent methodological advancements, such as statistical foundations in the programming approach or flexible functional forms in econometric approach, the existing firm-level literature mostly relies on the application of DEA and SFA which were developed decades ago. Among these studies, only Sueyoshi and Goto (2012) applied a more advanced method in mathematical programming approach.

Most firm-level studies have used financial statements to extract the variables of efficiency models. Number of employees, operating expenses and total assets are among most common inputs and revenue is the most common output in these studies. Unlike mine-level studies, none of the firm-level studies have discussed the role of natural resource inputs in the efficiency performance of mining firms. While ore quality and accessibility are main drivers of production output given a certain level of input consumption, formulating a variable reflecting these characteristics of mining operations at corporate level seems to be a vital but challenging task.

Similar to mine-level studies, each firm-level study focuses on one specific mining activity. Although this approach sounds appropriate in terms of the homogeneity of the sample observations, it imposes some risks onto the efficiency modelling and data selection. Major mining companies across the globe are active in the exploration and extraction of several mining products. Diversification helps companies to achieve economies of scope. It enables them to utilise the available productive capacity and operation capabilities in areas requiring such resources (Chakrabarti et al. 2007; Nath et al. 2010). Furthermore, diversification reduces the risk associated with significant variations in mining commodity prices. If prices of one mining commodity experiences sharp decline, diversification weakens the adverse impact of such variation on business performance. The significance of price variations of mining commodities is evident in the economic trends. For instance, both International Trade Price Indexes (ABS, 2018b) and Producer Price Indexes (ABS, 2018c) show a significant price fluctuation in the mining sector, compared with other Australian economic sectors over the past two decades. Hence, mining companies are encouraged to diversify their portfolio. When it comes to the study of efficiency and productivity of mining firms, it is essential to understand if mining companies are involved in only one mining activity or in a diverse portfolio. The published financial statements of companies usually do not provide that level of detailed information to separate resources used in each mining activity. As financial statements have been the original source of most conducted studies, it is not clear how these studies distinguished the utilised resources in each mining activity in the case of diversified portfolios. Overall, there has been some progress toward firm-level studies of efficiency and productivity in the mining sector in the last decade. However, some areas such as efficiency modelling, variable selection and application of frontier methods require further work.

Table 3.2: Selected firm-level studies on efficiency and productivity of mining industry

Study	Method	Data	Inputs/Outputs	Indexes	Results
Fang et al. (2009)	DEA, Input Oriented	17 Chinese and 8 American coal mining companies between 2001 and 2005	Inputs: Operating costs, total assets, number of employees Outputs: Earning per share, operating revenue, net profit before tax	Overall technical efficiency Pure technical efficiency Scale efficiency	Chinese coal companies with an average of 77% were less efficient than American coal companies with an average of 93% in overall technical efficiency measure.
Putuma and Kumo (2010)	SFA	Panel 14 mining SMEs in South Africa from 2003 to 2006	Inputs: wage bill, sales revenue, gross interest income, interest expenses, other income, asset size Outputs: Taxable income	Profit efficiency	In terms of profit efficiency, selected mining SMEs in South Africa performed poorly over 2003 to 2006. High variation in efficiency performance was observed. Ranking of high performing firms was reasonably stable over this period.
Eller et al. (2011)	DEA, Output Oriented SFA	Panel of 78 national oil companies and private international oil companies from 2002 to 2004	Inputs: Number of employees, oil reserve, natural gas reserve Outputs: Revenue	Revenue efficiency	Using DEA method, on average revenue efficiency of national oil companies was 28% considerably less than revenue efficiency of five major private international oil companies with an average score of 73%. There was no significant difference between DEA and SFA results.
Das (2012)	Non-frontier TFP estimation (OLS and SPM)	872 observations on 65 Indian mining firms, public and private from 1988-1989 to 2005-2006	Inputs: Labour hours, gross fixed asset, energy Outputs: production value	TFP index	Except the petroleum sector, the estimated TFP of private companies was higher than public companies.
Sueyoshi and Goto (2012)	Non-radial DEA	19 national and private international oil companies from 2005 to 2009	Inputs: Oil reserve, natural gas reserve, operating cost, number of employees, Outputs: Oil production, gas production, CO2 emission	Technical efficiency	Efficiency of private international companies was higher than the national oil companies under a managerial disposability assumption. But under a natural disposability assumption, national oil companies outperformed those in private companies. Under managerial disposability, the minimum efficiency score among companies was 81%.
Geissler et al. (2015)	Input-oriented DEA	24 world-leading companies in phosphate rock mining in 2012	Inputs: Operating costs, total assets, number of employees Outputs: Turnover, EBIT	Overall technical efficiency Pure technical efficiency Scale efficiency	With an average of 93%, publicly quoted companies seemed to be more efficient than state-owned companies with an average of 88%; however, the difference was not statistically significant.

(iii) Sector-Level Efficiency and Productivity Studies

In a study on the Indian mining sector, Kulshreshtha and Parikh (2002) analysed the efficiency and productivity changes of 30 major areas of underground and opencast coal mining for the period 1985 to 1997. This study used the Malmquist index to estimate and compare the total factor productivity (TFP) growth for the periods 1985-1990, 1990-1995 and 1995-1997. Also, data envelopment analysis (DEA) is used to investigate the technical efficiency of underground and opencast mining for the years 1985, 1990, 1995 and 1997. Total coal production used as main output in both underground and opencast mining. The amount of overburden removal was considered as an output in opencast mining, in addition to actual output of coal. Inputs in this study consisted of labour input (labour employed in manshifts), machineries (specific to underground and opencast mining aggregated in horse power unit), cranes and dumpers in the case of opencast mining, and rope haulage in the case of underground mining. Kulshreshtha and Parikh (2002) considered the geological characteristics of mining activities as a non-discretionary or non-controllable variable because of resource depletion. In the DEA model, the authors assumed that rope haulage used in underground mines to be a non-discretionary input variable (due to adverse effect of resource depletion on utilisation of rope haulage) and the overburden removal to be a non-discretionary output variable in opencast mining (due to the dependency of the volume of overburden on the natural resource accessibility and depletion). This study conceded that unlike common perceptions, the efficiency of Indian opencast mining declined over 1985-1990, 1990-1995 and 1995-1997 periods. The productivity growth in opencast mining was primarily due to technical changes while the main driving factor behind productivity changes in underground mining was efficiency gains.

Focusing on the limitation of conventional growth accounting methods to identify the source of productivity growth, Asafu-Adjaye and Mahadevan (2003) used a stochastic cost frontier model to investigate the factors driving productivity growth in the Australian mining sector. In their study, output growth was decomposed into input growth and total factor productivity (TFP) growth, and further TFP growth was decomposed into economic efficiency, returns to scale, technological progress and price effects. Asafu-Adjaye and Mahadevan (2003) used a panel data consisting of five major Australian mining sub-sectors including coal, iron ore, copper, gold and oil and gas from 1968-1969 to 1994-1995 period. In developing their econometric model, Asafu-Adjaye and Mahadevan (2003) adopted a parametric cost frontier function developed by Schmidt and Knox Lovell (1979). The set of variables in this study included gross output, total cost (sum of expenditure on all inputs) and input prices of capital, energy and labour. The authors found that the output growth in all mining industries in Australia was mainly due to the input growth owing to the nature of mining industries which are highly capital- and energy-intensive. On the other hand, it was found that Australian mining industries performed poorly in improving their productivity. They pointed out that both cost (allocative) and technical inefficiencies were the primary causes of poor productivity growth.

Based on their previous work, Mahadevan and Asafu-Adjaye (2005) attempted to test the link between inflation and productivity growth. This study furthermore examined the effects of mineral price inflation, interest rate and export growth on the productivity growth of the Australian mining industry. In the first stage, the authors estimated the TFP growth using a translog cost frontier function with variables including gross output, total cost and input (capital, energy and labour) prices. In the second stage, they applied the Granger-causality tests and the Vector Autoregressive (VAR) model to examine causality between exogenous economic variables and the productivity growth. The results of the study revealed a negative effect of inflation on productivity growth. Their findings supported the inflation-targeting policy implemented by the Reserve Bank of Australia (RBA) in 1993. Also, the authors commented that the mineral price inflation had a stronger negative impact on the productivity growth than the domestic inflation, through its adverse impact on mineral export. A higher mineral price can reduce foreign demand for Australian minerals in the global market in the presence of high competition from other counterparts.

In relation to the issues around a conventional productivity index using the Solow Residual technique in extractive industries, Rodríguez and Arias (2008) used a translog variable cost function to evaluate the productivity growth in Spain's coal mining sector from 1975 to 2001. The variable cost function was estimated using price and quantity information of inputs including labour, capital, materials and energy as well as information for prices and quantities of coal production as the only output in the model. To capture the effects of natural resource depletion, the authors included the level of mineral reserves in their model. This research reported that over the study period the effect of non-optimal allocation of fixed factors (capital), non-constant returns to scale and resource depletion on estimated Solow Residual TFP was sizeable. Among others, the resource depletion appeared to be a more significant factor determining productivity growth, demonstrating a consistently negative effect over the study period. Accounting for the effects of capital, scale of operation and resource depletion, Rodríguez and Arias (2008) reported differentials between their corrected estimates of the technological progress and those estimates from a conventional Solow Residual technique.

In another sector-level study, Tsolas (2010) applied both non-parametric and parametric approaches to evaluate the methodological variation of efficiency estimates in Greek bauxite mining over 1970 to 1996. The non-parametric approach followed a bootstrap DEA method introduced by Simar and Wilson (1998) to account for noise and random error in the sample data. The efficiency model in this study was constructed using real bauxite production as only output and total man-shift paid and fixed capital depreciation as proxies for labour and capital service inputs. The Wilcoxon/Mann–Whitney and Kruskal–Wallis tests revealed a significant variation among efficiency estimates obtained from DEA and SFA methods in this study. SFA tends to provide higher technical efficiency estimates than those derived from DEA. However, there is a strong correlation between efficiency estimates from the two approaches. This correlation improves if bias-corrected DEA estimates are used.

In a study in the Australian mining context, Lovell and Lovell (2013) questioned the magnitude of the productivity decline in the Australian coal mining industry reported by Productivity Commission in Topp et al. (2008). Following their index number methodology, Lovell and Lovell (2013) applied some minor revisions on the underlying data and re-estimated the productivity growth in the period 1991-92 to 2006-07. The outcomes of this re-evaluation present a reduction of 4 per cent in the size of productivity (from 25 per cent to 21 per cent) during the mining boom period of 2000-01 to 2006-2007. Both approaches, in estimating capital input quantity index – including the use of capital income share in factor income or the use of capital expense share in factor cost – led to negligible differences in estimates of productivity changes. Moving from a value-added framework to a gross output framework, the authors found consistent trends but a significant change in the estimated productivity index. Productivity declined from 21 per cent to 13 per cent over the period 2000-01 to 2006-07. They argued that due to the importance and significant contribution of intermediate inputs (including outsourcing) to gross output in coal mining, gross output framework is a useful complement to the value-added framework. In terms of the financial implications of productivity changes in Australian coal mining, Lovell and Lovell (2013) concluded that the financial performance of coal mining improved over the period of study; the productivity growth served as main contributor of financial performance to 2000-01, but due to the increased demand for coal, the price recovery induced the improving financial performance thereafter.

In another study in the Australian mining industry context, Zheng and Bloch (2014) investigated the poor mining productivity performance during the 2000s reported in conventional reports. They discussed that there is a systematic weakness in the growth accounting framework in measuring mining MFP. The growth accounting framework ignores the violations in the competitive markets and long-run equilibrium assumptions; also, this framework does not include resource inputs in mining productivity. They formed a dual measure of MFP for mining to analyse the relationship between true and conventional measured MFP. Their analytical model was based on a translog variable cost function to decompose the measured MFP to the components capturing the true MFP as well as the effects of return to scale, quasi-fixity of capital (capacity utilisation) and natural resource inputs. In their productivity analysis model, Zheng and Bloch (2014) included one output (gross value added) and three inputs (labour measured by labour service cost, capital measured by productive capital stock and resource inputs proxied by productive capital stock for mineral and petroleum exploration). Using sector-level data from 1974-75 to 2007-08, they found that unlike declining trends in conventional measured MFP (on average by 0.2 per cent per annum), the true productivity measure reflects productivity improvement by an average of 2 per cent per year. The presence of moderate decreasing returns to scale resulted in a negative scale effect on the measured productivity by an average of -0.2 per cent per annum. As production either above or below capacity incurs a higher cost, low capacity utilisation in the 1980s and 1990s, followed by over-capacity production in 2000s, had been responsible for a considerable negative effect (by around -1.4 per cent per annum) on the measured MFP. Resource inputs also played a negative role in the productivity performance of the Australian mining sector, influencing the measured MFP by -0.66 per cent per annum over the study period. The authors concluded that due to the effects of natural resource inputs as well as capacity utilisation and operating scale in conventional measured MFP, focusing on this measure without consideration of its components misinforms decision makers in the mining industry.

As presented above, more efficiency and productivity studies have been conducted at sector-level compared to mine-level or firm-level studies. Among all mining sub-sectors, coal mining has been the centre of most studies which shows the importance of this industry in the global market. The Australian mining industry also has attracted the most attention in the existing literature on mining efficiency and productivity. Given the position of the mining sector in Australia's economy, this focal point is not surprising. From a methodological perspective, most studies have applied econometric techniques. As expected, economy-wide and sector-level studies are dominated by economists, which is evident from their preference in the application of the econometric techniques as opposed to the mathematical programming techniques.

The sector-level studies reviewed in this section have largely focused on productivity growth. Consistent with economy-wide studies, it is more appropriate to study productivity growth and its contributing components in the sector-level research. Total factor productivity (TFP) or multifactor productivity (MFP) indices are used in these studies to evaluate productivity growth in the mining sector. Labour, capital and intermediate inputs are the three main inputs in the existing literature. With slight variations, the variables used to measure these inputs are consistent among these studies. Also, real value added, real gross output and production output are among the main variables used to measure output in productivity models. The main difference among these studies concerns the consideration of natural resource inputs. Only two studies have included natural resource inputs (or the effects of geological characteristics) in their productivity models. Kulshreshtha and Parikh (2002) included overburden removal as the undesirable output, which partially reflects the effects of natural resource characteristics. Zheng and Bloch (2014) is the other study that investigated the effects of natural resource inputs on productivity growth. They used mineral and petroleum exploration capital stock as a proxy for natural resource inputs.

Despite the low number of articles published in sector-level productivity studies, the developed literature covers various aspects of sector performance. Both productivity measures and driving factors have been discussed in these studies. Specifically, in the context of Australia, a valuable set of studies have been conducted over the past two decades such as Mahadevan and Asafu-Adjaye (2005), Lovell and Lovell (2013) and Zheng and Bloch (2014). These studies contributed to the literature by emphasising the importance of productivity components (including technological progress, operating scale, capacity utilisation and natural resource inputs) in the interpretation of productivity measures. Moreover, Mahadevan and Asafu-Adjaye (2005) is among the very few mining sector studies that investigated the role of macroeconomic factors (such as inflation, commodity prices, export and interest rate) in productivity growth.

Nevertheless, there are other areas to further explore in future sector-level studies. The development of more accurate methods to capture the effects of natural resource inputs, the investigation of undesirable outputs (specifically, environmental impacts of mining operations), and the testing of economic driving factors both nationwide and globally are among the possible future research topics.

Table 3.3: Selected sector-level studies on efficiency and productivity of mining industry

Study	Method	Data	Inputs/Outputs	Indexes	Results
Kulshreshtha and Parikh (2002)	DEA Malmquist Index	30 coal mining areas (Underground and Opencast) from 1985 to 1997 in India	Inputs: Man-shift, mining machineries (in horse power unit), cranes and dumpers (opencast), rope haulage Outputs: Production volume, overburden removal	Malmquist productivity Technical efficiency	There were rises and declines in both opencast and underground mine productivity over the study period. The productivity improvement in opencast mining was technology growth-driven, but efficiency growth-driven in underground mining.
Asafu-Adjaye and Mahadevan (2003)	SFA (translog cost frontier, input oriented)	Australian mining sub-sectors: Coal, Iron Ore, Copper Ore, Gold Ore, and Oil and Gas from 1968-1969 to 1994-1995	Inputs: Total cost (aggregation of all input prices including capital, energy and labour) Outputs: Value added	Output growth Input growth TFP growth Economic efficiency Returns to scale Technological progress	Mining output growth was largely input-driven, rather than productivity-driven. Cost inefficiency was the main factor causing low TFP growth.
Mahadevan and Asafu-Adjaye (2005)	SFA (translog cost frontier, input oriented)	Australian mining sub-sectors: Coal, Iron Ore, Copper Ore, Gold Ore, and Oil and Gas from 1967-1968 to 1997-1998	Inputs: Total cost (aggregation of all input prices including capital, energy and labour) Outputs: Value added	Output growth Input growth TFP growth Economic efficiency Returns to scale Technological progress	Price inflation (domestic inflation slightly and mineral prices strongly) had a negative effect on mining TFP growth. Interest rate had a slight negative effect, but export growth had a positive influence on the mining TFP growth.
Rodriguez and Arias (2008)	Translog vari able cost function (TFP growth study)	Spain's coal mining sector from 1975-2001	Inputs: Labour, material, energy, capital, reserves Outputs: Production volume	Solow Residual TFP growth Technical change effect Fixed factors Scale of production Resource depletion effect	On average, around 5% TFP growth was recorded over the period. Reserves depletion had a significant negative effect on productivity growth. Non-optimal allocation of fixed factors and non-constant return to scale showed slightly positive effects on productivity growth.
Tsolas (2010)	DEA (output-oriented NIRS DEA) Bootstrap-DEA SFA	Greek bauxite mining from 1970 to 1996	Inputs: Labour (total man-shift hours paid), Capital (fixed capital) Outputs: Production volume	Technical efficiency	SFA and DEA did not provide similar results (DEA exhibits more inefficiency than SFA), but there was a positive relationship between results of DEA and SFA.
Lovell and Lovell (2013)	Non-frontier TFP estimation (Cobb-Douglass production function)	Australian coal mining from 1990-91 to 2006-07	Inputs: Gross fixed capital formation, number of persons employed, intermediate inputs (only in the gross output model) Output: Value added / gross output	Tornqvist productivity index	Unlike previous reports, the magnitude of productivity decline was estimated to be 21% over 2000-01 to 2006-07 using the value-added framework; moreover, using the gross output framework the productivity decline shrinks to only 13%.
Zheng and Bloch (2014)	Translog vari able cost function	Australian mining sector between 1974–1975 and 2007–2008	Inputs: Labour service, capital service, mineral and petroleum exploration capital stock Outputs: Gross value added	Multifactor productivity index	After removing the effects of returns to scale, capacity utilisation and natural resource inputs, from 1974-75 to 2007-08 MFP grew by 2% per annum, significantly higher than the published MFP index of -0.02% per annum.

3.3.2 Mining Efficiency and Productivity Studies in Australia

Due to the importance of mining in the Australian economy, several studies have investigated the sector's productivity growth and its determinants. While these studies have focused on the productivity performance at the sector level, their findings can support decision makers in mining businesses in addition to those in federal and state governments. This section aims to look at the existing literature in the Australian context to understand, first, the productivity performance of the mining sector in Australia, and second, the determinants driving this performance particularly in recent years.

Among the early studies in efficiency and productivity analysis of the Australian mining industry, Asafu-Adjaye and Mahadevan (2003) and Mahadevan and Asafu-Adjaye (2005) in two separate papers argued the limitation of conventional growth accounting methods to identify the source of productivity growth. Using a stochastic cost frontier model, they investigated the components of TFP growth, namely economic efficiency, returns to scale, technological progress and price effects, in five major Australian mining sub-sectors including coal, iron ore, copper, gold and oil and gas between 1968-1969 and 1994-1995. Their study reported that the poor TFP performance of the Australian mining industry was associated with weak cost efficiency. Moreover, they revealed the strong relationship between productivity growth and economic factors of domestic inflation, mineral price inflation, interest rate and export growth.

Toward an investigation into the nature and causes of the mining productivity growth in Australia, Topp et al. (2008) analysed data from the ABS and other sources over the period 1974-75 to 2006-07. They found that the Australian mining industry had a negligible MFP growth of 0.01 per cent per annum over the study period, with a sharp decline by 24.3 per cent between 2000-01 and 2006-07. They reported that a slow output growth along with a strong growth in labour and capital inputs are to be blamed for this poor performance. To explain why output growth could not keep pace with input growth, Topp et al. (2008) discussed the role of resource depletion and investment-production lag in the mining activities. Accounting for the quality of natural resource inputs and the lag between capacity building investment and production, they estimated both the conventional and adjusted MFP growth of the mining sector and sub-sectors in Australia.

To capture the effects of resource depletion, the authors introduced a composite yield index using the average metal ore grades, the saleable to raw coal ratio, as well as the implicit oil and gas flow rates. According to this index, they found that the composite index of mining yield fell by 1.5 per cent per annum between 1974-75 to 2006-07. Taking into consideration the effect of resource depletion using the yield index, the MFP growth changes to 2.5 per cent per annum in comparison with 0.01 per cent per annum growth in the unadjusted MFP over this period. Furthermore, focusing on the sharp decline in the mining productivity index between 2000-01 to 2006-07, Topp et al. (2008) discovered that both resource depletion and capital-production lag contributed substantially to the deterioration of the mining MFP performance in Australia. By removing the adverse effects of these two factors, the MFP increases by 8 per cent from 2000-01 to 2006-07.

Loughton (2011) criticised the practicality of the composite yield index proposed by Topp et al. (2008) and argued that the required data to construct such measure is not readily available on an annual basis for a National Statistical Office. As an alternative method, Loughton (2011) proxied the natural resource inputs by the ratio of cumulative extraction to the total reserves available for extraction and found that the quality of natural resources in mining decreased significantly from 1985-86 to 2009-10. Controlling for the adverse effect of natural resource quality resulted in a positive annual MFP, changing by 2.05 per cent instead of a negative change of -0.15 per cent per year officially reported.

Syed et al. (2013) and Syed et al. (2015) examined the productivity growth in the Australian mining industry at national, regional and sector levels. Further to the estimation of productivity growth over 1985-86 to 2009-10 period, their research outlines the measurement and interpretation issues surrounding the conventional productivity reports in the context of the mining industry. In line with findings by Topp et al. (2008), they argued that the main contributors to the poor productivity performance are resource depletion and production lags. After removing the effects of resource deposit quality (proxied by energy consumption) and production lag (estimated as a two-year lag), the MFP growth of Australian mining increases from -0.65 per cent per annum to 2.5 per cent per annum between 1985-86 and 2009-10. Using a stochastic frontier production function, they also decomposed the components of productivity growth and found that, in contrast to insignificant technological progress, technical efficiency and scale effects contributed positively and significantly to the Australian mining MFP over the study period.

In a discussion on the reported productivity trends in the Australian coal mining, Lovell and Lovell (2013) revised data used by Topp et al. (2008) and re-estimated the MFP growth. They found that by applying some changes in the underlying data, the MFP changes over 2000-01 to 2006-07 decrease from 25 per cent to 21 per cent. Moreover, moving from a value-added framework to a gross output framework of MFP index, the MFP changes shrink to 13 per cent, which reflects the importance of intermediate inputs such as outsourcing in coal mining.

Topp and Kulys (2013) discussed the role of natural resource inputs on measured value added and the MFP estimates, while such inputs are not measured directly in the National Account. They emphasised that while the publication of an adjusted measure of MFP for the natural resource inputs by the ABS is useful to realise their contribution to productivity performance, the reliability of the gathered information is under question. Natural resource inputs are not generally tradeable in market; hence, there is no accurate way to calculate the effects of such inputs on production output.

Zheng and Bloch (2014) argued that the conventional published productivity performance for the Australian mining sector did not reflect true MFP growth and was biased by measurement issues and general conceptual weaknesses. Using a translog variable cost function method, they decomposed the measured MFP growth into the true MFP growth (or unbiased MFP growth) and the effects of returns to scale, capacity utilisation and natural resource inputs. They found that the MFP performance of Australian mining from 1974-75 to 2007-08 had deteriorated mainly due to the negative effect of returns to scale, capacity utilisation and natural resource inputs by -0.2 per cent, -1.4 per cent and -0.66 per cent per annum respectively; however, the average true MFP growth was 2 per cent per year over this period.

To provide a better understanding of the contribution of natural capital in the economic growth and productivity performance, Hoang (2018) compared the different methods of valuation of depletion or service flows from natural capital. This study used the ABS data over the 1989-90 to 2015-16 period. The adjusted MFP estimates in this study from all applied methods – including Resource Rent, Residual Method, Diewert and Fox, Jorgenson, Exogenous and No Capital Gains – show the strong presence of natural capital contribution to MFP growth. Given the consideration of natural capital, the MFP growth rates are estimated to be higher by at least 0.4 per cent per year over the study period. The author concluded that despite the importance of natural capital in economic growth and productivity performance, the inclusion of its effects on the estimation of MFP growth will be a remaining challenge due to the lack of appropriate data, difficulties in setting the price and accounting for quality change.

The review of the existing literature in efficiency and productivity analysis of the Australian mining industry shows the attempts of researchers to explain the poor MFP performance across the sector, particularly during the 2000s' mining boom. This research suggests that the official MFP index published by ABS is substantially influenced by changes in natural resource inputs. Using different time periods and methodologies, these studies reported consistently moderate and positive adjusted estimates of MFP growth between 2 per cent to 2.5 per cent per cent per annum over the past three decades (see e.g. Topp et al. ,2008; Loughton, 2011; Zheng and Bloch, 2014; Syed et al., 2015). Hence, the official MFP growth estimates are negatively biased-indicators of technological progress of the mining industry in long run. Penney et al. (2012) suggested that the rising cost structure in the Australian resources sector represents a new challenge to mining companies. The direct impact of this structural change on mining companies is an increase in the input prices, which adversely affect industry productivity. However, Tilton (2014) argued that while the association between mineral commodity prices and productivity is strong and negative, also the natural resource depletion imposes increasing cost to mining operations, the technological progress can keep up pace to maintain prices reasonably low.

In addition to resource depletion, there are a range of other factors contributing to the productivity challenge in the Australian mining sector. Sharp increases in input prices, considerable lags between the investment and production phases, scale inefficiency and capacity utilisation have been among main factors behind poor mining MFP performance during the mining boom of 2000s. Syed et al. (2015) suggested that due to the positive true MFP growth and technological progress in the mining industry, the mining industry does not need any specific policy implemented beyond general advice in improving productivity. The productivity decline in the Australian mining industry is not due to a poor policy implementation, but rather it has resulted from the influence of exogenous factors such as price fluctuations and resource depletion. The improvement of productivity performance in the mining industry can be supported by growth in innovation, an upskilled workforce and faster technological progress.

In the mining productivity literature, only two studies attempted to decompose the productivity growth to investigate the pattern of efficiency in the mining industry. Asafu-Adjaye and

Mahadevan (2003) reported that cost inefficiency is responsible for the poor productivity growth in the mining industry. The lack of using a least-cost combination of inputs (i.e. allocative inefficiency) and the existing excess capacity of inputs in producing outputs (technical inefficiency) resulted in negative efficiency effects on mining productivity over 1968-69 to 1994-95. In contrast, Syed et al. (2015) found a positive and strong influence of technical efficiency on the adjusted measure of MFP growth during 1990-1991 to 2009-2010 period. Although these two studies provide opposite views on the efficiency of Australia's mining industry, it cannot be easily concluded that efficiency in the sector has improved over time. The difference might arise from the way productivity was estimated. The former study applied a cost frontier technique while the latter used the production frontier method in estimation of efficiency changes. In addition, the combination of variables included in the productivity model was different. Unlike Asafu-Adjaye and Mahadevan (2003), Syed et al. (2015) introduced a proxy into the productivity model to reflect changes in quality of natural resource depletion.

Another highlight from the literature review concerns the scope of study; that is, the conducted research is limited to sector-level studies. Given the importance of mining activities in the Australian economy, extending the efficiency and productivity analysis to firm-level and mine-level studies can support policy makers and mining businesses to explore the dimensions of economic performance and implement improving actions across mining enterprises and operations. Mining companies make up the largest division listed on the Australian Securities Exchange (ASX). Hence, evaluation of the economic performance of mining companies can benefit the Australian community who are contributing to the sector through the share market.

In summary, there is a rich body of knowledge in assessing the productivity of the Australian mining sector. In particular, great attention has been paid to the contributing factors of poor productivity in the sector. However, the existing literature presents a gap in the evaluation of efficiency performance. The existing efficiency analyses of the mining sector provide ambiguous results and no work has been published discussing the efficiency of mines or mining businesses in Australia.

Table 3.4: Selected Productivity Studies in the Australian Mining Sector

Study	Industry	Aims	Main Findings
Asafu-Adjaye and Mahadevan (2003)	Mining sectors (coal, iron ore, copper, gold, and oil and gas) Study period: 1968-69 to 1994-95	– Adressing the limitation of growth accounting methods in identifying the source of productivity growth – Testing the components of mining productivity growth	– Over the period of study, mining output growth was largely input-driven, rather than productivity-driven. – Both allocative and technical inefficiencies played as primary causes of poor productivity growth.
Mahadevan and Asafu-Adjaye (2005)	Mining sectors (coal, iron ore, copper, gold, and oil and gas) Study period: 1967-68 to 1997-98	– Testing the link between inflation and productivity growth	– Both domestic and mineral price changes influence the mining TFP growth, but mineral price changes have an stronger negative effect. – Interest rate negatively and export growth positively contribute to the mining TFP growth.
Topp et al. (2008)	Mining sector (coal, oil and gas, iron ore, and other metal ore) Study period: 1974-75 to 2006-07	– Identifying measurement and interpretation issues in the estimation of the productivity performance of the mining industry in Australia	– Long lead times between investment and production have a significant adverse effect in the short term, while depletion of natural resource has a long-term negative impact on mining MFP. – By controlling investment-production lags and natural resource depletion, MFP growth turns out to be positive over the 2000s' mining boom.
Loughton (2011)	Mining sector Study period: 1985-86 to 2009-10	– Introducing practical method of resource depletion estimation for a National Statistical Office in an annual basis	– The quality of natural resources in mining decreased significantly from 1985-86 to 2009-10. – Adjusting for resource depletion, the annual productivity growth turned to be 2.05% instead of -0.15% from conventional measure.
Syed et al. (2013) Syed et al. (2015)	Mining sector Study period: 1985-86 to 2009-10	– Explaining the apparent decline in mining productivity growth published in a report by the ABS report which showed a decline by almost a half between 2000-2001 and 2012-2013	– Resource depletion and the lags between capital investment and output response are the two main drivers of declining MFP. – Accounting for resource depletion and investment-production lags, the annual MFP growth becomes 2.5% (adjusted) from -0.65% (unadjusted) for the period 1985-1986 to 2009-2010.
Lovell and Lovell (2013)	Coal mining Study period: 1990-91 to 2006-07	– Investigating the productivity decline in the 2000s reported in a PC paper – Comparing productivity estimated from value added and gross output frameworks	– The magnitude of productivity declines in Australian coal mining was estimated to be 21% over 2000-01 to 2006-07. – A gross output framework of MFP suggests a decline by 13% over this period.
Topp and Kulys (2013)	Mining, Agriculture, and Utilities sectors Study period: 1974-75 to 2006-07	– Review of the effect of natural resource inputs on MFP growth	– The reliable data for measuring natural resource inputs and their use in production, in a way that can be readily incorporated in a growth accounting framework, is not available.
Zheng and Bloch (2014)	Mining sector Study period: 1974-75 to 2007-08	– Testing the mining sector's poor MFP performance as measured by the growth accounting formula – Decomposing MFP to technical change, returns to scale, capacity utilisation and natural resource inputs	– Declining natural resource inputs, the effects of capacity utilisation and returns to scale are main components responsible for deteriorated MFP. – After removing the effects of return to scale, capacity utilisation and natural resource inputs, the true MFP growth become 2% per annum from 1974-75 to 2007-08 rather than the published MFP index of -0.02%.
Hoang (2018)	Mining sector Study period: 1989-90 to 2015-16	– Understanding the contribution of natural capital to productivity growth	– The inclusion of natural capital results in a higher mining MFP growth by at least 0.4 percent per year over 1989-90 to 2015-16.

3.4 Determinants of Economic Efficiency and Productivity in Mining Industry

The examination of efficiency and productivity determinants has been a long-standing interest in economics literature in the context of the mining industry. Along with the evaluation of efficiency and productivity, some studies have extended their analysis to the driving factors of economic performance at the mine, firm or sector level. In the application of both econometric and mathematical programming approaches, researchers have investigated the role of the micro-level and macro-level factors in determining efficiency and productivity performance. Although most studies discussed the causes of economic performance, the current research limits its review to those studies that employed a quantitative approach to explore contributing elements of efficiency and productivity. Table 3.5 summarises the reviewed literature on determinants of efficiency and productivity in mining industry.

3.4.1 Studies in Determinants of Mining Efficiency and Productivity

An early study into the mining industry conducted by Byrnes et al. (1984) analysed the relationship between technical efficiency and mine characteristics of a sample of 15 coal mines in Illinois. The authors examined the relationship between mine efficiency estimates derived from a DEA model and mine characteristics including average number of seams, average labour output ratio, average non-fatal accidents, average years of mine opening and average earth-moving capacity. Furthermore, they discussed the effect of mine size on technical efficiency. The results of this evaluation, which were purely based on a comparison of descriptive statistics of efficient versus inefficient mines, show that on average, efficient mines have more coal seams than inefficient mines. Also, efficient mines have a higher stripping ratio. Stripping ratio depends on the mine geological characteristics and by definition it is the ratio of removed overburden to retrieved coal. Labour productivity (i.e. labour-output ratio) is higher in efficient mines than in those deemed inefficient. Moreover, comparing against inefficient mines, they found that efficient mines are safer, reporting less non-fatal accidents. In terms of vintage of the mine, this study showed that newer mines are technically more efficient. Finally, they concluded that the efficiency of mines positively depends on their capital capacity measured by total earth-moving capacity.

Using an efficiency model developed by Byrnes et al. (1984), Byrnes and Färe (1987) analysed the association of mine characteristics and the efficiency performance of a large sample of 186 surface coal mines in the U.S. In addition to overall technical efficiency, they investigated the effects of mine characteristics on three components of technical efficiency; namely, pure technical efficiency, input congestion and scale efficiency. Five characteristics were examined in this study including mine location, union status, mine age, captive status and acreage reclaimed. This study used descriptive statistics (arithmetic averages) to discuss the relationship between technical efficiency and mine characteristics. This research found that mine location is a main determinant of efficiency gain. On average, the overall technical efficiency as well as each efficiency component of mines located in Texas were higher than mines located in the other states. Yet, compared to the other states, mines located in Arkansas performed poorly as a result of low scale efficiency. In addition, this study reported that union mines are more efficient than non-union mines. While none of the non-unionised mines were efficient overall, over 11 per cent of unionised mines were fully efficient. Unionised mines also outperformed non-unionised mines in all efficiency components. The other finding from Byrnes and Färe (1987) study is the relationship between mine operating age and its efficiency. Except in mines with an operating age of 3 years or less, age exhibited a negative impact on efficiency performance (i.e. aged mines experienced lower efficiency). Moreover, captive mines performed better than non-captive mines in terms of overall technical efficiency as well as each efficiency component. Unlike non-captive mines, captive mines do not sell all their output on the open market, but instead a proportion of their production is consumed by a parent or subsidiary company. Lastly, no specific patterns were reported in this study regarding the relationship between efficiency and reclamation ratio (ratio of acres reclaimed to acres stripped).

Byrnes et al. (1988) applied both parametric and non-parametric approaches to examine the effects of unionisation on efficiency performance of the two samples of surface coal mines in the Interior and Western U.S. This study in the first stage applied non-parametric technique of DEA, and then conducted the second-stage analysis by regressing each of the calculated efficiency measures against variables representing natural condition and mine union status. The results of their second-stage analysis showed that variation in two geological characteristics, including thickness of coal seams and amount of overburden removed, has a minor effect on variation in efficiency performance. On the other hand, the status of unionisation has a significant effect on the efficiency performance of mines in the sample. They concluded that controlling for the effect of natural condition, union mines are more efficient than non-union mines. The results of the parametric approach based on the Cobb-Douglas production function also broadly supported the results achieved from the non-parametric approach.

In a study of mining productivity in Australia, Mahadevan and Asafu-Adjaye (2005) investigated the association between productivity and inflation. TFP estimates for five Australian mining industries including coal, iron ore, copper, gold and oil and gas obtained from a parametric translog cost frontier technique were used to conduct causality tests between productivity growth and macroeconomic variables of domestic inflation, changes in mineral prices, mineral export growth and real interest rate. Their results of the Granger-causality tests based on the VAR model showed that productivity growth in the Australian mining sector is driven by domestic inflation, movement in mineral prices and changes in the export volume. The results from the ordinary least square (OLS) regression model showed that domestic inflation and mineral price changes impact the productivity growth adversely, while the magnitude of effects of mineral price changes on productivity growth is greater than those effects from domestic inflation. The export growth was shown to have a positive effect on mining productivity. The authors discussed that higher mineral prices reduce the international demand for Australian mining products, causing a reduction in export volume and productivity growth. The research findings also revealed that real interest rate negatively influences mining productivity growth, implying that higher interest rates reduce productivity growth through lowering incentives for investment in mining industry. While the outcomes of this study support the macroeconomic directions in monetary policy around inflation, targeting and lowering interest rate by the Reserve Bank of Australia (RBA), it expressed concern about trends in the mining production costs which negatively impact productivity.

Koop and Tole (2008) investigated the effects of ownership and location on the environmental and technical efficiency of gold mines. In their study, using a Bayesian stochastic production frontier technique, Koop and Tole (2008) analysed the role of environmental bad outputs (i.e. mining operation waste such geological waste, chemical waste and non-tradable low-grade ore), ore grade, ore resources and mine operation type in production of gold. Their findings show while there is strong evidence confirming that the amount of waste and ore quality positively contribute to gold production, the volume of ore resources seems to be less associated with output. Moreover, the findings suggest that the technological differences between open-pit mining and underground mining result in a difference in transformation of inputs to outputs from an environmental perspective. While the model specification – in terms of inclusion of environmental impact, geological characteristics and operation type – turns out to be crucial in determining operation output, the mine ownership and the county of operation do not appear to have significant effects on production output. Mines operating under control of a foreign firm have marginally higher efficiency performance and mines located in rich countries are slightly more efficient; nevertheless, the differences are not statistically supported. The authors discussed that in the case of mines operating under multinational gold mining companies, producing pollution is not necessarily associated with the location of operations. These multinational companies defined and implemented a standard of performance covering all operation locations. While these findings do not ascertain that the gold mining operations produce low pollution, they show multinational companies do not produce significantly more pollution in poor countries.

In a firm-level study, Eller et al. (2011) applied both DEA and SFA to investigate the differences in efficiency performance among 78 national and private oil companies in the period of 2002 to 2004. In the application of a non-parametric approach, they used a two-stage procedure. The first stage involved the estimation of the efficiency scores from a CRS DEA model, and the second stage investigated the relationship between vertical integration, ownership and efficiency performance through a linear regression model. In the application of a parametric technique of SFA, they followed a single-step method proposed by Battese and Coelli (1995) to simultaneously estimate the efficiency estimates and the coefficients of explanatory variables of vertical integration and government ownership. Consistent findings from both parametric and non-parametric techniques showed that vertical integration and government ownership influence the revenue efficiency performance of oil companies. Vertical integration, i.e. being engaged in both upstream (exploration and production) and downstream (refining and marketing) operations, positively affect revenue efficiency. However, greater government ownership results in less revenue efficiency. National oil companies tend to hire excess employees and sell their products to domestic consumers at subsidised prices, which in turn reduces their ability to produce revenue from a certain level of inputs. Once controlling for excess employees and subsidised domestic prices, this study found that the government ownership contributes positively in revenue efficiency gains in oil companies.

Using a large sample of mining firms in India, Das (2012) investigated the role of private versus public ownership in the productivity performance of mining firms across metallic, non-metallic, coal and petroleum sector. The comparison of results from the application of Cobb-Douglass production function in a semi-parametric method showed that private companies perform better than public companies in terms of productivity, especially in metallic, non-metallic and coal sectors. Further analysis using a fixed effect GMM regression model showed that private ownership as well as initial (or last year) productivity performance are the two main determinants of productivity gains among mining firms. Moreover, age contributes positively in the productivity of metallic, non-metallic and coal mining firms.

Questioning the belief of the permanent rise of real mineral commodity prices in the future due to the inability of new technology to offset the effects of resource depletion, Tilton (2014) discussed the determinants of productivity changes and technological progress in the copper, aluminium, iron ore and coal mining industries. This study categorised the common productivity determinants in the mining industry to innovation and technological change, resource depletion and ore quality, government regulations, worker quality, investment lags, economies of scale, capacity utilisation, unplanned production stoppages (e.g. strikes and accidents) and other factors. While the first two factors govern the long-run productivity performance, the remaining factors have a short-term and cyclical influence on the mining productivity. Moreover, the author discussed that while these factors are mainly attributed to the cyclical changes over the past decade due to the global mining boom and severe fluctuation in mineral commodity prices, there is a strong association between mineral prices and productivity. In periods with low mineral prices, there is substantial pressure on management and labour to work together to reduce cost and enhance productivity. On the contrary, the mining industry is less motivated to reduce costs and improve productivity if mineral markets are strong and prices are high. This review concluded that unlike existing beliefs, the new technology can continue to offset the adverse effects of resource depletion; hence, real mineral commodity prices will be lower than what are normally expected.

3.4.2 The Literature Gaps in Analysis of Efficiency and Productivity Determinants

The review of studies investigating the determinants of efficiency and productivity in the mining industry indicates differences in the analysis approach depending on the level of study. Table 3.5 presents a summary of studies in this context. Despite similarities in the modelling of efficiency and productivity among mine-level, firm-level and sector-level studies, the variables of interest in the analysis of performance determinants are highly attributed to the level of studies. Mine-level studies tend to focus on the role of operational factors and mine characteristics in efficiency performance. Geological characteristics are among the most important factors investigated in mine-level efficiency studies. Firm-level studies seem to be interested in the influence of firm-specific factors such as ownership, firm age and firm size on the firm's performance. Meanwhile, the macroeconomic factors that contribute to productivity growth have been the focus of sector-level studies. In particular, factors such as domestic inflation, export and interest rate have been discussed in the productivity literature of the mining industry.

The existing literature explains some driving factors behind changes in the efficiency and productivity of mining activities; however, the existing body of knowledge is unable to provide a comprehensive picture describing the causes of economic performance of mining industry. Very limited studies have examined the contributing factors to mining efficiency and productivity. These studies have reviewed certain variables while a broader view is needed to assist business management and policy makers in improving mining industry performance. The analysis of performance determinants in mining studies, especially in non-parametric approaches, has relied on simple regression techniques; however, two-stage DEA has been developed significantly in the last decade. Better modelling is required to eliminate the issues surrounding the second stage of DEA (Simar and Wilson, 2007, 2011). These shortcomings indicate the need for further work in evaluating the driving factors of efficiency and productivity in the context of the mining industry.

Unlike the mining sector, the body of knowledge on the analysis of efficiency and productivity determinants in other sectors seems to be developed and rich. In recent years, scholars in economics and management science have advanced the application of frontier techniques toward identifying the contributing factors of efficiency and productivity. In the application of non-parametric models, the two-stage bootstrap techniques developed by Simar and Wilson (2007, 2011) have been largely utilised in recent literature. For instance, Biener et al. (2016) studied the role of factors including international diversification, size, specialisation, organisational form, leverage, premium growth, age and year-specific effects on the efficiency and productivity of insurance companies in Switzerland. Sufian et al. (2016) examined the determinants of efficiency in the Malaysian banking sector, given a set of variables describing bank characteristics (e.g. credit risk, diversification, operating cost stability, liquidity risk, size, capitalisation and bank origin) and a set of variables explaining economic and financial market conditions (e.g. GDP, inflation, banking system concentration, Z-Score and size of the equity market). Chowdhury and Zelenyuk (2016) applied DEA with a truncated regression approach to investigate the drivers of hospital service performance in Ontario. They tested the effects of factors such as geographical location, size, teaching status, occupancy rate, non-price competition, outpatient-inpatient ratio, rate of unit producing personnel, quality, case-mix index and year-specific factors.

Table 3.5: Selected studies on determinants of mining efficiency and productivity

Study	Method	Country and Industry	Level of Study	Efficiency / Productivity Indexes	Determinants
Byrnes et al. (1984)	DEA Descriptive analysis	U.S.; Coal mining	Mine	Overall technical efficiency	Average number of seams Average labour output ratio Average non-fatal accidents Average years of mine opening Average earth-moving capacity Mine size (output)
Byrnes and Fare (1987)	DEA Descriptive analysis	U.S.; Coal mining	Mine	Overall technical efficiency Pure technical efficiency Input congestion Scale efficiency	Location of mine Union status of mine Year mine opened for operation Production not sold in open market (captive) Acres reclaimed to acres stripped ratio
Byrnes et al. (1988)	DEA Regression analysis Econometric analysis (Cobb-Douglas)	U.S.; Coal mining	Mine	CRS technical efficiency NIRS technical efficiency VRS technical efficiency Input congestion Scale efficiency	Union status (non-union, UMWA, other unions) Geological characteristics (thickness of coal seams, overburden removal)
Mahadevan and Asafu-Adjaye (2005)	SFA (translog cost frontier, input oriented)	Australia; Mining sector (coal, iron ore, copper, gold, and oil and gas)	Sector	Output growth Input growth TFP growth Economic efficiency Returns to scale Technological progress	Domestic inflation rate Change in the price of mineral products Real interest rate Real mineral export growth rate
Koop and Tole (2008)	Bayesian stochastic frontier	Global; Gold mining	Mine	Technical efficiency Environmental efficiency	Ownership (domestic or foreign) Location county (rich or poor)
Eller et al. (2011)	DEA, Output Oriented SFA Linear regression analysis	Global; Oil	Firm	Revenue efficiency	Vertical integration (upstream and downstream operations) Government ownership Excess employees and subsidised domestic prices
Das (2012)	TFP estimation (OLS and SPM) Fixed effect GMM regression	India; Mining industry (metallic, non-metallic, coal and petroleum)	Firm	TFP index	Ownership Age Initial TFP
Tilton (2014)	Discussion on existing literature for TFP estimation	Global; Copper, aluminium, iron ore and coal mining	Sector	TFP index	Mineral commodity prices

Overall, there are gaps in the existing literature on the efficiency and productivity analysis of the mining industry, requiring further work. The existing literature contains the examination of a limited number of factors. Regardless of the level of study, the extant literature does not provide a broad picture of the influencing factors. Specifically, at firm level, the effects of various firm-specific factors are unknown, and for those investigated in the literature, the available knowledge is limited to one or two studies. This thesis attempts to provide a broader view on the effects of firm-specific factors on the efficiency performance of mining companies. The literature review in this chapter displayed the importance of factors such as ownership, size, age, location, product type, diversification, capacity utilisation, business risk and growth. Chapter 5 discusses these factors in detail.

The other gap in the literature is in relation to the applied methodology. The second-stage analysis of a DEA method is commonly involved in the application of a regression model using techniques such as OLS or Tobit. It has been the case for studies in the mining sector also. As Simar and Wilson (2007, 2011) showed, such models lead to inconsistent estimates of coefficient parameters. The utilisation of techniques like two-stage bootstrap DEA succeeds in dealing with issues such as the serial correlation among efficiency models and explanatory variables. Chapter 4 introduces a robust technique in the application of a two-stage DEA approach.

3.5 Summary

In the economics literature, efficiency and productivity are among most common measures of producers' performance. Productivity is simply the ratio of outputs to inputs. Labour productivity, capital productivity, capital-labour MFP and capital-labour-energy-material-service MFP are the most frequently used measures of productivity in the literature. In the public community and in the media, productivity and efficiency are used interchangeably; however, their economic definitions are different. While productivity measure looks at the input and output values in each individual producer, efficiency is a relative measure. It measures the performance of a producer by comparing the observed values of inputs and outputs against their optimum values lying on a corresponding frontier. Hence, the efficiency measurement involves the estimation of a production technology frontier and the estimation of producers' distance from the frontier. Such measure of efficiency is called the technical efficiency. In the presence of price information, one can also estimate the economic (cost, revenue or profit) efficiency.

There are two prominent approaches in efficiency measurement; parametric and non-parametric. The parametric frontier approach uses econometric techniques to formulate the linkage between outputs and inputs in a production system. Parametric techniques such as SFA separate the effect of statistical noise from that of technical efficiency. While these techniques provide the statistical inferences about the efficiency estimates, the need for selection of pre-defined functional forms has been the main critic in the application of parametric approach. In contrast, the non-parametric techniques are free from such rigidity in selection of functional forms. But this freedom is achieved at a cost; in the application of non-parametric frontier techniques, which are based on mathematical optimisation modelling, statistical noise and random errors are ignore.

Unlike most other economic sectors, there are limited studies conducted in the efficiency and productivity analysis of the mining industry using frontier approaches. The reviewed literature in this chapter showed that early literature on the efficiency and productivity analysis are limited to mine-level studies. Over the past two decades, sector-level studies have been the focus of scholars in mining efficiency and productivity. Nevertheless, firm-level studies have received attention only in recent years. Moreover, this review revealed that studies pursue different aims, modellings and implications depending on the level of study. For instance, mine-level studies used operational input/output variables such as total working hours, utilised equipment capacity, mine geological characteristics and production volume. Firm-level studies used input/output variables such total employees, total assets and operating revenue; while sector-level studies used the official data from national statistical organisations to extract input/output data such as aggregate working hours, capital service and value added. The mine-, firm- and sector-level studies are also dissimilar in their application of frontier techniques. Mine-level studies used mostly DEA; firm-level studies used both DEA and SFA; and sector-level studies widely applied SFA.

Another distinguishing factor among studies at mine, firm and sector levels is the investigated measure of efficiency and productivity. Efficiency measurement and analysis has been the topic of mine- and firm-level studies. Technical efficiency has been the main measure of mine efficiency while both technical and economic efficiency measures have been investigated in firm-level studies. On the other hand, sector-level studies have investigated the productivity growth. Analysis of the MFP growth and its main components including technical changes, efficiency changes and operating scale changes have been the centre of sector-level studies.

This chapter continued the review of literature with a focus on the studies conducted in the Australian mining industry. While the existing literature highlights the importance of mining productivity in the sector as well as for the whole economy, its main aim has been explaining the undesirable productivity performance of the sector as published in government reports. These studies emphasised the issues surrounding the official MFP indices and argued that resource depletion, capital-production lags and operating scale have been the most influential factors adversely affecting the sector's MFP during the latest resource boom. Once controlling for such factors, the MFP growth turns out to be positive and moderate. Among productivity growth components, technical efficiency and operating scale have been reported to positively contribute to MFP growth, while technical progress seemed to have negligible effects. Despite the rich literature in productivity analysis of the Australian mining sector, the lack of mine- or firm-level studies and the absence of efficiency analysis is evident.

The last section of this chapter provided a detailed review on the determinants of mining efficiency and productivity. The investigated factors are significantly different among studies at mine, firm and sector levels. The evaluated factors at the mine level have been mainly related to mine characteristics, whereas the firm-level studies have looked at the association of firm-specific factors and firm efficiency. On the other hand, the role of macroeconomic factors in productivity performance has been tested in sector-level studies.

The review of the existing literature in this chapter revealed that the examination of efficiency and productivity drivers in the mining sector has been limited to a small number of factors. In the firm-level studies, various firm-specific factors have not been tested, and for those investigated in the literature, the available knowledge is limited to one or two studies.

Yet, little is known about the efficiency of Australian mining companies. The existing knowledge is mostly restricted to performance at the industry level (see e.g. Lovell and Lovell, 2013; Zheng and Bloch, 2014; Syed et al., 2015). Due to significant differences between individual companies in this sector, efficiency studies at the firm level are essential to complement industry level analysis. Further to the gaps in efficiency measurement, there is limited knowledge on the determinants of efficiency performance. Gaps also exist in the application of robust frontier techniques, particularly in relation to the deterministic mathematical programming approach.

4 Methodology

4.1 Introduction

The measurement of a firm's efficiency performance is primarily linked to the modern literature in frontier production. A seminal paper by Farrell (1957) introduced the foundations of frontier efficiency measurement, and since then the frontier approach in efficiency analysis has evolved and expanded significantly from both theoretical and empirical perspectives. Such measure of economic performance is different from conventional productivity measure. In economic literature, the economic performance of firms has commonly been referred as their productivity or efficiency performance. The productivity of a firm refers to the ratio of a firm's aggregate output to its aggregate input. In line with this definition pioneered by Solow (1957), productivity growth refers to the difference between aggregate output growth and the aggregate input growth. Such productivity growth may be attributed to differences in production technology, operating scale, operating efficiency or operating environment. The Organisation for Economic Co-operation and Development - OECD (2001) provided detailed concepts and instruction to productivity measurement.

On the other hand, the efficiency of a firm refers to the comparison of a firm's observed and optimal values of its input and output. The optimal values are defined in terms of production possibility. This can be viewed as the comparison of observed output to maximum output obtainable from a given input set, or the comparison of observed input to the minimum input required to produce a given set of output in the production possibility space. This measure of firm efficiency is called technical efficiency. Subject to the availability of price information, it is possible to compare the observed and optimum cost, revenue or profit of a firm and calculate its economic efficiency. Since the efficiency measure is based on the comparison of observed input and output to their optimum values, it is a more accurate measure of firm performance in comparison with the productivity measure which is only based on the ratio of aggregate output and aggregate input (Daraio and Simar, 2007).

From the production frontier literature, the efficiency analysis of firms commonly involves three steps: first, estimation of a production technology frontier; second, measurement of the technical efficiency (inefficiency) of each firm in the sample relative to the estimated frontier; and finally, the investigation of inefficiency causes. Since Farrell (1957) introduced the application of frontier method in efficiency analysis, the theory and application of frontier techniques have been broadly extended. These efforts can be classified into two main streams: one, in economics involving parametric econometric techniques; and the other, in management science which applies nonparametric mathematical programming techniques. The parametric econometric techniques, pioneered by the independent work of Aigner et al. (1977) and Meeusen and van Den Broeck (1977), are basically stochastic and try to distinguish the effects of statistical noise from that of technical inefficiency. While these techniques are enriched by the statistical inference, the requirement of adopting pre-defined functional form of production frontier and the error terms remains a major shortfall for their application.

The mathematical programming techniques, commonly known as data envelopment analysis (DEA) as introduced by Charnes et al. (1978), construct a piece-wise frontier over observed data. These flexible techniques do not require a pre-defined functional form; however, the deterministic nature of them leaves these techniques unable to address the statistical noise and measurement error in the process of efficiency analysis. Simar and Wilson (1998, 2000a) proposed a solution to address this shortcoming of non-parametric techniques through the application of bootstrapping. Bootstrapping techniques rely on re-sampling to calculate statistical properties of efficiency scores. In this study, we apply bootstrap DEA. In addition to the flexibility of DEA in modelling efficiency, especially with the lack of a large sample, this method enables us to obtain statistical properties of efficiency scores such as standard errors and confidence intervals.

Chapter 4 discusses the main approaches in efficiency analysis with a focus on the mathematical programming techniques applied in this study. The reminder of this chapter is organised as follows. Section 4.2 introduces concepts in economic efficiency analysis. Adopting an analytical approach, the mathematical foundation of efficiency concepts is provided and illustrated where applicable. Section 4.3 reviews the main two approaches in efficiency analysis, namely parametric econometric and non-parametric mathematical programming techniques. Section 4.4 provides further details of the econometric approach to efficiency measurement, particularly focusing on their cross-section and panel-data applications. Section 4.5 discusses the mathematical programming techniques. The mathematical modelling of the basic DEA models is presented in detail in this section. Section

4.6 discusses the statistical foundation of DEA by introducing bootstrap techniques and its application in a DEA setup. Finally, Section 4.7 outlines the methods in evaluation of influence of business environment and firm-specific factors on firm efficiency. This section presents the new developments in the application of bootstrap techniques in the two-stage DEA. Section 4.8 summarises the methodological topics discussed in the chapter.

4.2 Frontier Approach in Economic Efficiency Analysis

Economic efficiency is comprised of technical and allocative efficiency components. The technical efficiency refers to the ability of a firm to produce maximum output given a set of inputs and available technology or, alternatively, a firm's ability to consume the minimum input required by the available technology in production of output. The allocative efficiency refers to the ability of a firm in choosing an optimal set of inputs given different input prices.

Koopmans (1951) stated that a firm is technically efficient if increases in any output requires reduction in at least one other output production or increases in at least one input consumption, and if reduction in any input requires increase in at least one other input or reduction in at least one output. Thus, firms that are technically inefficient can produce the same amount of outputs with a less amount of at least one input; or they can produce more of at least one output with the same amount of inputs consumed in production process. Koopmans' definition establishes two orientations in measuring and analysing technical efficiency: output-augmenting orientation and input-conserving orientation.

Farrell (1957) introduced a frontier efficiency measurement approach based on Koopmans' (1951) technical efficiency definition and Debreu's (1951) defined measure of technical efficiency to estimate the overall efficiency and to decompose it to its components, namely technical and price (allocative) efficiencies. With an input-conserving orientation, the Farrell (1957) measure of technical efficiency is defined as (one minus) the maximum equiproportionate (i.e., radial) reduction in all inputs that is feasible with the given technology and set of outputs. With an output-augmenting orientation, this measure is defined as the maximum feasible radial expansion in all outputs given the available technology and inputs. In both orientations, a firm with a technical efficiency value of unity is fully efficient and no radial adjustment is feasible to improve its technical efficiency. Any values different from unity indicate a degree of technical inefficiency in the firm's performance.

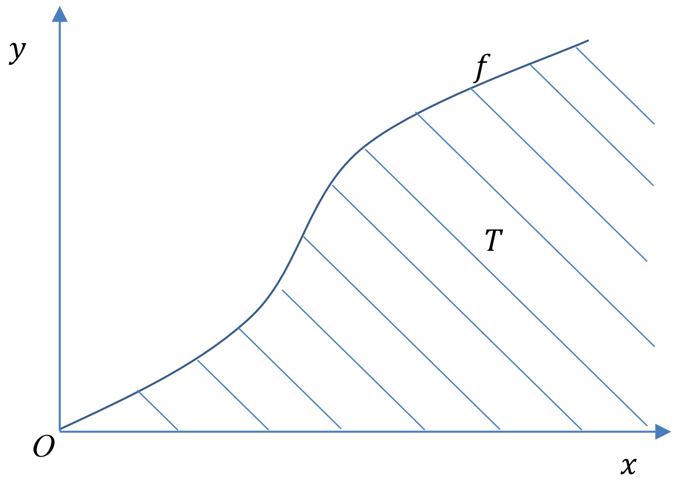
To model the Farrell measure of technical efficiency, we use the notations and terminology described in Fried et al. (2008).

We can view an economic system (such as a firm) as a system where some technology transforms a set of inputs (x) to a set of outputs (y). If the economic system under investigation uses $x = (x_1, \ldots, x_n) \in \mathbb{R}_+^N$ to produce $y = (y_1, \ldots, y_m) \in \mathbb{R}_+^M$, production technology can be described as:

$$T = \{(x, y) \in \mathbb{R}_+^N \times \mathbb{R}_+^M : y \in \mathbb{R}_+^M \text{ is produceable from } x \in \mathbb{R}_+^N\}. \tag{4.1}$$

T is a set of input-output pairs (x, y); the output element of the pair, y, is producible from the input element of the pair, x. Figure 4.1 shows a simple example of an economic system with one input and one output. The technology set consists of all combinations of inputs and outputs, (x, y), located to the right of curve f including this curve. Curve f, which is called technology frontier, represents the maximum output producible from the available input.

Figure 4.1: Example of technology set

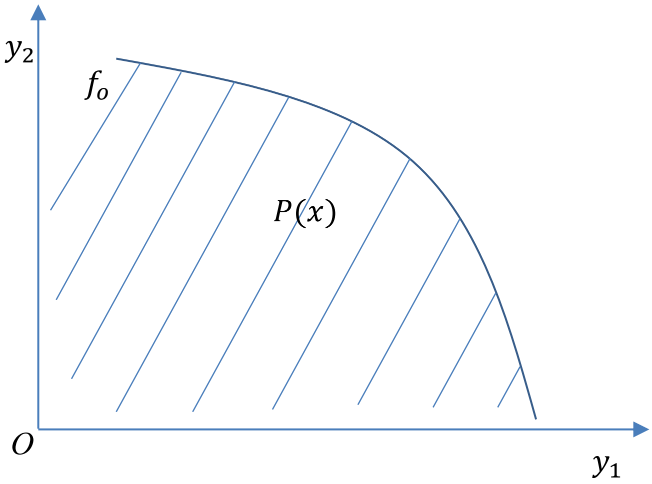


Alternatively, input and output sets can represent the technology. The output set can be defined as:

$$P(x) = \{y \in \mathbb{R}_+^M : y \in \times \mathbb{R}_+^M \text{is produceable from } x \in \mathbb{R}_+^N\}. \tag{4.2}$$

Output set P(x) consists of all possible combinations of outputs that are producible from each particular level of $x \in \mathbb{R}_+^N$.

Figure 4.2: Example of output set

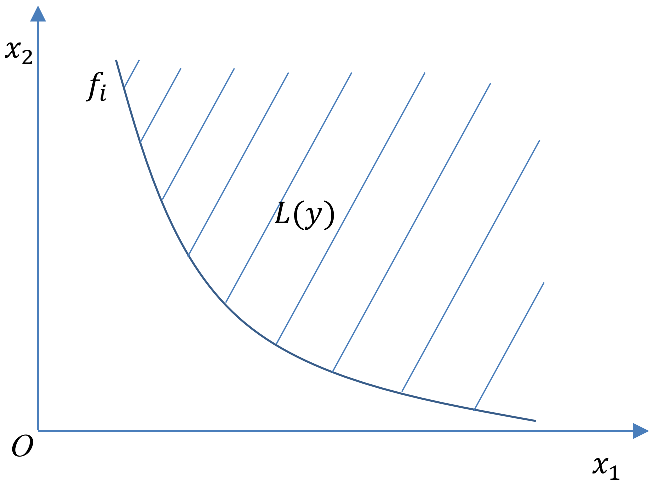


Also the input set can be defined as

$$L(y) = \{x \in \mathbb{R}_+^N : y \in \times\mathbb{R}_+^M \text{ is produceable from } x \in \mathbb{R}_+^N\}. \quad (4.3)$$

That is, L(y) is a set of all possible combinations of inputs that can produce each particular level of output $y \in \mathbb{R}_+^M$.

Figure 4.3: Example of input set



As these three sets equivalently represent the technology, we have

$$(x, y) \in T \Leftrightarrow y \in P(x) \Leftrightarrow x \in L(y). \quad (4.4)$$

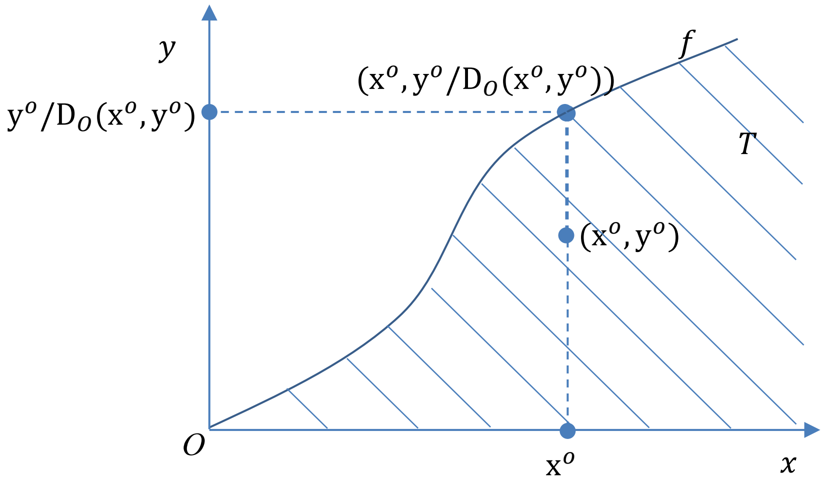
Shephard (1953, 1970) introduced the distance function to represent the production technology. From an output augmentation approach, Shephard's (1970) output distance function is thus given by:

$$\begin{aligned} D_O(x,y) &= \min\{\lambda > 0 : (x, y/\lambda) \in T\} \\ &= \min\{\lambda > 0 : (y/\lambda) \in P(x)\} \end{aligned} \tag{4.5}$$

For $(x,y) \in T$ or alternatively $y \in P(x)$, $D_O(x,y) \le 1$ and for all points lying on the frontier curve f, $D_O(x,y) = 1$. The output distance function $D_O(x,y)$ is non-increasing in all inputs, $x \in \mathbb{R}_+^N$, and non-decreasing, homogenous of degree +1 and convex in all outputs, $y \in \mathbb{R}_+^M$.

For all possible combinations of pairs in the input-output space, i.e. $(x,y) \in \mathbb{R}_+^N \times \mathbb{R}_+^M$, $D_O(x,y) = y / f(x)$. In fact, the distance function is a generalisation of the production function. Using a simple example of one-input-one-output technology set, Figure 4.4 shows the intuition of the output distance function and its relationship with production function. In a one-input-one-output technology set, such as the example in Figure 4.4, the area representing the technology set, T, is the same as the area representing output set, $P(x)$; furthermore, the technology frontier curve f is the same as production frontier f^o.

Figure 4.4: Output distance function for one-input-one-output technology set



As we can see from Figure 4.4, $f(x^o) = y^o / D_O(x^o, y^o)$. Through the simple example, we can explain that the Shephard's output distance function is the ratio of actual output to the maximum output, i.e. $f(x)$, that is producible with the same level of input. Hence, for a firm located at point $(x^o, y^o) \in T$, $D_O(x^o, y^o)$ the output distance function reflects the efficiency of the firm.

Such measure of technical efficiency is often expressed in the form of the reciprocal value of distance function, which is known as the Farrell output-oriented measure of technical efficiency defined by:

$$\begin{aligned} TE_O(x,y) &= \max\{\phi > 0 : (x, \phi y) \in T\}, y \in \mathbb{R}_+^M, x \in \mathbb{R}_+^N \\ &= \max\{\phi > 0 : \phi y \in P(x)\}, y \in P(x), x \in \mathbb{R}_+^N \\ &= 1 / D_O(x,y), y \in P(x), x \in \mathbb{R}_+^N \end{aligned} \tag{4.6}$$

If we consider the output isoquant as the upper boundary of $P(x)$ defined as

$$I(x) = \{y : y \in P(x), \lambda y \notin P(x), \lambda > 1\}, x \in \mathbb{R}_+^N \tag{4.7}$$

a firm at point (x^o, y^o) is technically efficient if and only if

$$D_O(x^o, y^o) = 1 \Leftrightarrow y^o \in I(x) \tag{4.8}$$

and a firm at point (x^o, y^o) is technically inefficient if and only if

$$0 < D_O(x^o, y^o) < 1 \Leftrightarrow y^o \in P(x), y^o \notin I(x), y^o \neq 0 \tag{4.9}$$

In other words, for any firm with outputs belonging to the output set, the value of the output distance function is equal to, or less than, unity. Alternatively, the value of the output-oriented Farrell technical efficiency for a firm under a given technology is equal to, or greater than, unity. A value equal to unity for the Farrell output measure of technical efficiency represents a fully efficient firm while any values greater than unity reflect some degree of inefficiency in the firm performance.

Similarly, we can develop the model of technical efficiency from an input-conserving orientation. Shephard's input distance function is given by:

$$\begin{aligned} D_I(x,y) &= \max\{\lambda > 0 : (x / \lambda, y) \in T\} \\ &= \max\{\lambda > 0 : (x / \lambda) \in L(y)\} \end{aligned} \tag{4.10}$$

For $(x, y) \in T$ or alternatively $x \in L(y)$, $D_I(x, y) \geq 1$ and for all points lying on the frontier curve f, $D_I(x, y) = 1$. The input distance function $D_I(x, y)$ is non-increasing in $y \in \mathbb{R}_+^M$, and non-decreasing, homogenous of degree +1 and concave in $x \in \mathbb{R}_+^N$.

The Farrell input-oriented measure of technical efficiency is expressed in the form of the reciprocal value of the distance function as follows:

$$\begin{aligned} TE_I(x, y) &= \min\{\theta > 0 : (\theta x, y) \in T\}, y \in \mathbb{R}_+^M, x \in \mathbb{R}_+^N \\ &= \min\{\theta > 0 : \theta x \in L(y)\}, x \in L(y), y \in \mathbb{R}_+^M \\ &= 1 / D_I(x, y), x \in L(y), y \in \mathbb{R}_+^M \end{aligned} \tag{4.11}$$

If we let the input isoquant $I(y)$ to be the lower boundary of $L(y)$ as

$$I(y) = \{x : x \in L(y), \lambda x \notin L(y), \lambda < 1\}, y \in \mathbb{R}_+^M \tag{4.12}$$

a firm located at point (x^i, y^i) is technically efficient if and only if

$$D_I(x^i, y^i) = 1 \Leftrightarrow x^i \in I(y) \tag{4.13}$$

and a firm located at point (x^i, y^i) is technically inefficient if and only if

$$0 < D_I(x^i, y^i) < 1 \Leftrightarrow x^i \in L(y), x^i \notin I(y), x^i \neq 0 \tag{4.14}$$

That is, the value of the input distance function is equal to, or greater than, unity for any firm with inputs belonging to the input set. As Farrell's technical efficiency is the reciprocal of the corresponding distance function, the value of input-oriented measure of technical efficiency is equal to, or less than, unity for any firms. A value of one for the Farrell input-oriented measure of technical efficiency represents a fully efficient firm, whereas any values between zero and one show a firm operates inefficiently.

4.3 Efficiency Measurement Techniques

To measure technical efficiency, one needs to compare the actual performance with the corresponding potential (optimal) performance located on the technology frontier. However, the true technology frontier is unknown. Therefore, the measurement of technical efficiency requires constructing the technology frontier through some empirical examinations. Such empirical examinations result in the approximation of technology frontier by a best practice frontier. Since Farrell's (1957) seminal work, a broad range of techniques have been developed and empirically applied to construct the technology frontier and measure economic efficiency. The developed techniques of economic efficiency measurement can be classified into two distinguished categories based on the tools used to solve the efficiency models: (1) the econometric approach and (2) the mathematical programming approach. The econometric approach consists of techniques which are basically stochastic. Such stochastic techniques enable us to provide statistical inference to distinguish the effects of statistical noise effects and technical inefficiency. However, these techniques require adopting a pre-defined functional form for the technology frontier and the inefficiency error terms. Use of econometric techniques introduces the risk of confounding the effects of misspecification of the functional form of technology or inefficiency with sample inefficiency effects.

In contrast, the mathematical programming techniques calculate the efficient frontier from the sample observations without any requirements for pre-established functional form. However, the major shortcoming of these techniques is their deterministic nature. Therefore, these techniques cannot distinguish the effects of noise from those of inefficiency.

Recent development in efficiency analysis has attempted to overcome such disadvantages in both approaches. The mathematical programming techniques have been developed to include the statistical foundations for identifying the statistical noise. In addition, the econometric approach has been improved through application of flexible functional forms and semiparametric, nonparametric and Bayesian techniques to limit the effects of functional form misspecification.

4.4 The Econometric Approach to Measure Efficiency

The economic approach involves specifying the form of production frontier and the distribution of the inefficiency and random noise (error terms). The efficiency measurement techniques in this approach can be classified in different ways: based on the specification of production frontier (deterministic or stochastic), the number of equations in the model, the distributional assumptions of the inefficiency and random components, according to the type of variables they use (quantities only or quantities and prices) and the type of data they use (cross-section or panel). The econometric approach literature provides a broad range of techniques and their classifications (e.g. see Murillo-Zamorano, 2004; Fried et al., 2008; Eling and Luhnen, 2010). Among different classifications of the econometric techniques to efficiency measurement, we introduce here two main categories of techniques according to the type of data used in efficiency measurement, namely cross-section models and panel models, and then we introduce some new developments in the econometric measurement of efficiency.

4.4.1 The Cross-Section Models

A single-equation cross-section frontier model can be represented as

$$y_i = f(x_i;\beta)\exp\{v_i - u_i\}, x \in R_+^N, y \in R_+^M, i = 1,...,I \tag{4.15}$$

where parameter vector β characterises the structure of production technology, i indicates firms, v_i represents the random disturbance term and $u_i \geq 0$ captures the effect of inefficiency.

The Farrell output-oriented measure of technical efficiency, which is the ratio of maximum attainable output to actual output, then can be presented by:

$$TE_O(x_i, y_i) = f(x_i;\beta)\exp\{v_i\}/y_i = \exp\{u_i\} \geq 1 \tag{4.16}$$

To estimate technical efficiency, $TE_O(x_i, y_i)$, one needs to estimate the production frontier as per (4.15), and also decomposes the residuals into separate estimates of v_i and u_i. To do so, first one needs to parameterise the production technology; for instance, assuming that the efficient frontier follows the Cobb-Douglas production function form. Once the specifications of production function have been adopted, the vector of parameters and the estimates of inefficiency effects can be obtained using goal programming or econometric techniques. In this process, the main challenge is separating the effects of random noise from the effects of inefficiency.

Corrected ordinary least squares, which was initially suggested by Winsten (1957), is an approach that simplifies the model in (4.15) by assuming that $u_i = 0, i = 1,...,I$, and $v_i \sim N(0,\sigma_v^2)$. These assumptions transform (4.15) to an ordinary least squares (OLS) model, which intersects the data. Through an upward shift of the OLS estimated production function by the size of maximum positive residual to the estimated intercept, $v_i^{\max}$, a production frontier is constructed that bounds all sample observations. Using $v_i^{\max}$ the residuals are then corrected in the opposite direction to estimate $\hat{v}_i = v_i - v_i^{\max} \leq 0, i = 1,...,I$ as a proxy for u_i and $T\hat{E}_O(x_i, y_i) = \exp\{-\hat{v}_i\} \geq 1$.

Due to providing an easy way to estimate the inefficiency effects, COLS is widely used. However, there are severe shortcomings in this approach that make it unfavourable in current efficiency measurement studies. The COLS estimated inefficiency effects are vulnerable to outliers as the production frontier is constructed based on the largest positive OLS residual. The COLS production frontier form is exactly similar to the one from OLS function, whereas empirical investigations do not support the similarity of production frontier and OLS function forms. Also, the estimation of efficiency depends only on the single firm with most favourable maximum residual (Fried et al, 2008).

Aigner and Chu (1968) assumed that $v_i = 0, i = 1,...,I$, which transform (4.15) to a deterministic production function that can be estimated by goal programming techniques to minimise $\sum_i u_i$ or $\sum_i u_i^2$ subject to constraint $u_i = \ln[f(x_i;\beta)/y_i] \geq 0$ for all firms. Then the technical efficiency is estimated by $T\hat{E}_O(x_i, y_i) = \exp\{\hat{u}_i\} \geq 1$. Some later studies, such as Schmidt (1976) and Green (1980), attempted to identify the specifications of production frontier and the distribution of inefficiency effects. However, the lack of robust statistical inference, due to the deterministic formulation of production functions, has remained as the main drawback of this approach.

The stochastic frontier analysis (SFA) is an approach, introduced independently by Aigner et al. (1977) and Meeusen and van Den Broeck (1977), that incorporates the effects of both statistical noise and inefficiency into analysis. In terms of the distributional form in SFA, it is assumed that $v_i \sim N(0, \sigma_v^2)$ and $u_i \geq 0$ is distributed half-normal or exponential. The SFA assumption is also expanded to consider the independency of these terms, i.e. v_i and u_i, from each other and also from inputs x_i. Given these assumptions, one can define the likelihood function and estimate the maximum likelihood estimates. This results in obtaining the consistent estimates of parameter vector β and composed error term $v_i - u_i$. To separate the effects of inefficiency from those of statistical noise, Jondrow et al. (1982) suggested deriving the expected value of inefficiency effect conditional on the composed error term, i.e. $E[-\hat{u}_i \mid (v_i - u_i)]$. Once the conditional estimates of u_i are obtained, the technical efficiency can be estimated as $T\hat{E}_O(x_i, y_i) = \{\exp\{E[-\hat{u}_i \mid (v_i - u_i)]\}\}^{-1} \geq 1$. Battese and Coelli (1988) suggested an alternative estimator for technical efficiency as $T\hat{E}_O(x_i, y_i) = \{E[\exp\{-\hat{u}_i\} \mid (v_i - u_i)]\}^{-1} \geq 1$. Later studies, such as Hjalmarsson, Kumbhakar and Heshmati (1996), Horrace and Schmidt (1996) and Bera and Sharma (1999), proposed confidence intervals for efficiency estimates.

4.4.2 The Panel-Data Models

In the case of availability of observations over a period of time for each firm in the sample, panel-data techniques can be applied to estimate the efficiency performance. Schmidt and Sickles (1984) proposed the application of panel data techniques in a frontier context. Given the availability of panel data, equation (4.15) can be written as:

$$y_{it} = f(x_{it}; \beta) \exp\{v_{it} - u_i\}, x \in R_+^N, y \in R_+^M, i = 1,...,I, t = 1,...,T \qquad (4.17)$$

As in (4.17), the efficiency term u_i does not change over time; such model is called time-invariant. Based on earlier research, Fried et al. (2008) summarised four strategies to estimate efficiency using panel data.

The first approach introduced by Pitt and Lee (1981) is to estimate efficiency terms in panel-data cases using the cross-section maximum likelihood estimation (MLE) procedures. Battese and Coelli (1995) extended the panel data model to allow the technical efficiency term to be a function of firm-specific variables and time by setting $u_{it} = u_{it}(z_{it}; \gamma)$. The time-variant model of technical efficiency is more desirable in long panels while the inefficiency effects of firms may change over time. Although the technical efficiency estimates from this approach are consistent in T and I, the need for maintaining distributional and independency assumptions in MLE application has remained its main limitation.

The fixed-effects model is the second approach to estimate efficiency in the panel-data context. Similar to cross-section COLS, the fixed-effects model does not require any distributional assumption on efficiency effects, u_i , also these terms are allowed to be correlated with statistical noise terms, v_{it} , and the input values, x_{it}. The fixed-effects model treats the efficiency effects as the firm-specific constants $\beta_{oi} = (\beta_o - u_i)$ which can be estimated by OLS. The efficiency estimates are obtained from $\hat{u}_i = \beta_o^* - \beta_{oi} \geq 0$ where $\beta_o^* = \beta_{oi}^{\max}$, thus the efficiency estimates are generated by $T\hat{E}_O(x_i, y_i) = [\exp\{-\hat{u}_i\}]^{-1}$. The advantage of applying the fixed-effects model is deriving consistent estimates in both T and I with no need to distributional and independency assumptions on efficiency effects. The main shortcoming of this model is that the firm-specific constants may capture the variation in other time-invariant firm-specific factors in addition to the technical efficiency. Moreover, the assumption of time-invariant technical efficiency is not desirable in long panels.

The random-effects model is an approach that allows some of regressors to be time-invariant. This model assumes that efficiency effects, u_i , are random variable with unspecified distribution and constant mean and variance, but uncorrelated with statistical noise terms, v_{it} , and the input values, x_{it}. The generalised least square (GLS) can be applied in (4.17) by defining $\beta_o^{**} = \beta_o - E(u_i)$ and $u_i^{**} = u_i - E(u_i)$. The firm efficiency effects and the technical efficiency estimates are obtained from $\hat{u}_i = u_i^{**\max} - u_i^{**}$ and $T\hat{E}_O(x_i, y_i) = [\exp\{-\hat{u}_i\}]^{-1}$ respectively. The estimates from the random-effects model are consistent in T and I with the advantage of allowing some regressors to be time-invariant. The disadvantage of the random-effects model, in comparison with the fixed-effects model, is the requirement of independency of efficiency effects from the model regressors.

The last approach to estimate the technical efficiency in a panel-data case is a mixture of fixed-effects and random-effects models shown by Hausman and Tylor (1981). In this approach, $u_i s$ are allowed to be correlated with some regressors and the model can include some time-invariant regressors.

4.4.3 Developments in the Econometric Approach to Efficiency Measurement

During the past three decades the econometric approach to efficiency measurement has extensively been developed. In addition to the time-invariant models explained in the previous sections, the time-variant models have been developed to account for time-varying effects of (in) efficiency in the panel-data context. Cornwell et al. (1990) and Lee and Schmidt (1993) were the first among all to propose inclusion of time-varying efficiency effects in a generalised model of Schmidt and Sickles (1984).

In addition to the primal approach to efficiency measurement, which uses the input-output information to construct the production frontier, at the presence of price information, a dual approach can be utilised through the indirect estimation of efficient frontier using cost, revenue or profit functions. The dual approach allows us to deal with multiple outputs, quasi-fixed inputs, alternative behavioural objectives and the joint analysis of technical and allocative efficiencies (Murillo-Zamorano, 2004; Green, 2008).

To overcome the requirement of parametric approach to restrictive parametric assumptions, van Den Broeck et al. (1994) and Koop et al. (1994) were among the first to apply Bayesian techniques in a cross-section efficiency measurement context. Bayesian techniques do not require imposing priori sampling distributions on the efficiency term, u_i . Rather, the Bayesian method provides the ability to present the results in the form of probability density functions and to express the probability statements about the unknown parameters. Also, in the case of finite samples, the Bayesian estimation method overcomes some deficiencies of the classical econometric methods in terms of the statistical problems involved in the efficiency estimation. The application of Bayesian techniques was extended to the panel-data context by Koop et al. (1997) and Fernandez et al. (1997). Since van Den Broeck et al. (1994) and Koop et al. (1994), both the theoretical and the empirical literature on the Bayesian efficiency estimators have rapidly developed (e.g. see Green, 2008). The application of Bayesian techniques allows for dealing with multiple outputs and undesirable outputs in efficiency measurement (e.g. see Fernandez et al., 2002).

Further to the application of Bayesian techniques in efficiency measurement, the econometric approach literature has been developed to analyse multiple outputs technologies, and to deal with undesirable outputs using parametric frontier models (see e.g. Coelli and Perelman, 2000; Sickles et al., 2002).

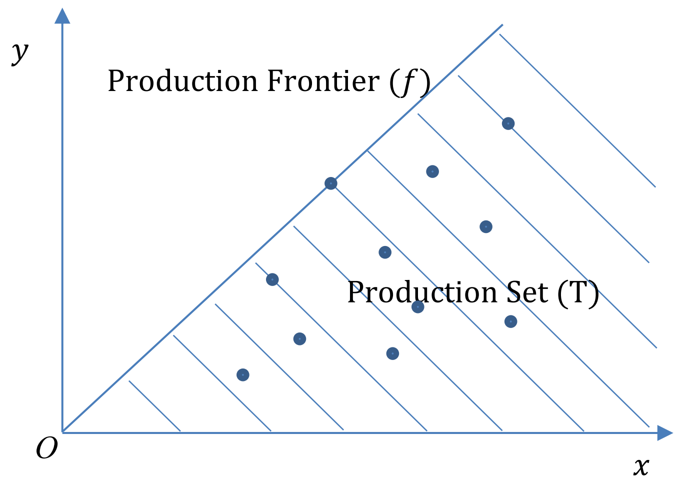
4.5 The Mathematical Programming Approach to Measure Efficiency

Based on the Farrell's (1957) method, Charnes et al. (1978) developed a mathematical programming method of efficiency measurement which later was called data envelopment analysis (DEA). DEA is a non-parametric method which aims to construct a frontier envelopment surface for all sample observations. The frontier surface is determined by efficient firms which lie on it. Inefficient firms are enveloped by frontier surface but do not lie on this surface. Since the introduction of DEA by Charnes et al. (1978) the mathematical programming approach to efficiency measurement has been significantly developed. In this section, among all developments and classifications of mathematical programming methods, we limit our introduction to the CCR model, BCC model and scale efficiency, and the statistical foundation of DEA.

4.5.1 CCR Model:

Charnes et al. (1978) generalised the Farrell's (1957) single input/output efficiency measure to a multiple input/output context. Their model, known as CCR, imposes three restrictions including constant returns to scale (CRS), convexity of the set of input-output combinations and strong disposability of inputs and outputs. The production set in a CCR model is illustrated in Figure 4.5, for a single input-single output case. The production frontier is a line connecting the origin to the observation point(s) which covers all other observations in the sample.

Figure 4.5: Production Set in CCR model



Suppose that firms use inputs $x \in \mathbb{R}_{+}^{N}$ to produce outputs $y \in \mathbb{R}_{+}^{M}$. The CCR model can be presented as the following fractional programming problem which seeks the values for input weights υ and output weights μ to minimise the weighted input-to-output ratio of the firm under evaluation subject to constraints that the weighted input-to-output ratios for all firms in the sample are greater than or equal to unity:

$$
\begin{aligned}
& \underset{\upsilon,\mu}{Min}\, \upsilon^{T} x_{o} / \mu^{T} y_{o} \\
& s.t. \\
& \upsilon^{T} x_{i} / \mu^{T} y_{i} \geq 1, i = 1, \ldots, o, \ldots, I \\
& \upsilon, \mu \geq 0
\end{aligned}
\tag{4.18}
$$

In (4.18), the vectors of inputs and outputs of firm under evaluation are represented by (x_{o}, y_{o}) and the vectors of inputs and outputs of the *i*th firm in the sample are represented by (x_{i}, y_{i}). As this fractional mathematical program results in an infinite number of solutions, one needs to transform it to a linear form. The fractional program (4.18) can be converted to the linear multiplier problem (4.19) and its dual envelopment program (4.20):

$$
\begin{aligned}
& \underset{\upsilon,\mu}{Min}\, \upsilon^{T} x_{o} \\
& s.t. \\
& \mu^{T} y_{o} = 1 \\
& \upsilon^{T} X - \mu^{T} Y \geq 0, \\
& \upsilon, \mu \geq 0
\end{aligned}
\tag{4.19}
$$

$$
\begin{aligned}
& \underset{\phi,\lambda}{Max}\, \phi \\
& s.t. \\
& X\lambda \leq x_{o} \\
& \phi y_{o} \leq Y\lambda \\
& \lambda \geq 0
\end{aligned}
\tag{4.20}
$$

where X is an N x I sample input matrix and Y is an M x I sample output matrix. Through running the multiplier program I times (number of observations in the sample), one can obtain the set of weights required to calculate the efficiency scores for all sample observations. In the envelopment program, ϕ is a scalar and λ is an I x 1 intensity vector. The performance of a firm in the envelopment program is evaluated as the firm's ability to expand its output subject to constraints imposed by the best practice observations in the sample. ϕ is the DEA estimator of technical efficiency defined in (4.6). The possibility of a radial expansion of output for a producer is equivalent to $\phi > 1$ from solving the envelopment program, which represents some degree of inefficiency in the firm performance. If the radial expansion is not possible, solving the envelopment program results in $\phi = 1$, which represents a technically efficient firm based on the definition of Debreu-Farrell output-oriented technical efficiency measure. In the sense of Koopmans technical efficiency definition, an efficient firm is characterised by $\{\phi = 1, X\lambda = x_o, \phi y_o = Y\lambda\}$ to avoid any slacks in inputs or outputs. Similar to the multiplier model, to obtain the efficiency estimates corresponding to all observations the CCR model should be run I times, once for each firm. From the CCR envelopment problem in (4.20), we can obtain the production set in (4.1) as $T^{CCR} = \{(x, y) : y \leq Y\lambda, X\lambda \leq x, \lambda \geq 0\}$ which is restricted by constant returns to scale assumption.

4.5.2 BCC Model and Scale Efficiency

The CCR model assumes that all firms in the sample operate at their optimum scale. If firms are surrounded by some limitations such as imperfect competition or government regulations, they may not be able to operate at their optimum scale; hence, the constant returns to scale assumption may not be valid in the efficiency measurement (Coelli et al., 2005). Banker, Charnes and Cooper (1984) relaxed the constant returns to scale assumption and introduced the variable returns to scale (VRS) model, which is known as the BCC model. The consideration of variable returns to scale assumption allows us to divide the operating efficiency performance from the effect of the operating scale (scale efficiency).

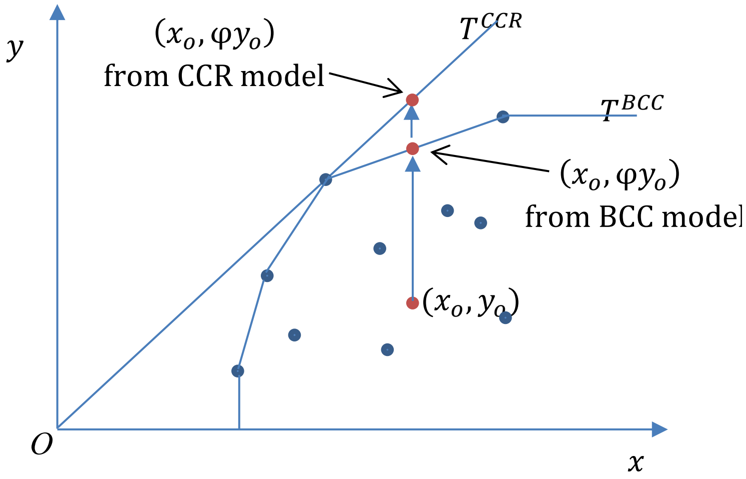
One can construct the BCC model by adding a free variable υ_o to the multiplier program or equivalently adding a convexity constraint $\sum_i \lambda_i = 1$ to the envelopment program. The BCC multiplier and envelopment programs can be shown as formulas (4.21) and (4.22):

$$
\begin{aligned}
&\underset{\upsilon,\upsilon_o,\mu}{Min}\, \upsilon^T x_o + \upsilon_o \\
&s.t. \\
&\mu^T y_o = 1 \\
&\upsilon^T X + \upsilon_o - \mu^T Y \geq 0, \\
&\upsilon, \mu \geq 0, \upsilon_o \text{ free}
\end{aligned}
\tag{4.21}
$$

$$
\begin{aligned}
&\underset{\phi,\lambda}{Max}\, \phi \\
&s.t. \\
&X\lambda \leq x_o \\
&\phi y_o \leq Y\lambda \\
&\lambda \geq 0, \sum_i \lambda_i = 1
\end{aligned}
\tag{4.22}
$$

The production set in the BCC model envelops the data more tightly than the production set in CCR model. As only the convex combination of efficient firms constructs the frontier, the production set shrinks, becoming $T^{BCC} = \{(x, y) : y \leq Y\lambda, X\lambda \leq x, \lambda \geq 0, \sum_i \lambda_i = 1\}$. Figure 4.6 graphically illustrates the production frontiers in both CCR and BCC models in a single input/output case. As shown in this figure, observations have shorter distance to the BCC frontier than the CCR frontier; hence, the efficiency estimates from the BCC model are generally higher than those obtained from the CCR model. What's more, the production frontier in BCC model exhibits increasing returns to scale, constant returns to scale and decreasing returns to scale in different regions of the production set. By definition, the constant returns-toscaleassumption applies when a proportional increase (decrease) in inputs results in a same proportional increase (decrease) in outputs. If a proportional change in inputs results in a greater proportional change in outputs the underlying technology exhibit the increasing returns to scale. Finally, if a proportional change in inputs results in a proportionally smaller change in outputs, the decreasing returns to scale exist in the underlying technology. In Figure (4.6), the firm $(x_{o,}y_o)$ is operating above it optimal size as $(x_{o,}\phi y_o)$ is located in the decreasing returns to scale region of the production frontier. In general, if the free variable υ_o in the multiplier program is negative, zero or positive, then the corresponding observation is located in the increasing returns to scale, constant returns to scale or decreasing returns to scale regions of production frontier respectively.

Figure 4.6: Production Frontiers in CCR and BCC Models



The CRS measure of technical efficiency captures the effects of both operating inefficiency (pure technical inefficiency) and the lack of operating on the optimum scale (scale inefficiency). To obtain the scale efficiency measure, one needs to conduct both a CRS and a VRS DEA and divide CRS efficiency score by the corresponding VRS efficiency score. If we denote the efficiency score obtained under the CRS assumption as ϕ_{CRS} and the efficiency score obtained under VRS assumption as ϕ_{VRS}, we can present the relationship among CRS efficiency, VRS efficiency and scale efficiency as follows:

$$S = \frac{\phi_{CRS}}{\phi_{VRS}} \tag{4.23}$$

The knowledge of scale efficiency aids us to understand whether the operating scale condition influences the efficiency performance of a firm. As Coelli et al. (2005) highlighted, further to the size of scale (in)efficiency, the nature of returns to scale can be obtained by conducting an additional non-increasing return to scale (NIRT) model. If the technical efficiency from the NIRT model is equal to the technical efficiency from the VRS model, then the decreasing returns to scale exist; meaning that the firm under investigation operates above its optimum scale (too big). If the VRS and NIRT efficiency scores are unequal, then the increasing returns to scale are exhibited; that is, the firm under investigation operates under its optimum scale (too small). In the condition that the CRS and VRS efficiency scores are equal, the constant returns to scale apply and the firm under investigation operates at its optimum scale.

The CCR and BCC models represented here are output-oriented. To obtain the input-oriented CCR and BCC models, taking into account the adjustment of the required variables, one needs to convert the multiplier program to a maximisation program and convert the envelopment program to a minimisation program.

4.5.3 Allocative Efficiency

Further to the estimation of technical efficiency using DEA models, the DEA literature has been extended to estimate the allocative efficiency (e.g. see Ferrier and Lovell, 1990; Fare et al., 1985; Fare et al., 1997). If the price information is available and objectives (such as cost minimisation, revenue maximisation or profit maximisation) are appropriate, it is possible to calculate both technical and allocative efficiencies. In doing so, first, the technical efficiency should be estimated using an envelopment program such as (4.20) for a CRS model or (4.22) for a VRS model, the economic efficiency should then be estimated using appropriate cost minimisation, revenue maximisation or profit maximisation programs.

From an input-oriented perspective, the cost efficiency (CE) can be defined as the ability of a firm to produce a given set of output by using minimum level of inputs at the optimum input price. Hence, the allocative efficiency is the ability of a firm to produce its given set of outputs at the minimum price. The allocative efficiency is the cost efficiency (CE) divided by technical efficiency (TE). Similarly, from an output-orientation perspective, the revenue efficiency (RE) can be defined as the ability of a firm to produce the maximum combination of its output at the maximum revenue by using a given set of inputs. Therefore, when the output price information is given, allocative efficiency can be measured as the firm's ability to produce at the maximum output prices. The output-oriented allocative efficiency is revenue efficiency (RE) divided by technical efficiency (TE). Finally, if both input and output prices are available, one can construct the profit maximisation problem to estimate profit efficiency (Coelli, 2005).

4.5.4 Statistical Foundation of DEA

A main drawback of DEA models is their inability to incorporate the impact of statistical noise. In the past two decades, the frontier literature has been developed to accommodate the statistical inferences in the deterministic DEA models. The two main approaches to develop the statistical foundation of DEA measure of technical efficiency are chance-constrained DEA and bootstrap DEA.

Based on an idea from Timmer (1971), Land et al. (1993) introduced the chance-constrained DEA by imposing probability to constraints on the envelopment problem. Therefore, a firm denoted by $(x_{o,}y_o)$ is required to radially expand its outputs subject to the constraints that $(x_{o,}\phi y_o)$ is "probably" feasible. Solving a chance-constraints DEA program requires distribution assumptions of the sample data. For instance, one needs to assume that outputs and inputs follow normal distributions with defined expected values and variance-covariance matrices. The required assumptions on the expected values as well as variance-covariance matrices of all variables for all firms make this approach implausible for empirical studies. Furthermore, this approach allows for stochastic inputs and outputs but fails to derive the statistical properties of the frontier and estimated efficiency scores (Grosskopf, 1996).

The other approach to incorporate random errors in the DEA estimates is applying bootstrapping techniques. The efficiency scores derived from DEA models are estimators for true but unknown efficiency. The structure of the true but unknown technology as well as the data generating process (DGP) determines the properties of the efficiency estimators (Fried et al., 2008). Simar and Wilson (1998) developed some assumptions on DGP and introduced a bootstrapping technique which provides statistical properties for the DEA efficiency estimators. Their work emphasised on the need for defining a reasonable data-generating process to derive a proper set of efficiency estimators. The bootstrap DEA provides the bias-corrected efficiency estimates with corresponding confidence intervals. The following section discusses in detail the bootstrapping technique and its application in DEA estimation of efficiency measures.

4.5.5 Bootstrapping Techniques and DEA

One of the main drawbacks of the data envelopment method is its deterministic nature. Basically, there is no statistical foundation in the DEA estimation. The estimated frontier output (or input) depends on the particular set of inputs-outputs and a different observed sample set would lead to a different estimated frontier. Hence, the estimated technical efficiency would be different from one sample to another. The conventional DEA models cannot provide the statistical properties that reflect sample variations and statistical noise. To obtain confidence intervals that cover statistical errors, one would need the sampling distribution of the frontier output (or input). However, usually only one sample is available. Applying the bootstrapping techniques is a practical way to accommodate the measurement errors and statistical noise in the deterministic DEA models, identifying the confidence intervals for efficiency estimates.

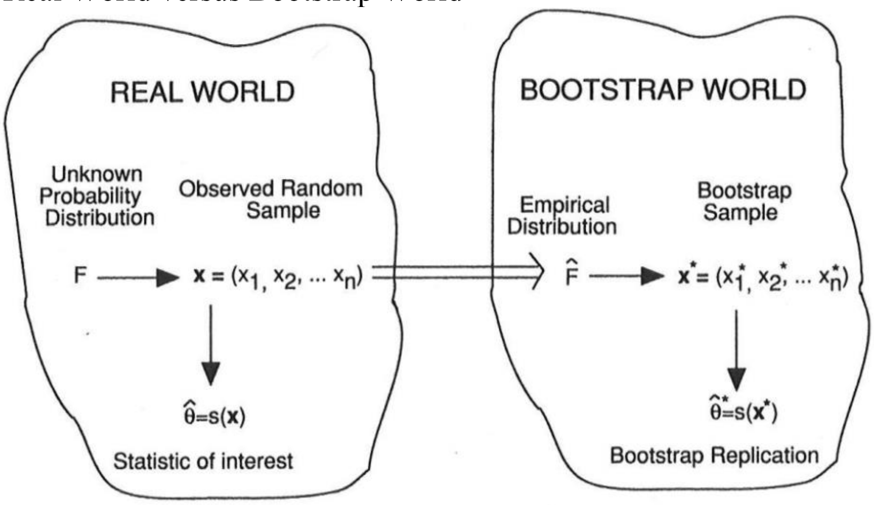
4.5.6 Bootstrapping Technique

Bootstrapping is one of the techniques of nonparametric statistics, introduced by Efron (1979) as an alternative resampling method. The bootstrapping technique estimates values of interest (statistics) based on an available sample from a corresponding population. These statistics are the estimators of statistical parameters of the population. The derived statistics depend on the sample and they vary from one sample to another. By drawing more samples, the accuracy of estimated statistics as estimators of the corresponding population increases. However, drawing many samples mostly is not feasible in practice. The bootstrapping technique uses a resampling procedure to generate a large number of resamples based on an original sample.

The bootstrapping technique estimates a parameter, such as mean or standard deviation, based on available data. The technique aids in constructing confidence intervals of the values of interests using the original sample data without imposing overly restrictive assumptions about the distribution form of the corresponding population. The bootstrap idea is about using only what is known from the data without extraneous assumptions about the population distribution (Chernick and LaBudde, 2011). In doing so, bootstrapping considers the random sampling from the observed data as the representation of the random sampling from the true population. This technique assumes that the empirical distribution of observed data mimics the distribution of the true population (Moradi, 2013).

Suppose $X = (X_1, \dots, X_n)$ is a random sample from a population with an unknown distribution F. The empirical distribution denoted by $\hat{F}$ represents the distribution of sample data. Our aim is to estimate a population parameter θ using the random sample X. The common population parameters are mostly functionals of the unknown population distribution F. We denote the parameter functional by θ and its empirical (sample) statistics by $\hat{\theta} = S(X)$. Based on the bootstrapping principles, for a population with unknown distribution F and a parameter of interest θ that we aim to estimate based on the available sample $X = (X_1,...,X_n)$, we use $\hat{F}$ as the representation of F and the bootstrap distribution $\hat{F}^*$ as the representation of $\hat{F}$ in the resampling process. In the resampling process we draw a random sample $X^* = (X_1^*,...,X_n^*)$ from the original sample $X = (X_1,...,X_n)$ with replacement. The bootstrap distribution $\hat{F}^*$ is the distribution for sampling with replacement from $\hat{F}$ with the bootstrap estimate of $\hat{\theta}^* = S(X^*)$. If we repeat this process many times, we can obtain a histogram of values for the bootstrap estimate which enables us to approximate the statistic distribution and also its statistical inferences such as bias and variance estimation, confidence interval construction and hypothesis testing.

Figure 4.7- Real World versus Bootstrap World



Source: Efron and Tibshirani (1994, p87)

The relationship between the real world and bootstrap world is demonstrated in Figure 4.7. In the real world, there is only one sample available, i.e. $X = (X_1,...,X_n)$, from an unknown probability distribution F . The statistic $\hat{\theta} = S(X)$ is the estimator of true parameter θ. On the other hand, the bootstrap sample $X^* = (X_1^*,...,X_n^*)$ is drawn from the empirical distribution $\hat{F}$ using a resampling procedure. The bootstrap estimate $\hat{\theta}^* = S(X^*)$ is the estimator of the sample statistic $\hat{\theta} = S(X)$. Unlike the real world wherein only one sample statistic is calculated, we can generate a bootstrap estimate as many as the replication number; therefore, the distribution of statistic estimator can be approximated. It allows us to obtain the statistical inferences for the statistic estimator and consequently, the parameter of interest from the true population. The accuracy and consistency of the estimates depends on the data generating process. If $\hat{F}$ is a reasonable estimator of F, the bootstrap distribution of $\hat{\theta}^* - \hat{\theta}$ mimics the sampling distribution of $\hat{\theta} - \theta$.

Naïve bootstrap is a simple technique in which the empirical distribution is a discrete distribution that gives equal weight to each data point by assigning equal probability $1/n$ to the original n observations. In this technique, it is possible in each random draw to have some observations repeated more than one time while some other observations are omitted. Efron and Tibshirani (1994) developed the following algorithms to compute the standard errors, bias and confidence intervals for the statistic of interest:

(i) Algorithm to Estimate Standard Errors of Statistic of Interest

1- Form B independent bootstrap samples $X^{*1}, X^{*2}, ..., X^{*B}$ by repeating B times drawing n values with replacement randomly from $X = (X_1, ..., X_n)$.

2- Calculate the bootstrap statistic of interest for each bootstrap sample:

$$\hat{\theta}^*(b) = S(X^*); b = 1, 2, ..., B \tag{4.24}$$

3- Compute the standard deviation of $\hat{\theta}^*(b); b = 1, 2, ..., B$ as the estimator of the standard error of the statistic of interest:

$$s\hat{e}_B = \{\textstyle\sum_{b=1}^{B} [\hat{\theta}^*(b) - (\sum_{b=1}^{B} \hat{\theta}^*(b)/B)]^2 /(B-1)\}^{1/2} \tag{4.25}$$

(ii) Algorithm to Estimate Bias of Statistic of Interest

1- Select B independent bootstrap samples $X^{*1}, X^{*2}, ..., X^{*B}$ in which n data values in each sample are selected randomly with replacement from the original sample $X = (X_1, ..., X_n)$.

2- Calculate the bootstrap statistic of interest for each bootstrap sample using (4.24).

3- Calculate the expected bootstrap statistic of interest as the arithmetic average of bootstrap statistics:

$$E(\hat{\theta}^*) = \textstyle\sum_{b=1}^{B} \hat{\theta}^*(b)/B \tag{4.26}$$

4- Calculate the bootstrap estimate of bias $\hat{\theta}^*$ as the estimator of bias of the statistic of interest $\hat{\theta}$:

$$Bias(\hat{\theta}^*, \hat{\theta}) = E(\hat{\theta}^*) - \hat{\theta} \tag{4.27}$$

5- Calculate the bias-corrected estimate of the statistic of interest:

$$\tilde{\hat{\theta}} = \hat{\theta} - Bias(\hat{\theta}^*, \hat{\theta}) = 2\hat{\theta} - E(\hat{\theta}^*) \tag{4.28}$$

(iii) Algorithm to Construct Confidence Intervals for Statistic of Interest

1- Form B independent bootstrap samples $X^{*1}, X^{*2}, ..., X^{*B}$ by drawing n data values from the original sample $X = (X_1, ..., X_n)$ with replacement.

2- Calculate the bootstrap statistic of interest for each bootstrap sample using (4.24).

3- Sort the bootstrap estimates of the statistic of interest in ascending order:

$$\hat{\theta}^{*(1)}, ..., \hat{\theta}^{*(b-1)}, \hat{\theta}^{*(b)}, ..., \hat{\theta}^{*(B)} \text{ where } \hat{\theta}^{*(b-1)} \leq \hat{\theta}^{*(b)}; b = 2, ..., B \tag{4.29}$$

4- Construct the $100(1-\alpha)$ confidence interval for the statistic of interest based on the percentile method by finding the $[(\alpha/2)100]th$ and $[(1-\alpha/2)100]th$ the empirical percentiles of ascending sorted bootstrap estimates:

$$[\hat{\theta}^*_{low}, \hat{\theta}^*_{up}] = [\hat{\theta}^{*([(\alpha/2)100]th)}, \hat{\theta}^{*([(1-\alpha/2)100]th)}] \tag{4.30}$$

4.5.7 Bootstrap DEA

The non-parametric methods of efficiency measurement do not account for the possibility of measurement error and natural randomness. As the frontier is constructed based on the extreme points in the observed data, the estimation of efficiency scores is highly sensitive to outliers. This limitation of deterministic methods, such as DEA, in providing statistical inference of efficiency estimates has encouraged scholars in the efficiency measurement field to explore some way-out solutions.

Bootstrap DEA is one of the stochastic DEA approaches developed to overcome this limitation. Ferrier and Hirschberg (1997) introduced a method to derive the stochastic properties of the estimated efficiencies. In their method they computed the bias of efficiency estimates and constructed the confidence intervals of efficiency scores using the bootstrap technique introduced by Efron (1979).

Based on Efron's (1979) work, Simar (1992) and Simar and Wilson (1998), Simar and Wilson (2000b) set the foundation for applying bootstrapping techniques to obtain the statistical inference in DEA estimates. A simple bootstrapping procedure, called naïve bootstrap, requires taking n independent draws from the empirical distribution of the observations in S_n to construct a pseudo sample S_n^*. Simar and Wilson (1999) presented that the naïve bootstrap procedure, such as the bootstrap technique used by Ferrier and Hirschberg (1997), results in inconsistent inference for DEA estimators. Simar and Wilson (1998) discussed the importance of the data generating process (DGP) and introduced a smoothed bootstrapping procedure to avoid inconsistent estimates of efficiency. Simar and Wilson (2000a) dropped the homogeneity requirement in their earlier work and extended their bootstrapping method to allow for heterogeneity in the structure of efficiency.

The consistency of the efficiency estimates in the bootstrap DEA depends on the data generating process (DGP). If a reasonable DGP is employed, the empirical distribution is a consistent estimator of the population distribution and the bootstrap efficiency scores are consistent estimators of the efficiency scores. The naïve bootstrap techniques, as shown by Simar and Wilson (1999), does not lead to consistent efficiency estimates. This means that even if the number of replications B and the sample size n approach infinity, the Monte Carlo empirical distribution of bootstrap efficiency estimates $\hat{\theta}^*$ will not approximate the sampling distribution of sample efficiency estimates $\hat{\theta}$. Two main alternative bootstrap techniques, developed to overcome the inconsistency issue in applying the naïve bootstrap technique, are sub-sampling and smoothing. The sub-sampling technique draws pseudosamples of size $m = n^k$, where $k < 1$. The smoothing version of the bootstrap method employs a smooth estimate of the joint probability density to simulate pseudosamples $X^{*b}, b = 1, \ldots, B$ (Simar and Wilson, 2008).

Kneip et al. (2008) discussed the consistency of bootstrapping procedures and concluded that both sub-sampling and smoothing procedures are consistent to obtain statistical inference based on the asymptotic distribution of DEA estimators under variable returns to scale assumption.

(i) Bootstrapping DEA Efficiency Scores

The aim of bootstrapping is to approximate the sampling distribution of $\hat{\theta}(x,y)-\theta(x,y)$ by computing $\hat{\theta}^*(x,y)-\hat{\theta}(x,y)$ from resampled data $X^{*b}, b=1,...,B$. Suppose Ψ is the production set, $f(x,y)$ is the probability density function of inputs/outputs, and $\mathrm{P}=\mathrm{P}(\Psi, f(.,.))$ is the DGP. We denote a consistent estimator of the DGP as:

$$\hat{\mathrm{P}}(X)=\mathrm{P}(\hat{\Psi},\hat{f}(.,.)) \tag{4.30}$$

Unfortunately, in the real world, we do not have the knowledge of P, Ψ and $\theta(x,y)$. Therefore, we intend to construct the estimates of P, Ψ and $\theta(x,y)$ using the only available observation set $X=(X_1,...,X_n)=\{(x_i,y_i), i=1,...,n\}$. $\hat{\mathrm{P}}$, $\hat{\Psi}$ and $\hat{\theta}(x,y)$ are the estimates of P, Ψ and $\theta(x,y)$ in the real world. However, in the bootstrap world, they are considered to be true DGP, true production set and true efficiency respectively. Bootstrap data set $X^*=(X_1^*,...,X_n^*)=\{(x_i^*,y_i^*), i=1,...,n\}$ can be drawn from the known DGP estimate $\hat{\mathrm{P}}$. From an output orientation point of view and under variable returns to scale assumption, the bootstrap estimate of production set can be shown as:

$$\begin{aligned}&\hat{\Psi}^*=\hat{\Psi}(X^*)=\\&\{(x,y)\in\mathbb{R}_+^N\times\mathbb{R}_+^M:\sum_{i=1}^{n}\lambda_i y_i^*\geq y,\sum_{i=1}^{n}\lambda_i x_i\geq x,\sum_{i=1}^{n}\lambda_i=1,\lambda_i\geq 0\quad\forall i=1,...,n\}\end{aligned} \tag{4.31}$$

and the bootstrap estimate of efficiency score can be attained by solving the following linear program which is similar to the envelopment program (4.22):

$$\begin{aligned}&\hat{\theta}^*(x,y)=Max\{\theta:(x,\theta y)\in\hat{\Psi}^*\}=\\&Max\{\theta:\sum_{i=1}^{n}\lambda_i y_i^*\geq\theta y,\sum_{i=1}^{n}\lambda_i x_i\geq x,\sum_{i=1}^{n}\lambda_i=1,\lambda_i\geq 0\quad\forall i=1,...,n\}\end{aligned} \tag{4.32}$$

If the bootstrap is consistent, the sampling distribution of bootstrap efficiency scores provides approximations of the sampling distribution of efficiency scores. Mathematically, it can be shown as:

$$(\hat{\theta}^*(x,y)-\hat{\theta}(x,y))\,|\,\hat{\mathrm{P}}(X)\ \sim\ (\hat{\theta}(x,y)-\theta(x,y))\,|\,\mathrm{P} \tag{4.33}$$

The DGP estimator $\hat{\mathrm{P}}(X)$ is used to generate B samples $X^{*b}, b = 1,..., B$, by size of *n*. Therefore, B times solving of the linear program (4.32) results in B pseudoestimates of efficiency scores $\hat{\theta}^{*b}(x,y), b = 1,..., B$. Monte Carlo simulations are used to approximate the sampling distribution of $\hat{\theta}^{*}(x,y)$, which is assumed to be known in the bootstrap world. In theory, by approaching B toward infinity, the Monte Carlo approximation error due to bootstrap resampling tends to be zero. What's more, a larger sample size gives better approximations (Simar and Wilson, 2008).

(ii) Bootstrap Confidence Intervals

Assuming knowledge of the distribution of $(\hat{\theta}(x,y) - \theta(x,y))$, one can find $c_{\alpha/2}$ and $c_{1-\alpha/2}$ such that:

$$\mathrm{prob}(c_{\alpha/2} \le \hat{\theta}(x,y) - \theta(x,y) \le c_{1-\alpha/2}) = 1 - \alpha \tag{4.34}$$

where $c_{\alpha/2}$ and $c_{1-\alpha/2}$ are the $(\alpha/2)$th and $(\alpha/2)$th quantiles of the sampling distribution of $(\hat{\theta}(x,y) - \theta(x,y))$ and $\alpha \in [0,1]$. Hence a $(1-\alpha) \times 100\%$ confidence interval for $\theta(x,y)$ can be expressed as:

$$\hat{\theta}(x,y) - c_{1-\alpha/2} \le \theta(x,y) \le \hat{\theta}(x,y) - c_{\alpha/2}. \tag{4.35}$$

To estimate the unknown values of $c_{\alpha/2}$ and $c_{1-\alpha/2}$, the empirical bootstrap distribution of $\hat{\theta}^{*b}(x,y), b = 1,..., B$ can be used. Hence (4.34) can be transformed into:

$$\mathrm{prob}(\hat{c}_{\alpha/2} \le \hat{\theta}^{*}(x,y) - \hat{\theta}(x,y) \le \hat{c}_{1-\alpha/2} \mid \hat{\mathrm{P}}(X)) = 1 - \alpha \tag{4.36}$$

where $\hat{c}_{\alpha/2}$ and $\hat{c}_{1-\alpha/2}$ are the $(\alpha/2)$th and $(\alpha/2)$th quantiles of the empirical distribution of $(\hat{\theta}^{*b}(x,y) - \hat{\theta}(x,y)), b = 1,..., B$ sorted in ascending order. Therefore, the bootstrap approximation of (4.34) is:

$$\mathrm{prob}(\hat{c}_{\alpha/2} \le \hat{\theta}(x,y) - \theta(x,y) \le \hat{c}_{1-\alpha/2}) \approx 1 - \alpha \tag{4.37}$$

and the estimated $(1-\alpha)\times 100\%$ confidence interval for $\theta(x,y)$ is:

$$\hat{\theta}(x,y)-\hat{c}_{1-\alpha/2} \le \theta(x,y) \le \hat{\theta}(x,y)-\hat{c}_{\alpha/2}. \tag{4.38}$$

The bootstrap confidence interval procedure should be repeated n times (the number of observations in the original sample) to construct confidence intervals for all observations. The construction of confidence intervals explained above is suitable for the output-oriented Farrell efficiency measure, in which efficiency scores are bounded by a minimum of unity. In the case of using efficiency measures that lead to efficiency scores between zero and one, a reciprocal transformation is required to avoid negative lower-bound confidence intervals (Simar and Wilson, 2008).

(iii) Bootstrap Bias Corrections

Bias of efficiency estimates can be presented by the following equation:

$$bias(\hat{\theta}(x,y)) \equiv E(\hat{\theta}(x,y)) - \theta(x,y). \tag{4.39}$$

The bootstrap bias estimator of the original efficiency score $\hat{\theta}(x,y)$ can be defined as:

$$\widehat{bias}_B(\hat{\theta}(x,y)) = B^{-1}\sum_{b=1}^{B}(\hat{\theta}^{*b}(x,y)) - \hat{\theta}(x,y). \tag{4.40}$$

Using (4.40) we can construct a bias-corrected estimator of $\theta(x,y)$ as:

$$\hat{\hat{\theta}}(x,y) = \hat{\theta}(x,y) - \widehat{bias}_B(\hat{\theta}(x,y)) = 2\hat{\theta}(x,y) - B^{-1}\sum_{b=1}^{B}(\hat{\theta}^{*b}(x,y)). \tag{4.41}$$

The bias corrections procedure may introduce additional noise as $\hat{\hat{\theta}}(x,y)$ can have a mean square error greater than the mean square error of $\hat{\theta}(x,y)$. Hence, the bias correction formula of (4.41) should not be used unless $\frac{|\widehat{bias}_B(\hat{\theta}(x,y))|}{\hat{\sigma}} \ge \frac{1}{\sqrt{3}}$ where $\hat{\sigma}$ is the sample standard deviation of the bootstrap values $\hat{\theta}^{*b}(x,y), b=1,\dots,B$ (Simar and Wilson, 2008).

(iv) DEA Bootstrap Algorithm

Subsampling and smoothing techniques are two approaches to construct consistent pseudosamples. Subsampling is similar to naïve bootstrap techniques except for the pseudosample size. In subsampling techniques, the size of pseudosamples is $m = n^k$ where $k \in (0,1)$. As Kneip et al. (2008) showed, the subsampling techniques results in consistent bootstrap estimates, however the choice of $k \in (0,1)$ is critical to the technique.

As an alternative approach, the pseudosamples can be drawn from a smooth nonparametric estimate of the unknown probability density function of inputs/outputs, $f(x, y)$. In comparison with the subsampling technique, the smoothing technique is more complicated as the corresponding production set, Ψ, of the probability density function of inputs/outputs, $f(x, y)$, is unknown as well. Simar and Wilson (1998, 2000a) provide the stepwise procedures to run the smoothing technique. The smooth bootstrap DEA algorithm for the output-oriented technical efficiency can be outlined as per the below steps:

1- Estimate the technical efficiency score $\hat{\theta}_j$, for each firm $j = 1,...,n$ using the envelopment program (e.g. using (4.20) for a CRS model or (4.22) for a VRS model).

2- Generate a simple (naïve) bootstrap sample $\beta_1^*,...,\beta_n^*$ drawn (with replacement) from $\hat{\theta}_1,...,\hat{\theta}_n$.

3- Calculate the smoothed bootstrap sample, $\tilde{\theta}_1^*,...,\tilde{\theta}_n^*$, from the naïve bootstrap sample via the following equations:

$$\tilde{\theta}_j^* = \begin{cases} \beta_j^* + h\varepsilon_j^* & \text{if } \beta_j^* + h\varepsilon_j^* \geq 1 \\ 2\text{-}\beta_j^* - h\varepsilon_j^* & \text{otherwise} \end{cases}$$

where h is the bandwidth of a standard normal kennel density and ε_j^* is a randomly generated term from the standard normal. This formula set a bound to ensure that $\tilde{\theta}_j^*$ is equal or greater than unity. Simar and Wilson (2000b) described a procedure to obtain an optimum h.

4- To correct the variance of the smoothed bootstrap sample, calculate θ_j^* via

$$\theta_j^* = \bar{\beta}^* + \frac{1}{\sqrt{1 + h^2 / \hat{\sigma}_{\hat{\theta}}^2}} (\tilde{\theta}_j^* - \bar{\beta}^*)$$

where $\bar{\beta}^*$ is the mean value of $\beta_1^*, ..., \beta_n^*$ and $\hat{\sigma}_{\hat{\theta}}^2$ is the sample variance of $\hat{\theta}_1, ..., \hat{\theta}_n$.

5- Calculate the pseudo-data set as $\left\{(x_j, y_j^*) : y_j^* = y_j \hat{\theta}_j / \theta_j^*; j = 1, ..., n\right\}$.

6- Using the pseudo-data set, solve the DEA problem below:

$$\hat{\theta}_j^* = \max\{\theta > 0 | \sum_{k=1}^{n} z_k y_k^* \geq \theta y_j, \sum_{k=1}^{n} z_k x_k \geq x_j, \theta > 0, \sum_{k=1}^{n} z_k = 1, z_k \geq 0, k = 1, ..., n\}$$

7- Repeat steps (2) to (6) B times to provide $\left\{\hat{\theta}_{j,b}^*; b = 1, ..., B\right\}$.

8- Calculate statistics for the bootstrap bias-corrected measure of technical efficiency.

4.6 Analysis of Environmental Factor Effects on Technical Efficiency

In addition to inputs and outputs, business environment and firm-specific factors can influence the efficiency performance of a production unit. Unlike traditional inputs and outputs, such factors are generally assumed to be non-controllable for managers. For instance, ownership status, location of operations, and government regulations are factors that can influence the efficiency performance of a firm; however, such factors are not under control of managers toward optimising the transformation of inputs to outputs. The analysis of exogenous variables, which are called environmental variables here, is important given that improving the efficiency performance requires the knowledge of its determinants.

4.6.1 Environmental Factor Analysis in SFA

Early literature in SFA used a two-stage approach to analyse the determinants of efficiency performance. The first stage involved the estimation of efficiency; for instance, using the SFA model of Battese and Coelli (1988). Then in the second stage, an econometric model was constructed to regress the estimated efficiencies against environmental and firm-specific factors, potentially influencing the efficiency. This approach was criticised by Deprins and Simar (1989) for its statistical validity. To overcome the issues surrounding the two-stage SFA approach, Battese and Coelli (1995) proposed a single-stage model as

$y_i = f(x_i;\beta)\exp\{v_i - u_i(z_i;\gamma)\}$ where $u_i(z_i;\gamma) \geq 0$, z_i is a vector of exogenous factors and γ is the vector of parameters of exogenous factors.

4.6.2 Environmental Factor Analysis in DEA

DEA literature provides a range of techniques to deal with environmental factors. Coelli et al. (2005) recommend four methods for dealing with environmental factor analysis in a DEA setup. For the case that only one environmental variable from the categorical class is under investigation, the method proposed by Charnes et al. (1981) can be used. In this method, first the efficiency performance is calculated for each category, then all observations are projected onto their respective frontiers. Finally, all these projected observations are used to construct a single DEA model to assess if the mean efficiency of subsamples is statistically different.

In case that the environmental variable can be ordered from the least to the most adverse effect upon efficiency, as suggested by Banker and Morey (1986b), the efficiency performance of a firm can be compared with only those firms in the sample that their environmental variable is less than or equal to that of the firm under investigation. This method ensures that no firm is compared with another firm that has a more favourable environment. Similar to the previous method, only one environmental variable can be included in the analysis. A key problem with this method is its need for the direction of influence of the environmental variable on efficiency performance. Such knowledge is not known in many empirical studies.

Another method of dealing with environmental factors in DEA problems is to include them directly into the linear programming (LP) formulation. In doing so, one needs to decide if the direction of the influence of environmental factors on efficiency is known or not. In the case of having knowledge of influence direction, the environmental variables can be considered as non-discretionary input or output variables. If it is believed that the environmental variable positively influences the efficiency, such variable appears as a non-discretionary input variable in the LP formulation; for instance, as proposed by Banker and Morey (1986a). The aim of this DEA modelling is to contract only the discretionary factors in solving the constructed LP. Hence, the non-discretionary inputs are not scaled up or down within the reference firm while restricted to not exceed the non-discretionary input level. In the case of non-discretionary variables with a negative effect on efficiency, they should be included in the LP formulation as non-discretionary outputs. Therefore, the DEA program expands only the discretionary outputs while restricting the non-discretionary outputs to not fall below the non-discretionary output level.

If the direction of the influence of environmental factors is not known, they should be considered as non-discretionary neutral variables. In this case, the related constraints in the LP problem should be in equality form to ensure that a firm is compared with a theoretical frontier firm wherein its operating environment is no better and no worse (same) than the firm environment. A disadvantage of this method is that it is suitable for only continuous variables, and in the case of categorical variable presence among environmental factors, a more complicated mixed-integer LP problem, as presented in Banker and Morey (1986a), should be used.

The last method to handle non-discretionary factors in DEA applications is the two-stage approach introduced and developed by Ray (1988, 1991). The two-stage approach involves the estimation of efficiency using a traditional set of inputs/outputs in the first stage and regressing the estimated DEA efficiency scores against non-discretionary factors in the second stage. The second-stage regression aims to estimate the part of efficiency that is explained by non-discretionary factors. To do so, the DEA efficiency scores are corrected for environmental factors by using the estimated regression coefficients. This adjusts all efficiency scores corresponding to a common operating environment. Hence, the extent of managerial inefficiency, which is not associated with the influence of non-controllable factors, is the shortfall of DEA efficiency scores from the estimated efficiency score in the second stage and not from the unity. The two-stage method is superior to other methods as it can accommodate more than one variable with both continuous and categorical characterisations. Also a priori knowledge of the direction of the influence of environmental variables is not required, while this simple and transparent method enables us to conduct hypothesis testing on the significance of influence of environmental factors upon efficiency.

Nevertheless, the two-stage method suffers from some severe limitations. The regression analysis requires the specification of a functional form; therefore, a misspecification of the functional form can alter the results. Also, as a significant proportion of efficiency scores are frequently equal to one, the ordinary least square (OLS) regression may result in efficiency estimates greater than one. The Tobit regression method can account for truncated data to ensure that the dependent variable (efficiency estimate) is bounded between 0 and 1. Hence, it is recommended to use the Tobit model in the second-stage analysis.

A major problem of the two-stage approach arises from the fact that if the input-output factors used in the first stage are highly correlated with the independent variables (environmental factors) in the second-stage econometric model, the results are likely to be biased. Furthermore, as the efficiency scores are dependent on each other due to the nature of DEA problems, the basic regression analysis assumption of independency within sample is violated. Simar and Wilson (2007) show that these dependency issues lead to invalid results from the OLS or the Tobit regression analysis.

4.6.3 Two-Stage DEA Using Truncated Regression Model

In the two-stage approach, the efficiency estimates are first obtained from the DEA problem using traditional input-output specifications, then these estimated efficiency scores are regressed against environmental variables. The second-stage regression model can be specified as:

$$TE_j = Z_j\beta + \varepsilon_j, \quad j = 1,...,n. \tag{4.42}$$

where Z_j is a vector of firm-specific variables expected to influence the technical efficiency of firm j. The aim of second-stage analysis is to estimate the coefficient vector β and generate the stochastic error term ε_j for each individual firm. Thus, the corrected efficiency estimates for environmental factor influence can be attained for each firm in the sample.

The traditional two-stage approach mostly employs either OLS or Tobit method to regress the efficiency estimates from stage one. However, as Simar and Wilson (2007) explained, the underlying DGP is not described in these two methods. Additionally, the DEA efficiency estimates are biased as the conventional DEA methods do not account for statistical noise and measurement error. More importantly, the DEA efficiency estimates are serially correlated in a complicated and unknown way; also if any inputs or outputs are correlated with environmental factors, the error term ε_j is correlated with Z_j. To solve these dependency issues and to eliminate the efficiency estimates bias, Simar and Wilson (2007) proposed an alternative approach using a bootstrap truncated regression. Instead of conventional efficiency scores, the bias-corrected technical efficiency scores ($T\hat{E}_j^{bc}$) are used in equation (4.42). Since both sides of equation (4.42) are bounded by unity, the restriction $\varepsilon_j \geq 1 - Z_j\beta$ is applied for ε_j. It is assumed that ε_j is from a left-truncated normal distribution with zero mean and unknown variance. Hence, the initial regression model can be presented as per the formulation in (4.43) for the second-stage analysis:

$$T\hat{E}_j^{bc} = Z_j\beta + \varepsilon_j; \text{ where } \varepsilon_j \sim N(0, \sigma_\varepsilon^2), \text{ and } \varepsilon_j \geq 1 - Z_j\beta, \quad j = 1, \ldots, n. \tag{4.43}$$

A bootstrap method, such as the procedure in Simar and Wilson (2000a), can be used to calculate the bias-corrected efficiency estimates. Then a second parametric bootstrap can be used to calculate valid estimates of confidence intervals for the parameters in the second-stage regression. Simar and Wilson (2007) proposed two algorithms for the two-stage efficiency estimation problem. The following procedure is the second algorithm in Simar and Wilson (2007) which takes into account the bias term in the estimated efficiencies used in the second-stage regression in (4.43):

1- Estimate the efficiency score $\hat{\theta}_i$ for each firm using (4.20) for a CRS model or (4.22) for a VRS model.
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 $\{\hat{\theta}_{ib}^*, b = 1, \ldots, B\}$:
   3-1- draw ε_i from the $N(0, \hat{\sigma}_\varepsilon^2)$ distribution with left truncation at $(1 - z_i\hat{\beta})$ for $i = 1, \ldots, n$.
   3-2- Calculate $\theta_i^* = z_i\hat{\beta} + \varepsilon_i$ for each firm.
   3-3- Set $x_i^* = x_i$, $y_i^* = y_i\hat{\theta}_i/\theta_i^*$ for all $i = 1, \ldots, n$.
   3-4- 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 $\hat{\hat{\theta}}_i = \hat{\theta}_i - (\frac{1}{B}\sum_{b=1}^{B}\hat{\theta}_{ib}^* - \hat{\theta}_i)$.
5- Estimate the truncated regression of $\hat{\hat{\theta}}_i$ on z_i using the maximum likelihood method to obtain $(\hat{\hat{\beta}}, \hat{\hat{\sigma}})$.
6- Loop over the next three steps B times to provide $(\hat{\hat{\beta}}_b^*, \ \hat{\hat{\sigma}}_b^*, b = 1, \ldots, B)$.
   6-1- Draw ε_i from the $N(0, \hat{\hat{\sigma}}\ )$ with left truncation at $(1 - z_i\hat{\hat{\beta}})$ for $i = 1, \ldots, n$.

6-2- Calculate $\theta_i^{**} = z_i\hat{\hat{\beta}} + \varepsilon_i$ for each firm.

7- 6-3) Estimate the truncated regression of θ_i^{**}on z_i using maximum likelihood to obtain $(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*)$.

8- Construct the confidence interval for β and σ_ε using the bootstrap values $(\hat{\hat{\beta}}_b^*,\ \hat{\hat{\sigma}}_b^*, b = 1, \dots, B)$.

4.7 Summary

This chapter has discussed the concepts and techniques in efficiency analysis. The chapter provided a detailed analytical approach to present efficiency concepts. The attention in this chapter has mainly been to technical efficiency as adopted in analysis of this thesis. The introduction of concepts started with technology frontier, output set, input set, distance function and measures of technical efficiency. Where applicable, the mathematical formulation and graphical illustration have been adopted to aid in explaining the efficiency concepts.

Further to the concepts presented in this chapter, the efficiency analysis techniques from both dominant approaches, namely stochastic frontier analysis (SFA) and data envelopment analysis (DEA), have been discussed. SFA is a parametric econometric technique that separates the effects of inefficiency, which is under the control of managers, from that of statistical noise and measurement error, which managers do not have much control over. The stochastic nature of SFA enables this approach in providing statistical inference such as standard errors of efficiency estimates and hypothesis testing. Nonetheless, the techniques in this approach require selection of a pre-defined functional form for both frontier and error terms in the econometric modelling. Recent development in the econometric approach, such as flexible functional forms and semiparametric, nonparametric and Bayesian techniques, improved the limitation of the stochastic approach in the requirement of pre-defined functional forms (see e.g. Greene, 2008).

DEA is the most frequently used non-parametric model in productive efficiency literature. Emrouznejad and Yang (2018) reported an exponential growth in DEA-related publications in the past four decades. Using linear programming techniques, DEA constructs a piece-wise envelop (frontier) that covers all observations in the sample to calculate the distance of individual units from the respective point on the frontier. Such distance is used to estimate the efficiency performance of firms relative to the constructed frontier. Constant returns to scale (CRS) and variable returns to scale (VRS) are two common assumptions in DEA application. According to the CRS assumption, all firms in the sample are assumed to operate at their optimum scale; whereas VRS assumption is based on the fact that due to some limitations in operating environment, such as imperfect competition, government regulations and constraint on finance, firms may not be able to operate at their optimum scale. Hence, the total technical efficiency estimated from a CRS DEA model should be decomposed to two components; pure technical efficiency and scale efficiency (Coelli et al. 2005).

The popularity of the DEA approach is mainly due to its main advantages in no requirement for functional form and the ability to handle multiple input-multiple output problems. However, the deterministic nature of DEA leads to its inability in presenting the statistical properties of efficiency estimates. Simar and Wilson (1998) addressed the lack of statistical inference in DEA applications and they proposed a bootstrap procedure to generate statistical properties of efficiency estimates. The bootstrap DEA enables us to calculate the efficiency standard errors, efficiency confidence intervals and bias-corrected efficiency estimates. As the statistical properties of efficiency estimates are calculated by a bootstrapping technique, one can conduct hypothesis tests on efficiency parameters. Simar and Wilson (1999) argued that the naïve bootstrap procedure, as initially introduced by Efron (1979), does not produce consistent bootstrap efficiency estimates. Kneip et al. (2008) presented that both major resampling procedures, including subsampling and smoothing techniques, result in consistent bootstrap estimates. Therefore, in this study we follow the smooth bootstrapping procedure proposed by Simar and Wilson (1998, 2000a) to generate standard errors and confidence intervals of efficiency estimates.

A main question in efficiency analysis studies is how to improve it. To answer such question, one needs to investigate the exogenous factors which are potentially associated with the inefficiency observed among firms. The productive efficiency literature proposed different methods in both SFA and DEA environments in order to analyse the potential effects of environmental factors in efficiency gains. In the case of DEA application, which is our chosen approach in this study, two-stage DEA is the most common method to analyse the influence of business environment conditions and firm-specific factors on efficiency performance. The first stage follows a DEA model to estimate efficiency, and the second stage applies an econometric regression model to investigate the factors influencing the estimated efficiency. The application of OLS and Tobit regression methods is a common practice in the two-stage DEA empirical studies. Such models are simple and easy to construct for the inclusion of multiple regressors, either continuous or categorical. However, Simar and Wilson (2007, 2011) criticised these models in producing biased estimated coefficients due to the dependency issues in DEA setup. That is, the inputs and outputs may be correlated with the environmental factors. Also due to the nature of DEA methods, the efficiency of a firm is calculated relative to the rest of observations in the sample; therefore, the estimated efficiency scores are dependent on each other in a complicated way. These dependency issues are contrary to the independency requirement of regression analysis. Furthermore, the efficiency estimates from the first stage are biased due to the deterministic nature of DEA. To overcome these issues, Simar and Wilson (2007) proposed a bootstrap two-stage DEA approach. This approach, which is used in this study, includes bias-corrected efficiency estimates as the regressant and applies a bootstrap truncated regression to provide valid inference in the second-stage regression. Monte Carlo experiments confirm the improvement of second-stage DEA by way of the bootstrap truncated regression method (Simar and Wilson, 2007).

5 Data and Empirical Models

5.1 Introduction

The aim of this chapter is first to present the source of data and description of variables study, and second, to develop the empirical models of technical efficiency analysis with a two-stage DEA approach. Section 5.2 of this chapter introduces the data source used in our study. DatAnalysis provides financial data of Australian companies listed on the Australian Securities Exchange (ASX) including the Australian listed mining companies. The data required to construct some variables of our empirical model is available on the DatAnalysis database. We use this database to extract the related data and formulate those variables. Further to this database, the mining firms' annual reports are broadly used to obtain data on a number of variables in both technical efficiency and efficiency determinants models. The dataset covers study variables over the period of 2010 to 2014.

In Section 5.3, the variables used in the empirical model are discussed. Following our two-stage analysis approach, first we review the variables (inputs and outputs) used to construct a general model of technical efficiency. In addition to common inputs and outputs in the technical efficiency model, this section discusses the role of natural resource input as a specific input variable in the resource sector (such as mining). This section continues with discussion of variables used in the second-stage econometric analysis. In line with the firm-level approach of this study, the focus of the second-stage analysis is to investigate the firm-specific factors which influence the efficiency performance of mining companies. As discussed in Chapter 2 and Chapter 3, previous studies have identified a number of micro-level factors as influential to the efficiency and productivity gains of mining companies. This chapter summarises the major factors that potentially determine the efficiency performance of Australian mining companies.

Section 5.4 develops the model of technical efficiency estimation. We take into account the common approach of input and output selection in the production function theory as well as a natural resource-based approach which reflects the specifications of input and output selection in the non-renewable resource sector of mining. Therefore, we develop two technical efficiency models: Model I is constructed using one output, namely total production, and three inputs including labour, capital and intermediate inputs; and Model II which contains natural resource input in addition to the existing variables in Model I.

Stage-one analysis involves the application of data envelopment analysis (DEA) to estimate the technical efficiency of the Australian mining firms. The main advantage of DEA is that it does not require any pre-defined functional form; however, it does not take into account statistical noise resulting from measurement errors. To overcome the shortcoming associated with the lack of statistical properties in DEA, we use a bootstrap procedure proposed by Simar and Wilson (1998) to obtain bias-corrected DEA estimates. Both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions are considered in formulation of the technical efficiency models.

Section 5.5 provides the analytical model for stage two and examines the effects of firm-specific factors on the technical efficiency of mining firms in Australia. The econometric model of the stage-two analysis is constructed using variables defined in Section 5.3. To do this, we apply the bootstrap truncated regression method proposed by Simar and Wilson (2007). This method overcomes the limitation of commonly used methods, such as Tobit regression and Ordinary Least Square (OLS), to handle the issue arising from the serial correlation among estimated efficiency scores. In this method, instead of conventional efficiency scores, the bias-corrected technical efficiency scores derived from bootstrap DEA are used as the dependent variable in the second-stage econometric model.

5.2 Data Sources

The DatAnalysis database created and maintained by Morningstar Inc. provides a broad range of financial information on the ASX listed companies. Annual reports of companies listed on the ASX are the main source of data in this database. Part of the data for input, output and environmental variables is collected from this database. Moreover, through a comprehensive review of the annual reports of individual mining firms listed on the ASX, we extracted data for a number of variables which were not available in the DatAnalysis database. Our study focuses on major Australian mining firms listed on the ASX. Among the ASX listed companies classified as metals and mining industry, 34 firms have been fully operational for five years from 2010 to 2014. These 34 companies contribute to more than 85 per cent of the total market capitalisation in the metals and mining industry.

According to Global Industry Classification Standard (GICS), all 34 companies in our sample have the same six digit classification code (i.e. Metals and Mining; code=151040), which is one of the major industries of the material sector (code=15). The main activity of all companies in the sample is exploration and extraction of minerals and mining products. Table 5.1 illustrates the list of companies in our sample.

Table 5.1: Study sample: 34 mining companies listed on the ASX

DMU	Company Name	ASX Code	DMU	Company Name	ASX Code
1	Aditya Birla Minerals Limited	ABY	18	Norton Gold Fields Limited	NGF
2	AngloGold Ashanti Limited	AGG	19	OceanaGold Corporation	OGC
3	Atlas Iron Limited	AGO	20	OM Holdings Limited	OMH
4	Aquarius Platinum Limited	AQP	21	OZ Minerals Limited	OZL
5	BHP Billiton Limited	BHP	22	Panoramic Resources Limited	PAN
6	Evolution Mining Limited	EVN	23	PanAust Limited	PNA
7	Fortescue Metals Group Ltd	FMG	24	Rio Tinto Limited	RIO
8	Grange Resources Limited	GRR	25	Rand Mining Limited	RND
9	Independence Group NL	IGO	26	Resolute Mining Limited	RSG
10	Iluka Resources Limited	ILU	27	Saracen Mineral Holdings Limited	SAR
11	Kingsgate Consolidated Limited	KCN	28	St Barbara Limited	SBM
12	Mirabela Nickel Limited	MBN	29	Silver Lake Resources Limited	SLR
13	Mincor Resources NL	MCR	30	Tribune Resources Limited	TBR
14	Mount Gibson Iron Limited	MGX	31	Troy Resources Limited	TRY
15	Metals X Limited	MLX	32	Wollongong Coal Limited	WLC
16	Medusa Mining Ltd	MML	33	Western Areas Limited	WSA
17	Newcrest Mining Limited	NCM	34	Zimplats Holdings Limited	ZIM

5.3 Description of Variables

In this section we explain specifications of our technical efficiency model in terms of input and output variables. These variables are used in the first stage of our two-stage data envelopment analysis (DEA) to derive technical efficiency estimates. Furthermore, business environment and firm-specific factors used to construct the second-stage econometric model, are described in this section. Table 5.2 and Table 5.3 present the summary of key variables and their descriptions.

5.3.1 Variables of Technical Efficiency Estimation

First, we review the possible input and output variables to formulate our efficiency model. Coelli et al. (2005) stressed the importance of quality and appropriateness of data used in efficiency measurement studies. They emphasised consideration of quantities, prices and quality characteristics of inputs and outputs in the process of efficiency and productivity measurement. We discuss the most common approaches to nominate variables presenting inputs and outputs of an economic enterprise in the mining industry. Table 5.2 summarises the descriptive statistics of input and output variables.

(i) Outputs

If an economic enterprise produces a single output, the output of the firm is simply defined as the total of production volume in a calendar year. In case of multiple-output firms the aggregate output can be obtained upon availability of prices and quantities for all products. In the mining industry, major companies are mostly involved in a range of mining exploration and extraction activities. Hence, aggregate production output in mining firms includes diverse commodities with different prices and ore quality. In such case, a value aggregate can be formed using individual commodity quantities and prices. In the existing literature, value added and revenue are two common proxies for aggregate output (e.g. Mahadevan and Asafu-Adjaye, 2005; Fang et al., 2009; Eller et al., 2011; Das, 2012).

Using financial information from annual reports, the total revenue of a mining company represents the aggregate value of outputs of firm operations in delivering mining commodities and services. Therefore, we define total revenue excluding interest as proxy for mining enterprise aggregate output. This is the total of income a mining company earns through direct mining operations or services such as engineering, logistics and property rent.

(ii) Inputs

Coelli et al. (2005) summarised five common input categories in firm-level studies as capital (K), labour (L), energy (E), material inputs (M) and purchased services (S). The last three categories are commonly aggregated as intermediate input or other input category. The choice of inputs in the efficiency model depends on the output specifications. If value added is chosen as the output of an economic unit, only capital (K) and labour (L) are used as the inputs. To calculate value added, intermediate input is deducted from gross output. If a measure of gross output such as total revenue is used, the efficiency model can include measures for labour, capital and intermediate input categories. Following the later approach, we select labour, capital and intermediate inputs as three inputs for mining enterprises. In addition, a mining company's efficiency depends on the characteristics of natural resource input to its mining operations. Due to the natural resource depletion, the volume of output extracted from mining operations declines over time. The depletion of natural resources results in the consumption of more labour, capital and intermediate inputs to produce the same level of output. Hence, a decline in the economic performance of mining firms may not necessarily be related to technically inefficient operations but derived from their depleted natural resources. Therefore, to reflect such effect we extend the technical efficiency model to include the natural resource input to mining operations.

Labour (L)

Different measures can be used to quantify labour input. For instance, labour input can be defined as number of employees, number of hours of labour input, number of full-time equivalent employees or total wages and salaries bill (Coellie et al., 2005). In the context of the mining sector, different proxies have been chosen for labour input measurement. At mine level, total man-hours and total man-days are mostly used to measure labour input (e.g. Byrnes and Fare, 1987; Thompson et al., 1995; Kulshreshtha and Parikh, 2002). At firm level, number of employees is a common proxy for labour input when companies are involved in one specific mining activity. For example, Sueyoshi and Goto (2012) used the number of employees as a measure of labour input to evaluate the efficiency of 19 national and international petroleum companies from 2005 to 2009. Fang et al. (2009) applied similar proxy for labour input to investigate the efficiency difference between selected coal mining companies in the United States and China in the period of 2001 to 2005.

In our study we do not use such proxies for labour input, instead we proxy labour input with total employee benefits, which includes wages, salaries and other employee benefits. Our data are mainly extracted from annual reports. Wages, salaries and employee benefits are generally reported in the income statements of annual reports. However, no hourly-based data is available in annual reports for labour employed. What's more, information on number of employees is not available in multiple annual reports used to extract our data. In addition to the availability advantage of employee benefits as a proxy for labour input, the quality of labour is also reflected in the paid wages and salaries bill.

Capital (K)

Coellie et al. (2005) explained various types of measures to calculate enterprise capital input. Total capital service flow from different assets, capital stock (e.g. measured by perpetual inventory method (PIM)), replacement values, net capital stock from accounting reports and physical measures are some common methods to measure capital input. In the existing literature for firm-level mining efficiency and productivity studies, most physical measures and capital stock reported in financial statements are used to calculate capital input. In an output-oriented DEA model, Eller et al. (2011) used the oil and gas reserves as capital input. Reccardi et al. (2012) applied the installed cement capacity as the proxy for capital input in their DEA models. Das (2012) applied the value of gross fixed assets as a proxy for capital input to evaluate 65 Indian private and public mining firms from 1988-89 to 2005-06. Fang et al. (2009) used the value of total assets as capital input in their DEA model. Geissler et al. (2015) also used total assets to formulate the efficiency of 24 world-leading companies in phosphate rock mining in 2012 using DEA.

A major problem in using asset-based measures of capital input in the existing literature is that capital is measured as a stock variable rather than a flow variable. In production theory it is often assumed that inputs are transformed into outputs in the production process given the existing level of technology. Therefore, technical efficiency is a measure reflecting how well the inputs are used to produce the outputs using the prevailing technology. With this approach, it is more appropriate to measure the flow of capital service input instead of using a measure of capital stock. Use of capital stock represented by various measures of firms' assets may cause some issues in measuring capital used in the production process. For instance, some firms may have assets that they are not fully utilised but, due to asset specificity, cannot be disposed of easily, at least in the short term. Such firms turn out to be less efficient than those that utilise most of their assets in their ongoing operations. The asset-based measure of capital input does not account for unproductive capacity which may be associated with decline in production. Moreover, there is normally a considerable period from the time that a firm invests in a new operation capacity up to production from that new capacity. Such investment-production lag is not taken into consideration when using asset-based measures of capital input.

Coelli et al. (2005) explained that the value of capital services as the flow of services from capital goods into the production process is an appropriate measure of capital input. The cost of capital services used in the production process consists of depreciation and interest expenses (Coelli et al., 2003). We can obtain the depreciation cost from the notes to the balance sheet of firms' annual reports. In our model, we do not include the interest costs to the proxy for capital service since the interest expenses reported in the accounts only reflect the cost of debt and ignore the implicit (forgone opportunity) cost of equity. More importantly, in our study, a significant proportion of assets are related to mining development activities. Therefore, any incurred interest expenses related to these activities are not associated with the productive capital stock and hence do not contribute to the current production output. As separate interest expenses associated with utilised assets as well as development projects are not available in annual reports, and to avoid introducing bias in calculated capital services, we exclude the interest expenses from the capital input proxy.

Intermediate Inputs (M)

Intermediate inputs category is another input variable in our efficiency model, aggregating associated expenditure to material inputs, energy inputs and purchased services. In empirical studies, the value of operating costs are mostly used to present intermediate inputs (e.g. Fang et al., 2009; Sueyoshi and Goto, 2012; Geissler et al., 2015). Following this common approach for selection of intermediate inputs proxy, we use operating expenses calculated from expenses reported in the income statement section of annual reports. The operating expenses include costs associated with ongoing mining operations and expenditure on maintaining and improving the current condition in the existing mines. To construct a more precise proxy of intermediate inputs, we exclude exploration and evaluation expenditure from operating expenses as this expenditure does not contribute to the current production and hence may cause bias in efficiency estimates. We furthermore exclude any labour costs from operating expenses. Thus, our proxy for intermediate inputs is the total expenses of material, energy and purchased services used in the ongoing mining operations, which is reported in firms' financial statements.

Natural Resource Input (N)

A major difference between the resource sector and other economic sectors is the role of natural resource input in the production process. Similar to other production inputs, mineral deposits in their natural state contribute to the production of mineral and energy products (Topp et al. 2008). Mineral production from these non-renewable resources results in resource depletion. In the case of depletion of homogenous non-renewable natural resources, the quality of extracted ores may not change, however, the supply would fall and the price would rise. If the deposit is heterogeneous, which is the case in most mining activities, the most easily accessible and highest quality deposits are extracted first, while deposits with lower quality or less accessibility are the second priority. One consequence of such resource depletion is the consumption of greater amounts of labour, capital and intermediate inputs to maintain the same level of production output with a given technology. Alternatively, the resource depletion may lead to a lower ore quality in the remaining deposits. Hence, the lower mineral commodity is obtained from the same unit of mined ore over time (Zheng and Bloch, 2014).

The conventional productivity measurement methods do not take into account natural resource input. The difficulty in measuring natural resource input combined with the unavailability of its market price results in omitting this major input category in the official productivity measurement. Hence, the conventional productivity measurement provides a biased level of productivity in the mining sector.

However, there are a number of studies in the mining efficiency and productivity literature that reflect natural resource inputs in their developed models. In an early work, Wedge (1973) emphasised the importance of natural resource inputs in mining productivity estimates. He argued that by taking into account the effect of natural resource input, measured by a proxy of ore grade index, the Canadian mining productivity was significantly higher than the measured productivity from the conventional reports. In a mine-level study, Byrnes and Fare (1987) applied the geological characteristics of a mine including total seam thickness and inverse of overburden excavated among mining operation inputs to examine efficiency of 186 surface coal mines in the interior USA in 1978.

Rodriguez and Arias (2008) applied the level of coal reserves to control for the resource depletion effect on the Solow Residual model in Spain's coal industry. They found that the decrease in the level of reserve negatively contributed to total factor productivity (TFP) growth, and it required an annual increase of 1.29 per cent input use. They concluded that given the large magnitude of resource depletion effects, it is important to correct for the effects of coal reserves on extraction costs in the Solow Residual.

In a comprehensive study exclusively on Australian mining productivity, Topp et al. (2008) challenged the measurement errors surrounding the conventional reports and highlighted significant decline in the Australian mining multifactor productivity (MFP) indices. They stressed the significant adverse role of Australia's natural resource depletion resource on long-term mining MFP. To estimate the effect of declining resource quality in the mining industry, Topp et al. (2008) constructed yield variables to measure resource depletion in various mining sectors. Moreover, using the sector level yield indices, including the changes in ore grade, oil and gas flow rates and the ratio of saleable to raw coal, they estimated the aggregate yield index as a proxy of declining resource quality on the mining industry as a whole.

More recently, Zheng and Bloch (2014) examined the MFP growth in the Australian mining sector by a translog variable cost function. They decomposed the productivity growth to the effects of returns to scale, capacity utilisation and natural resource inputs. In their study, they assumed the exploration expenditure as a cost that a mining company spends for overcoming their resource depletion. Exploration expenditure is a cost that mining companies pay to discover new deposits for maintaining and enhancing the quality and quantity of resource inputs. The exploration expenditure can be seen as a response to the declining quality and quantity of natural resource reserves.

Following Zheng and Bloch (2014), in our study we use the exploration expenditure to construct an index representing resource depletion. Using financial information from annual reports, such expenditure appears as capitalised exploration expenditure reported in the balance sheet or operating costs reported in the income statement. In the case of renewable resource activities, this kind of expenditure is neither presented in assets nor operating expenses. From the capital input point of view, while there is a degree of resource decline, a part of the enterprise total assets would be assigned to the associated cost of exploration expenditure. This resource depletion effect can be presented as the share of exploration expenditure in the firm's total assets. If no exploration expenditures occur, the effect of resource depletion on the enterprise capital will be zero and the whole enterprise assets will be available to utilise for economic activities. Based on this assumption, to reflect resource depletion effects on the enterprise capital, we define the capital-based natural resource input index as follows:

Capital based natural resource input index = [(Total assets – Capitalised exploration expenditure) / Total assets] x 100

If no exploration expenditures occur, the capital-based natural resource input index is equal to 100; whereas any value less than 100 represents a degree of resource depletion effect of the enterprise capital.

Similarly, we can construct the cost-based natural resource input index to reflect the effect of natural resource depletion on the enterprise operating costs as follows:

Cost based natural resource input index = [(Total operating costs – Exploration expenditure expenses) / Total operating costs] x 100

Any presence of exploration expenditure on the firms' operating bills brings about a value less than 100 for the cost-based natural resource input index.

To combine the effects of exploration expenditure on the enterprise capital and operating costs, we formulate the natural resource input index simply as the average of capital-based and cost-based indices. Thus, in our efficiency model, the proxy for natural resource input is described as:

Natural resource input index = (Capital-based natural resource input index + Cost-based natural resource input index)/2

A value of 100 in the natural resource input index shows no resource decline, while any value below 100 shows the presence of exploration expenditure due to a degree of resource depletion. Such index provides a practical solution to include natural resource input in the efficiency model; whereas in a firm-level study, availability and aggregation of detailed information representing resource depletion, such as ore grades or saleable prices, are extremely challenging.

5.3.2 Variables of Firm-Specific Factor Effects

The data used in the second-stage regression analysis includes ownership concentration, size, age, property, plant and equipment (PP&E) ratio, financial leverage, type of product, product divarication, change pace, direction of change, location of operations and year. The summary of descriptive statistics of continuous firm-specific factors and dummy variables for firm-specific factors is presented in Table 5.2 and Table 5.3 respectively.

(i) Ownership

In the mining literature, few studies examined the role of ownership on efficiency gains. These studies focused on comparison of private versus state-owned companies (e.g. Eller et al. 2011; Das 2012). While all firms in our sample are private companies listed on the ASX, the ownership concentration is different from company to company. The effect of ownership concentration on the firms' performance is ambiguous as both positive and negative relationships have been reported in the literature. Margaritis and Psillaki (2010) reported a positive relationship between ownership concentration and efficiency of chemical manufacturers in France. Ma et al. (2010) examined the impact of ownership concentration on the performance of China's listed companies and concluded that ownership concentration enhances firms' performance. Using stochastic frontier analysis (SFA) and data envelopment analysis (DEA), Su and He (2012) found that the relationship between ownership concentration and firm performance is an inverted U-shaped and both low degrees and high degrees of ownership concentration affect the performance negatively.

Shleifer and Vishny (1997) argued that ownership concentration along with legal protection is an efficient governance mechanism. Anderson et al. (2012) evaluated that the level of protection afforded to shareholders under Australian law is relatively high in comparison with other countries. Hence, in our study we hypothesise that ownership concentration, as an efficient corporate governance mechanism, improves the efficiency gain of Australian mining companies. We use the percentage of shares held by the substantial shareholders as a proxy to measure the ownership concentration.

(ii) Firm Size

Furthermore, we investigate the association between firm efficiency and firm size. We use the natural logarithm of property plant and equipment (PP&E) assets as the proxy for size of a firm. PP&E assets represent the productive capital and reflect the operations capacity. Hence, it is an appropriate proxy for firm size. The existing literature provides mixed evidence on the relationship between firm size and firm efficiency. For instance, Diaz and Sanchez (2008) found a negative correlation between firm size and firm efficiency; whereas Badunenko (2010) showed a positive correlation and Schiersch (2013) presented a U-shaped relationship. To the best of our knowledge, there is no specific study in the mining sector applying a second-stage analysis to investigate size-efficiency relationship. Zheng and Bloch (2014) argued that operating scale is one of the major contributors of recent unfavourable productivity trends in the Australian mining sector. They added that the presence of a moderate level of decreasing returns to scale can describe 0.2 per cent of annual productivity decline over the period 1974-75 to 2007-08. This shows that larger mining companies are less agile than smaller companies to downsize and optimise their operating scales; and consequently, may be less productive than their smaller peers. Hence, it is expected that larger mining companies are less productive than their smaller counterparts.

(iii) Firm Age

Age is another firm-specific factor that may influence firm performance. Loderer and Waelchli (2010) showed a robust negative association between firm age and firm performance, particularly firm profitability. They stated that aged firms are characterised by higher expenses, lower output growth, less R&D and capital expenditure, and worse corporate governance. In an earlier study, Majumdar (1997) argued that while firm aging affects the profitability of firms, older firms are more productive than younger firms. Lumley and McKee (2014) explained that productivity in mining firms is heavily dependent on the way people act. The availability of the right people with the required skills is a key element of a success strategy to achieve higher productivity. A number of mining companies are long-established, having started their operations at the advent of the recent boom. A lack of mining business knowledge and required skills has been a major challenge for the young mining firms in Australia. 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 hypothesis in gaining the required knowledge and skills in their industry.

(iv) Capacity Utilisation

Topp et al. (2008) remarked that capital-output lag is a significant contributor to the productivity index decline in the Australian mining sector. Zheng and Bloch (2014) found that the declining productivity trends in the Australian mining sector are largely associated with the physical capital utilisation due to the long lead time from the investment in capital goods to their use in production. Sector-level studies argue that the declining productivity performance in the Australian mining sector has resulted from incorrect assumptions and mismeasurement of productivity changes in conventional reports. However, at an operational level, mining industry reports identified that a major reason for low efficiency among the Australian mining companies is inefficient utilisation of mining equipment (Lumley and McKee, 2014; Mitchell et al., 2014). In their report, Lumley and McKee (2014) highlighted that the differences between median performance and best practice output by equipment category can be over 100 Per cent.

In line with sector-level and mine-level findings, we test whether capacity utilisation is a contributor to efficiency gain. Using financial information from annual reports, the property, plant and equipment (PP&E) assets represent 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 assets to total assets as a proxy of operations capacity utilisation. Considering the findings from previous research, we expect a negative correlation between this ratio and firm efficiency.

(v) Financial Risk

The existing literature 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; Yazdanfar and Ohman, 2015). We proxy risk with financial leverage defined as total assets divided by total equity. A high leverage ratio indicates that a much greater proportion of firm capital is funded from lenders rather than shareholders. Higher leverage can provide opportunities to grow business at an accelerated rate. On the other hand, a large amount of debt is generally considered a sign of risky business practices. It is required by the law that companies must make payments on their debts regardless of business revenues. A company with a high leverage ratio that experiences financial downturn is in risk of loan default and bankruptcy. Considering the classic risk-return trade-off arguments, we expect that mining firms with higher leverage have higher economic performance.

(vi) Types of Product

According to the ABS (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 2013-14. Hence, in the list of exogenous variables, it is important to control for the type of products (including iron ore, gold and other minerals and metal ores) each company produces. We assume that iron ore companies, which are generally operating large-scale projects, gain higher efficiency performance. Moreover, gold mining is a well-established and mature industry in Australia. We expect that gold mining companies perform more efficiently than companies extracting other metal and mineral commodities.

(vii) Product Diversification

While most mining companies are involved in one or a few related mining activities, some companies expand their operations to a diverse portfolio of mining exploration and extraction activities. The existing literature has provided mixed evidence on the effect of product diversification on firm performance (e.g. Chang and Wand 2007; Chakrabarti et al. 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 that diversification positively affects the efficiency of mining firms through utilisation of unused productive capacity, reduction of business risk arising from falling prices, and employing operation capabilities across other mining activities.

(viii) Growth Status

Mining companies experience continual growth and decline in their operations output depending on their stages in mine life cycle. Furthermore, due to management decisions or natural factors, mines may record comparatively large changes in production from one year to the next. Even though mining firms are able to adjust their operating expenses along with output changes, they can unlikely optimise their capital assets in the short term, especially during declining periods. Mitchell and Steen (2014) commented that the lack of effective portfolio management can influence the capital productivity of mining companies. A balanced set of projects in the portfolio results in the stability of production outputs. To consider this point, we assume that mining companies with a steady state or gradual growth of outputs are more efficient than companies with rapid growth. Also, we expect that companies are more efficient during growth periods in comparison with declining cycles.

(ix) Location of Operations

A number of Australian mining companies have expanded their operations to other countries. Such international diversification may provide benefits to the Australian mining companies through lower operating expenses. Nath et al. (2010) argued that international diversification is not necessarily beneficial to parent companies. They discussed that success in this strategy requires extensive knowledge assimilation, understanding of 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 if international diversification benefits mining companies in terms of efficiency gain, we add the dummy variable of overseas operations to our econometric model.

(x) Year Dummies

In addition to firm-specific variables, we include the year dummies among the regressors to capture the effect of time on mining firms' efficiency. These time-varying effects can be related to some possible economic and structural changes across the mining sector which cannot be explained by firm-specific factors.

5.3.3 Adjustment for Price Changes

As we tend to measure technical efficiency in real terms, it is essential to remove the effects of price changes on employed variables. To do so, appropriate deflators matching the research data must be selected. Such selected deflators must relate to the commodities that constitute the aggregate as closely as possible (Coell et al., 2005). In our study, the production output measured by total revenue is deflated by the producer price index (PPI) for output of the mining sector. The intermediate input is deflated using the PPI for input of mining sector. To adjust the price effects of labour input, we apply the respective wage price index (WPI) for mining activities. Finally the capital input is deflated through applying the PPI for capital goods (ABS, 2015a, 2015b).

Table 5.2: Data description of continuous variables

Variables	Mean	Std. Deviation	Minimum	Maximum
Output variables				
Total revenue, thousands of AUD (*Q*)	4477175	14647918	14599	77883040
Input Variables				
Employee benefits, thousands of AUD (*L*)	565323	1805976	530	9604749
Total depreciation, thousands of AUD (K)	389981	1361589	385	8962845
Intermediate inputs, thousands of AUD (INT)	1960169	6317772	2471	34002611
Natural resource input, index (N)	94.66	6.16	62.00	100.00
Firm-Specific Factors				
Substantial shareholder, percentage (OWNER)	39.34	23.57	4.00	95.00
Firm size, ln(total 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)	53.69	17.66	11.00	93.00
Financial leverage, ratio (*LEV*)	1.64	0.64	1.03	4.66

Table 5.3: Data description of dummy variables

Variables	Description of variable	No.	
		0	1
Firm-Specific Factors			
Iron ore production (*IRON*)	= 1 if the main product is iron ore, 0 otherwise.	150	20
Gold production (*GOLD*)	= 1 if the main product is gold, 0 otherwise.	90	80
Product diversification (*DIV*)	= 1 if the product portfolio is diversified, 0 otherwise.	140	30
Change pace (*CH_PACE*)	= 1 if the firm total output changes rapidly (> 30%), 0 otherwise.	113	57
Change direction (*CH_DIR*)	= 1 if the firm total output grows, 0 otherwise.	55	115
Location of operation (*LOC_OPS*)	= 1 if firm operates in overseas projects, 0 otherwise.	80	90
Year 2011 (*Y2011*)	= 1 if observation is for 2011, 0 otherwise.	136	34
Year 2012 (*Y2012*)	= 1 if observation is for 2012, 0 otherwise.	136	34
Year 2013 (*Y2013*)	= 1 if observation is for 2013, 0 otherwise.	136	34
Year 2014 (*Y2014*)	= 1 if observation is for 2014, 0 otherwise.	136	34

5.4 The Empirical Model in Stage One: Estimation of the Efficiency Scores

To analyse the efficiency performance of the Australian mining companies, we apply a two-stage DEA method. The aim of the first stage is to obtain the efficiency estimates of mining firms and we examine the effects of firm-specific characteristics on the efficiency performance in the second stage. Taking into account the production function theory, we select labour, capital and intermediate inputs as the model inputs and total production as the model output. To analyse the role of natural resource input in the economic performance of mining companies, we extend our model and include the developed variable representing natural resource input to the efficiency model. Model I represents a general model of efficiency estimation and Model II includes the natural resource input, a main characteristic of mining activities. In the following sections we discuss the empirical models applied in our study.

5.4.1 The Choice of Efficiency Measurement Method

In the existing literature, there are no specific techniques for efficiency measurement recommend as the preferable approach. Each technique has its own advantages and disadvantages. The choice of efficiency method relies on a careful consideration of frontier techniques and the specification of data and industry under investigation. As Fried et al. (2008)

explained, there has been a considerable improvement in both approaches in providing more robust techniques and narrowing the gap.

This study follows the mathematical programming approach to efficiency analysis using data envelopment analysis (DEA) method. The first advantage in the application of DEA is its superior performance in handling a small sample size. On the other hand, techniques in the econometric approach to efficiency analysis such as stochastic frontier analysis (SFA) mostly require a large sample size. Our sample in this study consists of 34 Australian listed mining companies. Hence, the application of DEA sounds more plausible.

The other advantage in the application of DEA is its flexibility and ability in handling multiple input-multiple output problems. The SFA techniques, however, requires a pre-defined functional form of the production frontier. The SFA methods cannot directly account for a multiple input-multiple output production model, i.e. the econometric model can have only one dependent. Also, the researcher must select the cost or production function form such as a Cobb-Douglas or a translog function in advance.

The downside of DEA is mainly attributed to its deterministic nature. This method does not allow for random noise or statistical error. The efficiency frontier is highly sensitive to outliers. Fortunately, a remedy exists; Simar and Wilson (1998, 2000a) introduced a bootstrapping technique that generates the statistical properties of estimated efficiency scores. In this study, their proposed technique is used to derive the error estimates and confidence intervals for efficiency scores of the mining companies in our sample.

Using linear programming methods, DEA models construct a non-parametric piece-wise surface, which is called frontier, over the sample data. The efficiency performance of a firm is calculated relative to this frontier. The form of frontier depends on the returns to scale assumptions. The CRS assumption considers that all firms operate at an optimal scale. However, due to business constraints such as imperfect competition, government regulations and financial constraints, a firm may not be able to operate at the optimal scale. Therefore, CRS estimates of technical efficiency may contain the scale inefficiency effects when not all firms operate at their optimum scale. The technical efficiency estimates derived from the VRS model are free from such effects (Coelli et al., 2005). We estimate efficiency scores under both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions. Estimating efficiency performance using both CRS and VRS models enables us to identify the influence of operating scale on the efficiency scores across companies. We expect more efficiency variations assuming CRS rather than VRS.

The efficiency model that we employ is output-oriented. The mining industry plays a critical role in the Australian economy in terms of export revenue and value added. Furthermore, the existing global demand for mining products requires constant adjustments to export volumes in a competitive market. Hence, we consider the use of an output-oriented approach to be more appropriate than an input-oriented one. Nevertheless, assuming CRS the efficiency scores are just the reciprocal value of input-oriented measures.

5.4.2 The Empirical DEA Model

Based on the notations and terminology described in Fried et al. (2008), we define $x = (x_1, ..., x_n) \in \mathbb{R}_+^N$ as a vector of inputs and $y = (y_1, ..., y_m) \in \mathbb{R}_+^M$ as a vector of outputs. Production technology can be described as:

$$T = \{(x, y) \in \mathbb{R}_+^M \times \mathbb{R}_+^N : y \in \mathbb{R}_+^M \text{ is produceable from } x \in \mathbb{R}_+^N\} \cdot \tag{5.1}$$

and the Farrell output-oriented measure of technical efficiency defined by:

$$\begin{aligned} TE_O(x, y) &= \max\{\theta > 0 : (x, \theta y) \in T\}, y \in \mathbb{R}_+^M, x \in \mathbb{R}_+^N \\ &= \max\{\theta > 0 : \phi y \in P(x)\}, y \in P(x), x \in \mathbb{R}_+^N \end{aligned} \tag{5.2}$$

The value of the output-oriented Farrell technical efficiency for a firm under a given technology is equal to, or greater than, unity. To estimate technical efficiency, one needs to compare the actual performance of firms with the optimal level of performance on the technology frontier. The true technology frontier (optimal level of performance) is unknown. $\hat{T}$ as the DEA-estimate of T can be represented as follows:

$$\begin{aligned} &\hat{T} = \{(x, y) \in \mathbb{R}_+^N \times \mathbb{R}_+^M : \\ &\sum_{k=1}^{n} z^k y_m^k \ge y_m, m = 1, ..., M, \\ &\sum_{k=1}^{n} z^k x_i^k \le x_i, i = 1, ..., N, z^k \ge 0, k = 1, ..., n\} \end{aligned} \tag{5.3}$$

Under the assumptions of CRS, additivity and free disposability, the DEA-estimator of the Farrell output-oriented technical efficiency score of observations $j(j=1,\ldots,n)$ is formulated by:

$$
\begin{aligned}
&T\hat{E}(x^j, y^j) = \max_{\theta, z^1, \ldots, z^n} \theta \\
&s.t. \\
&\sum_{k=1}^{n} z^k y_m^k \geq \theta y_m^j, m = 1, \ldots, M, \\
&\sum_{k=1}^{n} z^k x_i^k \leq x_i^j, i = 1, \ldots, N, \\
&\theta \geq 0, z^k \geq 0, k = 1, \ldots, n
\end{aligned}
\tag{5.4}
$$

Assuming VRS, an additional constraint $\sum_{k=1}^{n} z^k = 1$ is added to (5.4). The efficiency scores estimated via (5.4) are bounded between unity and infinity. An efficiency score of one represents a fully efficient firm, while greater scores reflect the degree of inefficiency in firm performance. Table 5.4 shows the parameters of equation (5.4) assigned to Model I and Model II.

As we discussed in Chapter 4, the main advantage of DEA is that this method does not require any pre-assumptions for functional form but cannot provide any information for the statistical noise. The estimated frontier output (or input) depends on the particular combination of input-output mix and a different observed sample set would lead to a different estimated frontier. The estimated technical efficiency would thus be different from one sample to another. To obtain a confidence interval covering possible statistical errors, one would need the sampling distribution of the frontier output (or input). However, usually only one sample is available.

Bootstrap DEA is one of the stochastic DEA approaches developed to overcome this limitation. It estimates the sampling distribution and statistical properties for an estimator through re-sampling from the original sample. We use the smooth bootstrapping procedure developed by Simar and Wilson (1998) with 2000 iterations to obtain statistical inference for DEA estimates of technical efficiency from stage one.

Table 5.4: Specifications of the constructed DEA models

Model I	Model II
Number of outputs (*M*): 1	Number of outputs (*M*): 1
Number of inputs (*N*): 3	Number of inputs (*N*): 4
Number of observations (*n*): 170	Number of observations (*n*): 170
Outputs (y_m):	**Outputs (y_m):**
Production (y_1)	Production (y_1)
Inputs (x_i):	**Inputs (x_i):**
Labour (x_1)	Labour (x_1)
Capital (x_2)	Capital (x_2)
Intermediate input (x_3)	Intermediate input (x_3)
	Natural resource input (x_4)

Source: Author's classification

5.5 The Empirical Model in Stage Two: Examination of Effects from the Firm-Specific Factor on the Efficiency Estimates

At the second stage, we examine what factors determine the efficiency performance using a regression analysis. The regression model is specified as follows:

$$TE_j = Z_j\beta + \varepsilon_j, \quad j = 1,...,n \tag{5.5}$$

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

Tobit model is a common method in DEA literature to conduct the second-stage analysis using equation (5.5). However, Simar and Wilson (2007) criticised the use of this model because the serial correlation problem may plague the estimated parameters. They proposed an alternative approach using a bootstrap truncated regression. Instead of conventional efficiency scores, the bias-corrected technical efficiency scores ($\hat{TE}_j^{bc}$) are used in equation (5.5). As both sides of equation (5.5) are bounded by unity, the restriction $\varepsilon_j \geq 1 - Z_j\beta$ is applied for ε_j. Following Simar and Wilson (2007), we assume that ε_j is from a left-truncated normal distribution with zero mean and unknown variance. Hence, we formulate the following regression model to investigate the effects of firms' specific factors on technical efficiency:

$$\hat{TE}_j^{bc} = Z_j\beta + \varepsilon_j, \quad j = 1,...,n \tag{5.6}$$

where

$$\varepsilon_j \sim N(0, \sigma_\varepsilon^2), \text{ such that } \varepsilon_j \geq 1 - Z_j\beta, \quad j = 1, ..., n \tag{5.7}$$

Based on equation (5.6) and variables discussed in Section 5.3.2, the econometric model of stage two in our study is constructed as follows:

$$\begin{aligned} \hat{TE}_j^{bc} &= \beta_0 + \beta_1 OWNER_j + \beta_2 SIZE_j + \beta_3 AGE_j + \beta_4 PPE_j + \beta_5 LEV_j + \beta_6 IRON_j \\ &+ \beta_7 GOLD_j + \beta_8 DIV_j + \beta_9 CH\_PACE_j + \beta_{10} CH\_DIR_j + \beta_{11} LOC\_OPS_j \\ &+ \beta_{12} Y2011_j + \beta_{12} Y2011_j + \beta_{13} Y2012_j + \beta_{14} Y2013_j + \beta_{15} Y2014_j + \varepsilon_j, \quad j = 1, ..., 170 \end{aligned} \tag{5.8}$$

where

$OWNER_j$ = ownership concentration in firm *j*, represented by the ratio of substantial shareholders
$SIZE_j$ = size of firm *j*, proxied by the natural logarithm of the property plant and equipment (PP&E) assets
AGE_j = age of firm *j*, measured by the number of years since firm establishment
PPE_j = capacity utilisation in firm *j*, represented by the ratio of PP&E assets to total assets
LEV_j = leverage of firm *j*, measured by the ratio of total debt to total assets
$IRON_j$ = dummy for iron ore mining in firm *j*;
$IRON_j$ =1 if the iron ore is the main mining activity in firm j,
$IRON_j$ =0, otherwise
$GOLD_j$ = dummy for gold mining in firm *j*;
$GOLD_j$ =1 if the gold is the main mining activity in firm j,
$GOLD_j$ =0, otherwise
DIV_j = dummy for product diversification in firm *j*;
DIV_j =1 if firm j operates a diverse portfolio of mining activities,
DIV_j =0, otherwise
CH_PACE_j = dummy for pace of growth in firm *j*;
CH_PACE_j =1 if the absolute value of growth rate in firm j is among the top third of companies in our sample,
CH_PACE_j =0, otherwise
CH_DIR_j = dummy for direction of growth in firm *j*;
CH_DIR_j =1 if company *j* experiences a positive growth rate,

CH_DIR_j =0, otherwise

LOC_OPS_j = dummy variable for location of operation;

LOC_OPS_j =1 if company j operates mining projects overseas in addition to their domestic mining activities,

LOC_OPS_j =0, otherwise

$Y2011_j$ = dummy variable for year 2011 relative to observation j,

$Y2011_j$ =1 if the observation j is related to year 2011,

$Y2011_j$ =0, otherwise

$Y2012_j$ = dummy variable for year 2012 relative to observation j,

$Y2012_j$ =1 if the observation j is related to year 2012,

$Y2012_j$ =0, otherwise

$Y2013_j$ = dummy variable for year 2013 relative to observation j,

$Y2013_j$ =1 if the observation j is related to year 2013,

$Y2013_j$ =0, otherwise

$Y2014_j$ = dummy variable for year 2014 relative to observation j,

$Y2014_j$ =1 if the observation j is related to year 2014,

$Y2014_j$ =0, otherwise

ε_j = stochastic error for firm j $(\varepsilon_j \sim N(0, \sigma_\varepsilon^2))$

β = a vector of unknown coefficients to be estimated

j=1, … , 170.

In the estimation procedure we use Algorithm 2 of Simar and Wilson (2007) to run the regression model (5.6) with 2000 bootstrap iterations as described in Chapter 4.

5.6 Summary

Chapter 5 has presented the data source, the description of variables and the empirical models of technical efficiency analysis in the Australian mining context. The DatAnalysis database, which provides detailed financial information of the ASX listed companies, has been used to extract data required for part of variables in our model. Further to the DatAnalysis database, the annual reports of selected mining companies have been used to obtain data for a number of defined variables. Our sample consists of 34 major Australian mining companies which were operational over 2010-2014.

There are multiple reasons behind the selection of our sample. First, these companies cover more than 85 per cent of total market capitalisation of mining companies listed on the ASX. Hence, the efficiency performance of the Australian mining activities can be well represented by this sample. Second, to increase the homogeneity of our sample we include only fully operational companies over the period of study. Third, our sample includes large- to medium-sized companies. Such companies mostly acquire established management systems and they are capable of handling various exploration and extraction activities. We did not include small mining companies which mostly operate one mining field with a very limited capacity to their production output. The existing operational level studies have reflected the efficiency performance of such single mining operations. What's more, the exclusion of small companies in our study resulted in a more homogenous sample.

Further to the data source and sample selection discussion, this chapter has explained the variables used in our study. In the first-stage analysis, we estimated the efficiency performance of the Australian mining firms. Following the common approach in the production function theory, we selected total output (Q) represented by total revenue, labour input (L) measured by total employee benefits, capital service (K) measured by total depreciation, and intermediate inputs (M) calculated using operating expenses as the output / input variables of the constructed efficiency model. In addition, we expanded this common approach to comply with the geological characteristics influencing the efficiency performance in the resource sector. In doing so, we defined a variable reflecting the natural resource inputs to mining operations. Given the availability of financial information from firms' annual reports, we used the exploration expenditure of both capitalised and reported expenses to construct the Natural Resource Input Index. Our assumption to construct this variable is based on the fact that, due to depleting non-renewable resource deposits, mining companies are required to introduce exploration activities in order to maintain and continue their economic operations.

Chapter 5 has also explained the variables used in the second-stage analysis. To examine the effects of firm-specific characteristics on technical efficiency performance, major factors which potentially influence the efficiency of Australian mining companies have been identified. The second-stage econometric model includes 11 variables: ownership ratio of substantial shareholders (OWNER), firm size (SIZE), firm age (AGE), ratio of PP&E assets to total assets (PPE), financial leverage (LEV), dummy variables for main product as iron ore (IRON) and gold (GOLD), a dummy variable for product portfolio diversification (DIV), dummy variables for growth factors including production progress pace (CH_PACE), growth or decline status (CH_DIR), and a dummy variable for location of operations (LOC_OPS). In addition, four year-specific dummies have been introduced to the model to capture any significant influence caused by the external environmental factors and not explained by the internal variables.

Our empirical model developed in this chapter consists of modelling the technical efficiency estimation in stage one and constructing the econometric model of efficiency determinants in stage two. The stage-one analysis has been developed to include a model of technical efficiency in respect to commonly used input-output variables in production function theory. We designated this technical efficiency formulation as Model I, which include variables of labour, capital and intermediate inputs and total production output. Further, we extended our efficiency model to include natural resource input as a specific characteristic of the non-renewable resource sector of mining. This natural resource-based model of technical efficiency has been denoted as Model II.

We employed data envelopment analysis (DEA) method to formulate the technical efficiency model. DEA involves estimating the production frontier given the sample data and evaluation of observations performance relative to their corresponding frontier. Since DEA is a non-parametric method of efficiency estimation, it does not consider the sample variations; hence, the statistical noise is omitted in this method. This limitation of DEA method has been surmounted through applying the bootstrapping procedure proposed by Simar and Wilson (1998).

To examine the effects of firm-specific factors on firm efficiency at the second stage of the analysis, a bootstrap truncated regression method proposed by Simar and Wilson (2007) was utilised. This method improves the limitation of common methods used in the second-stage DEA, such as Tobit regression or OLS, to provide consistent estimated parameters at the presence of serial correlation among efficiency estimates. This study's constructed econometric model considered bias-corrected technical efficiency as the dependent variable and 15 explanatory variables including ownership ratio of substantial shareholders (OWNER), firm size (SIZE), firm age (AGE), ratio of PP&E assets to total assets (PPE), financial leverage (LEV), dummy variables for main product as iron ore (IRON) and gold (GOLD), dummy variable for product portfolio diversification (DIV), dummy variables for growth factors including production progress pace (CH_PACE) and growth or decline status (CH_DIR), a dummy variable for location of operations (LOC_OPS) and four year-specific dummies. Due to different variable specifications in Models I and II resulting in different efficiency estimates, a corresponding econometric model was formulated separately in stage two. The results from the application of the developed empirical models are presented and discussed in Chapter 6.

6 Empirical Results

6.1 Introduction

Chapter 6 aims to present the results from the empirical models of technical efficiency analysis with respect to data and variables discussed in Chapter 5 in a two-stage approach. Section 6.2 presents the empirical results from the application of Model I and Model II. The former consists of the common input/output variables of efficiency modelling including one output, namely total production, and three input variables of labour, capital and intermediate inputs. The latter maintains the common variables but includes a proxy for natural resource inputs.

Using specifications defined in the general model of technical efficiency, i.e. Model I, and the natural resource-based model of technical efficiency defined in Model II, data envelopment analysis (DEA) is used to derive the efficiency estimates in stage one. In addition to the original DEA estimates of efficiency, the results from a bootstrap DEA method proposed by Simar and Wilson (1998) are presented in Section 6.2. These estimates include the efficiency scores under both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions from an output-oriented perspective.

The variation of technical efficiency scores and underlying trends across different specifications applied in Model I and Model II are also discussed in this section. The Friedman test is applied to examine if the efficiency performance changed over the study period.

In addition to the evaluation of technical efficiency, it is important to understand the factors contributing to technical efficiency performance. This knowledge will aid us to identify relevant policy recommendations to improve the efficiency of mining firms in Australia. Section 6.3 presents and discusses the results derived from the second-stage analysis of the study’s two distinguished models. The aim of stage two is to examine the effects of firm-specific factors on the technical efficiency of the Australian mining firms. In the second-stage analysis, technical efficiency is regressed on 11 factors of ownership, firm size, firm age, capacity utilisation, financial risk, product type, portfolio diversification, growth variables of production progress pace as well as growth/decline status, location of operations, and time. The analysis in both stage one and stage two is conducted in the R programming environment using codes developed by the author and FEAR package provided by Wilson (2013).

The derived results from a bootstrap truncated regression method proposed by Simar and Wilson (2007) show that the firm-specific factors significantly influence the efficiency performance of the Australian mining firms. It is also assessed whether considering natural resource input in the technical efficiency modelling results in significant variations among estimated parameters of the second-stage regression model, compared with the results from the general efficiency model. The results obtained from the second analysis in both models have been discussed in detail and the findings are compared with those from the existing literature.

6.2 Efficiency Estimation Results

At the first stage of analysis, the aim was to estimate the Farrell technical efficiency of observed DMUs. Using an output-oriented DEA model, the production frontier was constructed over the sample and the efficiency scores relative to the corresponding frontier level were estimated.

This section presents the efficiency estimates obtained from Model I and Model II. First the efficiency scores are estimated using a conventional DEA model. Then, the bootstrap DEA model is applied on the sample to obtain the bias-corrected estimates of technical efficiency and the confidence intervals. The bootstrap DEA model results in efficiency estimates with valid statistical inference relative to the sampling variations of the estimated frontier (Simar and Wilson, 1998). Simar and Wilson's smooth bootstrapping procedure is employed to correct the bias in efficiency scores and to obtain the corresponding confidence intervals.

6.2.1 Original DEA Efficiency Estimates

As discussed in Chapter 5, this thesis applies an output-oriented DEA model. Both variable return to scale (VRS) and constant return to scale (CRS) models are utilised to obtain the efficiency scores. By focusing on firm-level efficiency, the sources of inefficiency are decomposed into pure technical inefficiency and scale inefficiency. Pure technical inefficiency indicates that the firm's 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 the 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.

Usually, firms are not able to change their operating scale in the short term. The VRS technical efficiency can be interpreted as what a company can achieve in the short run and CRS technical efficiency represents the potential for improvement in the long term (Coelli, et al, p. 60, 2005). Therefore, in addition to the overall technical efficiency estimates derived from the CRS model, this study extracts the components of technical efficiency, namely pure technical efficiency and scale efficiency, to identify the improvement potentials in the short term and long term.

Table 6.1 and Table 6.2 show the summary of efficiency estimates derived from Model I and Model II respectively. The details of efficiency estimates for individual firms are reported in Table 6.3 and Table 6.4. As the Farrell estimates of technical efficiency are calculated in the constructed model, a higher efficiency score indicates lower firm efficiency (Farrell, 1957).

The stage one results summarised in Table 6.1 show a significant inefficiency level among the Australian mining firms based on Model I and the CRS assumption. On average, 62 per cent inefficiency is observed across mining companies in the study's sample. Accounting for the VRS assumption in Model I, the pure technical efficiency improves over the period 2010-14. On average, the estimated VRS efficiency scores, i.e. pure technical efficiency scores, reach 1.67 points, representing 40 per cent inefficiency performance among mining companies. Comparison of the VRS and CRS results from Model I shows a significant scale inefficiency among mining companies. Over the entire sample, the average scale efficiency score is 1.59 points which can be interpreted as the presence of 37 per cent scale inefficiency in the Australian mining sector. Table 6.3 reveals that majority of observations in the sample are operating over the optimum scale. Around 90 per cent of observations require reducing their operating scale to achieve better efficiency performance.

This finding is in line with that of studies addressing the issue of operating scale in the Australian mining sector. In a sector-level study, Zheng and Bloch (2014) used the elasticity of cost with respect to output as a measure of returns to scale and found the presence of a moderate returns to scale in Australian mining. They reported that a non-optimal scale of operation had been responsible for the decline in MFP growth by 0.2 per cent per annum over the 1974-75 to 2007-08 period. In another sector-level study, Syed et al. (2015) decomposed the MFP growth to technical progress, technical efficiency and scale efficiency, and found that both technical efficiency and scale effects had positive contributions to the MFP growth of the Australian mining sector over the period 1990-91 to 2009-10. Although their study did not reveal the size of technical and scale inefficiency, Syed et al. (2015) estimated the contribution of technical efficiency and operating scale improvements to the annual MFP growth by 82.4 per cent and 27.8 per cent respectively, while technical progress contributed negatively by -10.2 per cent per year. Zheng and Bloch (2014) explained that the slight decreasing returns to scale phenomenon may be attributable to the natural constraints to expansion of natural resource production. An increase in production is not necessarily proportional to an increase in exploration expenditure, physical capital and labour when the most accessible deposits are discovered and extracted first.

Table 6.1: Summary of Model I technical efficiency scores - the original DEA model

Original CRS Model						Original VRS Model					
Year	Mean	Std. dev.	Min.	Max.	Ineff.[(a)]	Year	Mean	Std. dev.	Min.	Max.	Ineff.[(a)]
2010	2.56	1.08	1.10	4.67	61%	2010	1.68	0.60	1.00	3.17	41%
2011	2.50	1.38	1.00	6.69	60%	2011	1.58	0.62	1.00	3.74	37%
2012	2.59	1.23	1.00	5.16	61%	2012	1.64	0.69	1.00	3.83	39%
2013	2.79	1.40	1.00	6.51	64%	2013	1.73	0.73	1.00	3.99	42%
2014	2.79	1.72	1.00	9.76	64%	2014	1.74	1.05	1.00	6.99	43%
Total	2.65	1.37	1.00	9.76	62%	Total	1.67	0.75	1.00	6.99	40%

Source: Author's calculations
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.

Model II accounts for the natural resource inputs and resource depletion in efficiency measurement. Table 6.2 presents the summary of efficiency performance obtained from Model II. Under the CRS assumption in Model II, on average, 41 per cent inefficiency exists among mining firms in the sample, whereas this overall inefficiency reduces to 39 per cent considering the VRS technology assumption. These results reveal that once accounting for natural resource inputs, the deviations between CRS and VRS efficiency estimates are not significant. It illustrates that most mining firms operate close to their optimum scale when the natural resource input has been taken into consideration. The average scale efficiency score in the sample derived from Model II is 1.04 points which represents the existence of only 4 per cent scale inefficiency among mining companies.

Table 6.2: Summary of Model II technical efficiency scores - the original DEA model

Original CRS Model						Original VRS Model					
Year	Mean	Std. dev.	Min.	Max.	Ineff.[(a)]	Year	Mean	Std. dev.	Min.	Max.	Ineff.[(a)]
2010	1.74	0.58	1.00	3.09	43%	2010	1.66	0.60	1.00	3.07	40%
2011	1.59	0.62	1.00	3.74	37%	2011	1.55	0.62	1.00	3.74	35%
2012	1.65	0.68	1.00	3.85	40%	2012	1.58	0.67	1.00	3.83	37%
2013	1.73	0.73	1.00	4.01	42%	2013	1.70	0.71	1.00	3.99	41%
2014	1.75	1.05	1.00	7.00	43%	2014	1.73	1.05	1.00	6.99	42%
Total	1.69	0.74	1.00	7.00	41%	Total	1.64	0.74	1.00	6.99	39%

Source: Author's calculations
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.

Details of efficiency estimates from Model II presented in Table 6.4 show that a combination of decreasing returns to scale (DRS), increasing returns to scale (IRT) and optimum operating scale conditions have been observed among mining companies. Almost 42 per cent of firms have an operating scale above the optimum level; 30 per cent of firms are operating in a lower scale than the optimum scale; and 28 per cent are fully scale efficient. In several observations, the DRS or IRS conditions appear due to the presence of minor scale inefficiency. Once applying the effects of natural resource input, only 12 out of 170 observations in the sample have more than 10 per cent scale inefficiency.

This finding strongly suggests that the main reason behind poor scale efficiency among the Australian mining companies is the adverse effect of natural resource input and resource depletion. Lower ore grades or less accessible mineral ore deposit leads to consumption of greater amounts of labour, capital and intermediate inputs to maintain the same level of production output with a given technology. To overcome the adverse effects in natural resource quality, mining firms increase their labour, capital and intermediate inputs that does not result in proportional increase in production output. Therefore, the DEA method suggests that mining companies require a decrease in the size of their operations as they do not utilise their resources efficiently. However, this apparent inefficient utilisation of resources is not due to their non-optimum operating size, but due to natural resource quality decline. Inclusion of effects from natural resource inputs into the efficiency model reveal that most mining firms have been capable of operating close to their optimum scale.

The results support some major recent studies in the Australian mining sector that address the challenges of the resource depletion phenomenon and the evaluation of the productivity of mining activities. Topp et al. (2008) explained that resource depletion has been the main contributor to poor productivity performance of the Australian mining sector in the long run. They estimated that resource depletion caused 24.2 per cent decline in the mining MFP between 2000-01 and 2006-07.

While resource depletion and investment-production lags were reported to impact the MFP performance negatively, their study shows a positive influence on MFP growth from technology progress and efficiency improvement. Zheng and Bloch (2014) and Syed et al. (2015) also argued that the natural resource inputs to mining operations resulted in significant decline in the productivity performance. Zheng and Bloch (2014) reported a sizable decline 0.6 per cent per annum in the measured MFP due to the resource input effect. Also, Syed et al. (2015) showed that the MFP growth measure adjusted for construction-production lead time, as well as natural resource depletion, was 1.6 per cent per year from 2000 to 2010, compared to a decline of 3.1 per cent per year based on the unadjusted MFP measure. Although the scope of this study, the timeframe, the model variables and the methodology are different from these sector-level analyses, the results support their findings. The effect of natural resource inputs in the efficiency and productivity performance of the mining industry is evident. It is an important factor that cannot be ignored in the performance measurement of mining activities.

Table 6.3: Original DEA efficiency estimates – Model I (general model)

Firm	Year	CRS-TE	VRS_TE	SE	RTS
ABY	2010	2.12	1.66	1.28	drs
ABY	2011	2.36	1.78	1.32	drs
ABY	2012	2.02	1.65	1.23	drs
ABY	2013	2.17	1.75	1.24	drs
ABY	2014	2.89	2.17	1.33	drs
AGG	2010	1.26	1.00	1.26	drs
AGG	2011	1.00	1.00	1.00	-
AGG	2012	1.10	1.00	1.10	drs
AGG	2013	1.20	1.00	1.20	drs
AGG	2014	1.38	1.09	1.26	drs
AGO	2010	4.57	2.82	1.62	drs
AGO	2011	1.92	1.21	1.58	drs
AGO	2012	2.25	1.28	1.76	drs
AGO	2013	2.06	1.20	1.72	drs
AGO	2014	1.20	1.00	1.20	drs
AQP	2010	3.39	1.87	1.81	drs
AQP	2011	1.58	1.20	1.31	drs
AQP	2012	2.37	1.81	1.31	drs
AQP	2013	4.63	2.12	2.18	drs
AQP	2014	3.75	2.64	1.42	drs
BHP	2010	3.07	1.07	2.87	drs
BHP	2011	2.59	1.00	2.59	drs
BHP	2012	2.90	1.00	2.90	drs
BHP	2013	3.04	1.00	3.04	drs
BHP	2014	3.67	1.01	3.63	drs
EVN	2010	2.52	2.45	1.03	drs
EVN	2011	5.73	2.78	2.06	drs
EVN	2012	2.13	1.32	1.62	drs
EVN	2013	1.59	1.00	1.59	drs
EVN	2014	1.72	1.09	1.58	drs
FMG	2010	1.45	1.11	1.31	drs
FMG	2011	1.24	1.00	1.24	drs
FMG	2012	1.34	1.00	1.34	drs
FMG	2013	2.04	1.01	2.02	drs
FMG	2014	2.64	1.00	2.64	drs
GRR	2010	2.81	2.10	1.34	drs
GRR	2011	3.34	1.89	1.77	drs
GRR	2012	3.67	2.20	1.67	drs
GRR	2013	2.52	1.80	1.40	drs
GRR	2014	2.38	1.93	1.23	drs
IGO	2010	1.40	1.34	1.05	drs
IGO	2011	2.14	1.85	1.16	drs
IGO	2012	3.42	2.52	1.36	drs
IGO	2013	2.22	1.81	1.23	drs
IGO	2014	1.58	1.31	1.21	drs
NGF	2010	4.55	3.17	1.44	drs
NGF	2011	1.07	1.07	1.00	irs
NGF	2012	5.16	2.44	2.11	drs
NGF	2013	1.47	1.34	1.10	drs
NGF	2014	1.66	1.49	1.11	drs
OGC	2010	4.67	2.12	2.20	drs
OGC	2011	4.50	2.33	1.94	drs
OGC	2012	4.29	2.37	1.81	drs
OGC	2013	5.70	2.14	2.66	drs
OGC	2014	3.50	1.59	2.19	drs
OMH	2010	1.93	1.57	1.23	drs
OMH	2011	2.16	1.69	1.28	drs
OMH	2012	1.92	1.56	1.23	drs
OMH	2013	2.07	1.72	1.20	drs
OMH	2014	1.91	1.49	1.28	drs
OZL	2010	2.40	1.00	2.40	drs
OZL	2011	3.42	1.30	2.63	drs
OZL	2012	4.22	1.50	2.82	drs
OZL	2013	6.51	2.71	2.40	drs
OZL	2014	3.45	1.43	2.42	drs
PAN	2010	1.90	1.53	1.24	drs
PAN	2011	2.26	1.84	1.22	drs
PAN	2012	2.51	2.06	1.21	drs
PAN	2013	3.40	2.59	1.32	drs
PAN	2014	3.06	2.26	1.35	drs
PNA	2010	2.94	1.44	2.04	drs
PNA	2011	3.19	1.63	1.96	drs
PNA	2012	3.71	1.59	2.33	drs
PNA	2013	4.66	1.71	2.73	drs
PNA	2014	5.60	2.12	2.64	drs
RIO	2010	2.15	1.00	2.15	drs
RIO	2011	2.30	1.00	2.30	drs
RIO	2012	2.81	1.03	2.73	drs
RIO	2013	2.79	1.00	2.79	drs
RIO	2014	3.09	1.12	2.76	drs
RND	2010	1.68	1.00	1.68	irs
RND	2011	1.44	1.00	1.44	irs
RND	2012	1.58	1.00	1.58	irs
RND	2013	1.00	1.00	1.00	-
RND	2014	1.18	1.00	1.18	irs
RSG	2010	2.54	1.85	1.38	drs
RSG	2011	3.08	1.82	1.69	drs
RSG	2012	2.34	1.38	1.70	drs
RSG	2013	1.87	1.47	1.28	drs
RSG	2014	2.37	1.78	1.33	drs

Table 6.3 (continued): Original DEA efficiency estimates – Model I (general model)

Firm	Year	CRS-TE	VRS_TE	SE	RTS	Firm	Year	CRS-TE	VRS_TE	SE	RTS
ILU	2010	4.66	1.90	2.45	drs	SAR	2010	2.25	1.00	2.25	irs
ILU	2011	2.94	1.11	2.63	drs	SAR	2011	1.00	1.00	1.00	-
ILU	2012	2.02	1.34	1.51	drs	SAR	2012	1.13	1.06	1.07	drs
ILU	2013	3.64	1.83	1.98	drs	SAR	2013	1.84	1.60	1.15	drs
ILU	2014	4.12	1.93	2.14	drs	SAR	2014	1.78	1.54	1.16	drs
KCN	2010	2.51	1.78	1.41	drs	SBM	2010	2.26	1.78	1.27	drs
KCN	2011	5.00	2.53	1.97	drs	SBM	2011	2.07	1.63	1.27	drs
KCN	2012	3.89	1.68	2.32	drs	SBM	2012	1.47	1.17	1.26	drs
KCN	2013	4.13	1.80	2.30	drs	SBM	2013	2.07	1.56	1.32	drs
KCN	2014	5.13	2.20	2.34	drs	SBM	2014	2.32	1.82	1.27	drs
MBN	2010	4.56	2.81	1.62	drs	SLR	2010	2.15	1.99	1.08	drs
MBN	2011	3.41	2.17	1.58	drs	SLR	2011	2.30	2.05	1.12	drs
MBN	2012	4.93	2.91	1.69	drs	SLR	2012	1.73	1.53	1.13	drs
MBN	2013	4.91	3.99	1.23	drs	SLR	2013	3.59	2.84	1.26	drs
MBN	2014	1.00	1.00	1.00	-	SLR	2014	2.48	1.95	1.27	drs
MCR	2010	4.26	2.37	1.79	drs	TBR	2010	1.10	1.00	1.10	irs
MCR	2011	6.68	3.74	1.79	drs	TBR	2011	1.25	1.23	1.01	drs
MCR	2012	4.60	3.14	1.47	drs	TBR	2012	1.31	1.26	1.04	drs
MCR	2013	5.07	3.45	1.47	drs	TBR	2013	1.00	1.00	1.00	-
MCR	2014	4.86	2.87	1.70	drs	TBR	2014	1.25	1.22	1.02	irs
MGX	2010	1.32	1.00	1.32	drs	TRY	2010	2.83	2.36	1.20	drs
MGX	2011	1.20	1.00	1.20	drs	TRY	2011	2.50	1.77	1.42	drs
MGX	2012	1.00	1.00	1.00	-	TRY	2012	1.40	1.12	1.25	drs
MGX	2013	2.74	1.49	1.84	drs	TRY	2013	1.46	1.12	1.30	drs
MGX	2014	2.57	1.48	1.73	drs	TRY	2014	1.67	1.37	1.22	drs
MLX	2010	2.41	2.05	1.17	drs	WLC	2010	2.15	1.89	1.14	drs
MLX	2011	1.28	1.17	1.10	drs	WLC	2011	1.85	1.70	1.09	drs
MLX	2012	4.27	3.83	1.12	drs	WLC	2012	1.36	1.32	1.03	irs
MLX	2013	2.27	2.08	1.09	drs	WLC	2013	2.99	2.34	1.28	drs
MLX	2014	1.57	1.37	1.14	drs	WLC	2014	9.75	6.99	1.40	drs
MML	2010	1.31	1.14	1.15	drs	WSA	2010	1.53	1.31	1.16	drs
MML	2011	1.12	1.00	1.12	drs	WSA	2011	1.24	1.00	1.24	drs
MML	2012	1.54	1.35	1.15	drs	WSA	2012	1.52	1.18	1.29	drs
MML	2013	1.84	1.30	1.42	drs	WSA	2013	1.37	1.04	1.33	drs
MML	2014	3.18	1.73	1.84	drs	WSA	2014	1.60	1.30	1.23	drs
NCM	2010	2.09	1.14	1.83	drs	ZIM	2010	2.28	1.63	1.40	drs
NCM	2011	3.73	1.36	2.73	drs	ZIM	2011	2.22	1.72	1.29	drs
NCM	2012	3.52	1.25	2.81	drs	ZIM	2012	2.58	1.92	1.34	drs
NCM	2013	2.09	1.16	1.80	drs	ZIM	2013	3.09	1.95	1.58	drs
NCM	2014	1.00	1.00	1.00	-	ZIM	2014	3.47	1.89	1.84	drs

Source: Author’s calculations

Table 6.4: Original DEA efficiency estimates – Model II (natural resource-based model)

Firm	Year	CRS-TE	VRS_TE	SE	RTS	Firm	Year	CRS-TE	VRS_TE	SE	RTS
ABY	2010	1.67	1.66	1.00	drs	NGF	2010	3.09	3.07	1.01	irs
ABY	2011	1.79	1.78	1.00	drs	NGF	2011	1.06	1.00	1.06	irs
ABY	2012	1.65	1.65	1.00	drs	NGF	2012	2.38	2.36	1.01	irs
ABY	2013	1.76	1.75	1.00	drs	NGF	2013	1.33	1.31	1.02	irs
ABY	2014	2.17	2.17	1.00	drs	NGF	2014	1.48	1.41	1.05	irs
AGG	2010	1.00	1.00	1.00	-	OGC	2010	2.12	2.12	1.00	drs
AGG	2011	1.00	1.00	1.00	-	OGC	2011	2.34	2.33	1.01	drs
AGG	2012	1.00	1.00	1.00	-	OGC	2012	2.38	2.37	1.01	drs
AGG	2013	1.00	1.00	1.00	-	OGC	2013	2.16	2.14	1.01	drs
AGG	2014	1.10	1.09	1.00	drs	OGC	2014	1.59	1.59	1.00	-
AGO	2010	2.80	2.79	1.00	irs	OMH	2010	1.57	1.57	1.00	drs
AGO	2011	1.22	1.21	1.01	drs	OMH	2011	1.70	1.69	1.00	drs
AGO	2012	1.27	1.27	1.00	irs	OMH	2012	1.57	1.56	1.01	drs
AGO	2013	1.21	1.20	1.01	drs	OMH	2013	1.72	1.72	1.00	drs
AGO	2014	1.00	1.00	1.00	-	OMH	2014	1.50	1.49	1.01	drs
AQP	2010	1.89	1.87	1.01	drs	OZL	2010	1.00	1.00	1.00	-
AQP	2011	1.21	1.20	1.01	drs	OZL	2011	1.30	1.30	1.00	-
AQP	2012	1.82	1.81	1.01	drs	OZL	2012	1.49	1.49	1.00	irs
AQP	2013	2.14	2.12	1.01	drs	OZL	2013	2.71	2.71	1.00	-
AQP	2014	2.65	2.64	1.00	drs	OZL	2014	1.43	1.43	1.00	drs
BHP	2010	1.07	1.06	1.01	irs	PAN	2010	1.53	1.53	1.00	drs
BHP	2011	1.00	1.00	1.00	-	PAN	2011	1.84	1.84	1.00	-
BHP	2012	1.00	1.00	1.00	-	PAN	2012	2.05	2.04	1.01	irs
BHP	2013	1.00	1.00	1.00	-	PAN	2013	2.56	2.53	1.01	irs
BHP	2014	1.02	1.01	1.00	drs	PAN	2014	2.24	2.22	1.01	irs
EVN	2010	2.46	2.45	1.00	drs	PNA	2010	1.44	1.44	1.00	-
EVN	2011	2.80	2.78	1.01	drs	PNA	2011	1.61	1.61	1.00	irs
EVN	2012	1.34	1.32	1.02	drs	PNA	2012	1.57	1.56	1.00	irs
EVN	2013	1.00	1.00	1.00	-	PNA	2013	1.69	1.68	1.00	irs
EVN	2014	1.11	1.09	1.01	drs	PNA	2014	2.09	2.08	1.00	irs
FMG	2010	1.11	1.11	1.00	drs	RIO	2010	1.00	1.00	1.00	-
FMG	2011	1.00	1.00	1.00	-	RIO	2011	1.00	1.00	1.00	-
FMG	2012	1.00	1.00	1.00	-	RIO	2012	1.03	1.03	1.00	drs
FMG	2013	1.01	1.01	1.00	-	RIO	2013	1.00	1.00	1.00	-
FMG	2014	1.00	1.00	1.00	-	RIO	2014	1.13	1.12	1.01	drs
GRR	2010	2.10	2.10	1.00	-	RND	2010	1.68	1.00	1.68	irs
GRR	2011	1.87	1.87	1.00	irs	RND	2011	1.44	1.00	1.44	irs
GRR	2012	2.14	2.07	1.03	irs	RND	2012	1.58	1.00	1.58	irs
GRR	2013	1.79	1.78	1.00	irs	RND	2013	1.00	1.00	1.00	-
GRR	2014	1.94	1.93	1.00	drs	RND	2014	1.18	1.00	1.18	irs
IGO	2010	1.34	1.00	1.34	irs	RSG	2010	1.85	1.85	1.00	drs
IGO	2011	1.81	1.37	1.32	irs	RSG	2011	1.84	1.82	1.01	drs
IGO	2012	2.46	1.00	2.46	irs	RSG	2012	1.38	1.38	1.00	drs
IGO	2013	1.79	1.75	1.02	irs	RSG	2013	1.47	1.47	1.00	drs
IGO	2014	1.30	1.28	1.01	irs	RSG	2014	1.78	1.78	1.00	-

Table 6.4 (continued): Original DEA efficiency estimates – Model II (natural resource-based model)

Firm	Year	CRS-TE	VRS_TE	SE	RTS	Firm	Year	CRS-TE	VRS_TE	SE	RTS
ILU	2010	1.90	1.90	1.00	-	SAR	2010	2.25	1.00	2.25	irs
ILU	2011	1.12	1.11	1.00	drs	SAR	2011	1.00	1.00	1.00	-
ILU	2012	1.34	1.34	1.00	drs	SAR	2012	1.06	1.05	1.00	irs
ILU	2013	1.84	1.83	1.01	drs	SAR	2013	1.60	1.59	1.01	irs
ILU	2014	1.94	1.93	1.00	drs	SAR	2014	1.54	1.54	1.00	-
KCN	2010	1.78	1.78	1.00	drs	SBM	2010	1.78	1.78	1.00	drs
KCN	2011	2.53	2.53	1.00	-	SBM	2011	1.63	1.63	1.00	drs
KCN	2012	1.67	1.67	1.00	-	SBM	2012	1.17	1.17	1.00	drs
KCN	2013	1.80	1.80	1.00	-	SBM	2013	1.56	1.56	1.00	drs
KCN	2014	2.23	2.20	1.01	drs	SBM	2014	1.82	1.82	1.00	drs
MBN	2010	2.85	2.81	1.02	drs	SLR	2010	1.98	1.71	1.16	irs
MBN	2011	2.24	2.17	1.03	drs	SLR	2011	2.01	1.68	1.20	irs
MBN	2012	2.94	2.91	1.01	drs	SLR	2012	1.53	1.53	1.00	-
MBN	2013	4.01	3.99	1.00	drs	SLR	2013	2.82	2.77	1.02	irs
MBN	2014	1.00	1.00	1.00	-	SLR	2014	1.94	1.93	1.00	irs
MCR	2010	2.37	2.37	1.00	-	TBR	2010	1.10	1.00	1.10	irs
MCR	2011	3.74	3.74	1.00	-	TBR	2011	1.24	1.23	1.00	drs
MCR	2012	3.13	3.10	1.01	irs	TBR	2012	1.26	1.26	1.00	drs
MCR	2013	3.42	3.21	1.07	irs	TBR	2013	1.00	1.00	1.00	-
MCR	2014	2.86	2.85	1.00	irs	TBR	2014	1.25	1.19	1.05	irs
MGX	2010	1.00	1.00	1.00	-	TRY	2010	2.36	2.35	1.00	irs
MGX	2011	1.00	1.00	1.00	-	TRY	2011	1.77	1.77	1.00	drs
MGX	2012	1.00	1.00	1.00	-	TRY	2012	1.12	1.12	1.00	-
MGX	2013	1.49	1.49	1.00	-	TRY	2013	1.12	1.12	1.00	drs
MGX	2014	1.48	1.48	1.00	-	TRY	2014	1.38	1.37	1.00	drs
MLX	2010	2.03	1.96	1.04	irs	WLC	2010	1.90	1.89	1.00	drs
MLX	2011	1.17	1.17	1.00	drs	WLC	2011	1.70	1.70	1.00	drs
MLX	2012	3.85	3.83	1.01	drs	WLC	2012	1.36	1.32	1.03	irs
MLX	2013	2.05	1.73	1.19	irs	WLC	2013	2.35	2.34	1.00	drs
MLX	2014	1.36	1.32	1.03	irs	WLC	2014	7.00	6.99	1.00	-
MML	2010	1.14	1.11	1.02	irs	WSA	2010	1.31	1.28	1.02	irs
MML	2011	1.00	1.00	1.00	-	WSA	2011	1.00	1.00	1.00	-
MML	2012	1.35	1.34	1.00	irs	WSA	2012	1.18	1.16	1.01	irs
MML	2013	1.27	1.00	1.27	irs	WSA	2013	1.01	1.00	1.01	irs
MML	2014	1.73	1.73	1.00	drs	WSA	2014	1.30	1.30	1.00	drs
NCM	2010	1.14	1.14	1.00	drs	ZIM	2010	1.64	1.63	1.00	drs
NCM	2011	1.37	1.36	1.01	drs	ZIM	2011	1.72	1.72	1.00	-
NCM	2012	1.26	1.25	1.01	drs	ZIM	2012	1.93	1.92	1.00	drs
NCM	2013	1.16	1.16	1.00	drs	ZIM	2013	1.96	1.95	1.00	drs
NCM	2014	1.00	1.00	1.00	-	ZIM	2014	1.89	1.89	1.00	drs

Source: Author's calculations

Overall, the summary of efficiency scores shows that efficiency performance improved from 2010 to 2011; however, the performance gradually declined since 2011. To test whether there are any statistically differences among efficiency performance of the Australian mining firms from 2010 to 2014, this study applies the Friedman test. The Friedman test results, as presented in Table 6.5, suggest that despite the variations observed on the average estimate, there are no significant differences among efficiency performance of mining firms in the sample over the period of study. While no other study reported the efficiency performance of the Australian mining firms, the current study's results do not support the sector-level findings in relation to efficiency improvements in the Australian mining industry. Topp et al. (2008) expressed that taking into account the long-term effect of natural resource inputs and short-term effect from capital-production lags, the MFP grew by 2.3 per cent per year over 1974-75 to 2006-07 due to improvements in production efficiency. As their study did not decompose the productivity growth to components such as technical progress and efficiency improvement, it cannot be definitively concluded that the MFP growth was mainly attributable to technical efficiency improvements.

Table 6.5: Friedman test mean ranks and asymptotic significance.

Model 1 - Original CRS		Model 1 - Original VRS		Model 2 - Original CRS		Model 2 - Original VRS	
p-value: 0.229		p-value: 0.636		p-value: 0 .732		p-value: 0 .361	
M1_CRS_TE10	3.00	M1_VRS_TE10	2.90	M2_CRS_TE10	3.07	M2_VRS_TE10	2.94
M1_CRS_TE11	2.59	M1_VRS_TE11	2.76	M2_CRS_TE11	2.72	M2_VRS_TE11	2.74
M1_CRS_TE12	2.79	M1_VRS_TE12	2.90	M2_CRS_TE12	2.90	M2_VRS_TE12	2.76
M1_CRS_TE13	3.24	M1_VRS_TE13	3.24	M2_CRS_TE13	3.13	M2_VRS_TE13	3.21
M1_CRS_TE14	3.38	M1_VRS_TE14	3.21	M2_CRS_TE14	3.18	M2_VRS_TE14	3.35

Source: Author's calculations

Another study by Syed et al. (2015), which assessed the productivity growth of the mining in Australia, also reported a positive contribution of technical efficiency to MFP performance of the Australian mining industry. This study estimated that 82.4 per cent of productivity growth between 1990-91 to 2009-10 resulted from technical efficiency improvements and 27.8 per cent MFP improvement was achieved by improving the scale of operations, whereas technical progress contributed negatively by –10.2 per cent over the study period. While it is difficult to precisely identify the underlying reasons that explain the difference between the current study's results and the ones published in Syed et al. (2015), this difference can arise due to the type of study, the applied methodology or the study period. The current study looks at the efficiency measurement and applies DEA which is a non-parametric efficiency technique. On the other hand, Syed et al. (2015) looked at productivity and efficiency growth over time and used SFA which is a parametric method to productivity and efficiency measurement. Finally, the 2015 study covered a different time scope, one that does not overlap with that of the current study. It may explain why this study's findings are not supporting the previous studies.

6.2.2 Bootstrap DEA Efficiency Estimates

DEA is a deterministic method, which does not take into account sample variation and measurement errors. To overcome the shortcoming of this method in reflecting the statistical noise and errors, Simar and Wilson (1998) proposed a bootstrap procedure which allows researchers to examine statistical properties of the estimated DEA scores. Hence, the current study develops original R codes and uses FEAR package provided by Wilson (2013) to conduct the smoothing bootstrap procedure. This involved 2000 iterations to obtain bias-corrected efficiency estimates along with their 95% confidence intervals for 34 Australian mining firms. The technical details of this procedure are discussed in Chapter 4. Table 6.6 and Table 6.7 provide summaries of the bootstrap DEA estimated, while Table 6.8 and Table 6.9 present the bias-corrected efficiency estimates and corresponding 95% confidence intervals over the sample data. The pattern of efficiency estimates derived from the bootstrapped models is similar to the original estimates but with the presence of greater inefficiency degrees across sample observations. As per Table 6.6, the overall efficiency results of Model I increase to 2.97 and 1.87 based on the CRS and VRS assumptions, respectively, which reflect 4 per cent increase in CRS inefficiency and 7 per cent increase in VRS inefficiency levels.

The bootstrap DEA estimates from Model II also show increases in efficiency scores. The average efficiency score rises to 1.89 and 1.86 for CRS and VRS technologies, respectively. Almost 12 per cent bias is corrected in the efficiency estimates. Even after considering the natural resource input in efficiency modelling, 47 per cent technical inefficiency is still observed among Australian mining companies, which has been almost stable over the period 2010-2014. The aim of the second-stage analysis is to investigate the factors that determine this sizable inefficiency level among the Australian mining companies. In better understanding these factors, the suitable policy required to improve the efficiency performance can be introduced.

Table 6.6: Summary of Model I technical efficiency scores - the bootstrap DEA model

Bootstrap CRS Model						Bootstrap VRS Model					
Year	Mean	Std. dev.	Min.	Max.	Ineff.[(a)]	Year	Mean	Std. dev.	Min.	Max.	Ineff.[(a)]
2010	2.83	1.21	1.34	5.31	65%	2010	1.88	0.63	1.15	3.50	47%
2011	2.81	1.56	1.21	7.37	64%	2011	1.77	0.64	1.17	4.14	43%
2012	2.94	1.41	1.25	5.99	66%	2012	1.84	0.73	1.15	4.16	46%
2013	3.15	1.63	1.22	7.36	68%	2013	1.94	0.82	1.10	4.78	48%
2014	3.13	1.89	1.37	10.73	68%	2014	1.94	1.11	1.18	7.62	48%
Total	2.97	1.54	1.21	10.73	66%	Total	1.87	0.80	1.10	7.62	47%

Source: Author's calculations
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 6.7: Summary of Model II technical efficiency scores - the bootstrap DEA model

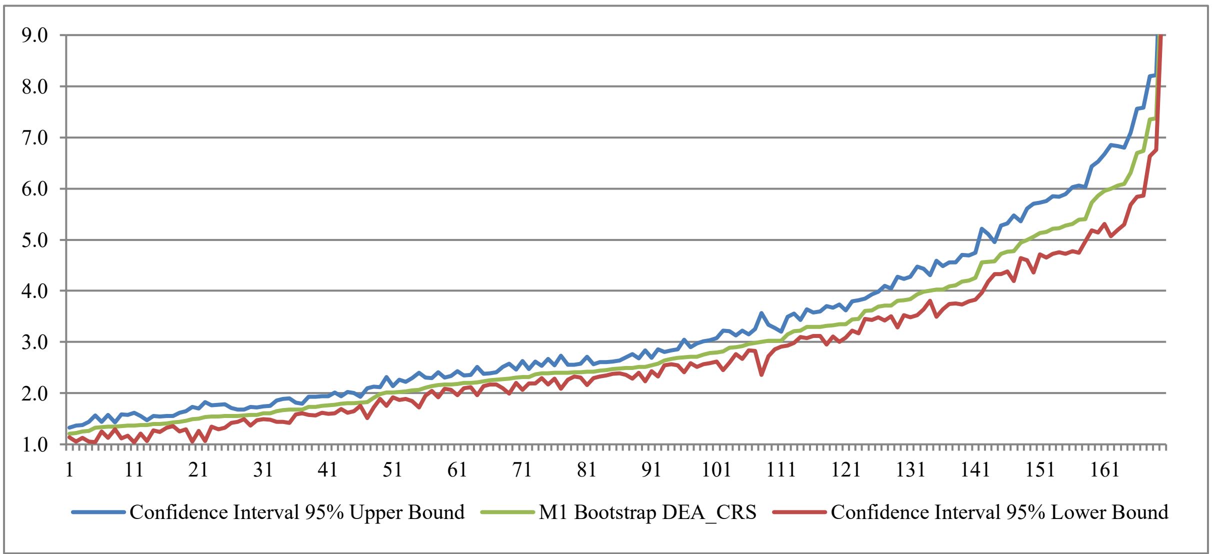
Bootstrap CRS Model						Bootstrap VRS Model					
Year	Mean	Std. dev.	Min.	Max.	Ineff.[(a)]	Year	Mean	Std. dev.	Min.	Max.	Ineff.[(a)]
2010	1.94	0.62	1.16	3.41	48%	2010	1.87	0.64	1.16	3.49	46%
2011	1.78	0.65	1.18	4.16	44%	2011	1.75	0.64	1.18	4.16	43%
2012	1.86	0.73	1.16	4.20	46%	2012	1.79	0.72	1.14	4.20	44%
2013	1.94	0.82	1.12	4.82	48%	2013	1.94	0.83	1.12	4.74	48%
2014	1.95	1.12	1.19	7.67	49%	2014	1.94	1.12	1.17	7.63	48%
Total	1.89	0.80	1.12	7.67	47%	Total	1.86	0.80	1.12	7.63	46%

Source: Author's calculations
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.

Interestingly, the inclusion of natural resource inputs in the efficiency model leads to almost similar results derived from the CRS and VRS DEA models presented in Table 6.7. That is, no significant scale effects deteriorated the technical efficiency of mining companies. Larger companies appear to be less efficient due to the adverse effects of natural resource quality, as opposed to a non-optimum operating scale. These results partially support the concluding remarks in Syed et al (2015). To reduce the adverse effects of resource depletion, which has been responsible for the low productivity of Australia's mining industry, the federal government could introduce policy interventions that encourage resource exploration. Such policies may include the provision of precompetitive resource and reserves data. However, the sizable inefficiency among mining companies, beyond the effects of natural resource inputs, presents room for improvement.

Since the results of the CRS and VRS models contain negligible deviations, only the results of the CRS DEA from both Model I and Model II are presented. Table 6.8 and Table 6.9 contain the efficiency results calculated from the bootstrap DEA method including the original results, bias-corrected efficiency estimates and the corresponding 95% confidence intervals. Figure 6.1 and Figure 6.2 present the bias-corrected bootstrap estimates of mining firms' efficiency along with the associated 95% confidence interval upper bounds and lower bounds for Model I and Model II respectively. The results in Figure 6.1 show that more than two-thirds of observations have efficiency scores above 2.0, suggesting a high level of inefficiency. As per results presented in Table 6.6, part of the low performance is owing to pure technical inefficiency. Notwithstanding, the large gap between the CRS and VRS estimates suggests the presence of fairly large-scale inefficiency among the mining companies.

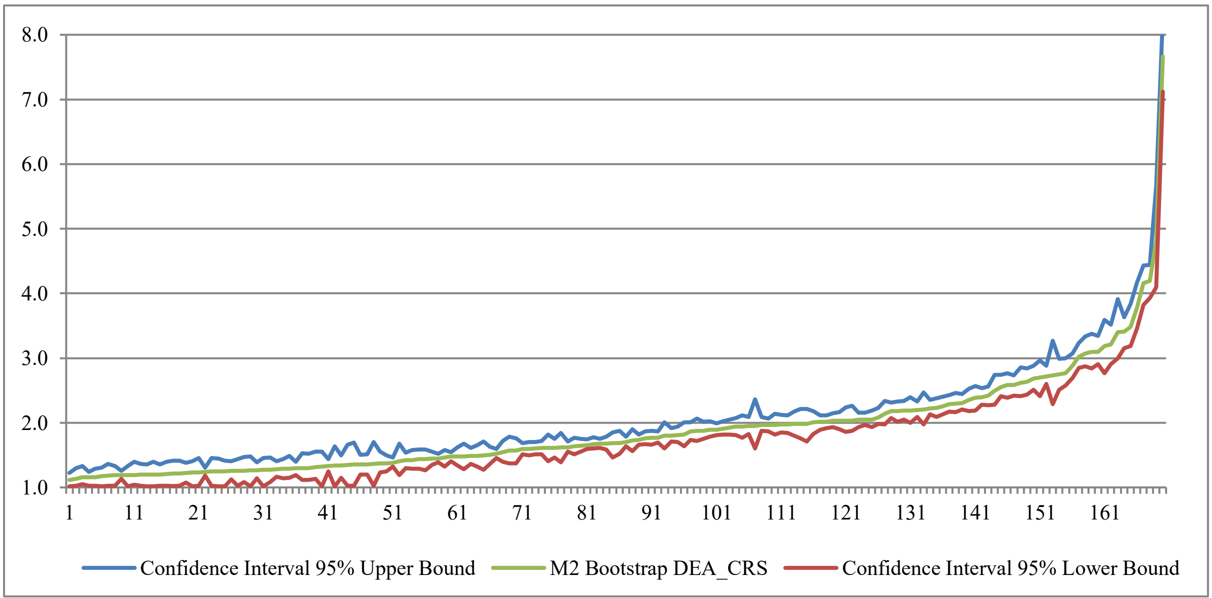
Figure 6.1: Model I bootstrap CRS efficiency scores and their 95% confidence intervals



Source: Author's calculations

The results from Model II, which represents the natural resource-based model of technical efficiency, are illustrated in Figure 6.2. Almost one-third of the observations have a bias-corrected efficiency score above 2.0. A major source of this poor performance is pure technical inefficiency, whereas most firms in the sample are almost scale-efficient. In other words, taking into account the natural resource input of the mining operations, the observed inefficiency in Figure 6.2 has basically resulted from the shortfall in capability of firms to transform their consumed inputs, namely labour efforts, capital service and intermediate inputs, into production outputs. The association between technical efficiency and firm-specific factors is examined in Section 6.3.

Figure 6.2: Model II bootstrap CRS efficiency scores and their 95% confidence intervals



Source: Author's calculations

Overall, the Australian mining firms perform differently in terms of their capability of transforming resources into desirable outputs. In the current study's sample, more than two-thirds of observations have achieved efficiency scores less than 2.0. As described in Chapter 4 on methodology, in the Farrell output-oriented measure of technical efficiency, an efficient firm's score is equal to unity and any scores greater than one represent some degree of inefficiency. Hence, observations with scores greater than 2.0 are far away from their corresponding benchmark. While all mining companies need to follow common productivity improvement programs such as investment in human capital and innovation, as discussed in Bradley and Sharpe (2009), as well as expansion in resource exploration, as suggested in Syed et al. (2015), specific improving actions seem to be necessary for the mining companies with fairly poor performance. Such actions require the knowledge of determinants of efficiency which are explored in the following section.

Table 6.8: Bootstrap DEA efficiency estimates – Model I (general model)

Firm	Year	Original	Bootstrap	Lower bound	Upper bound	Firm	Year	Original	Bootstrap	Lower bound	Upper bound
ABY	2010	2.12	2.23	2.14	2.37	NGF	2010	4.55	4.94	4.64	5.36
ABY	2011	2.36	2.47	2.38	2.62	NGF	2011	1.07	1.35	1.12	1.59
ABY	2012	2.02	2.14	2.04	2.29	NGF	2012	5.16	5.96	5.31	6.68
ABY	2013	2.17	2.30	2.20	2.46	NGF	2013	1.47	1.61	1.49	1.74
ABY	2014	2.89	3.03	2.91	3.21	NGF	2014	1.66	1.80	1.69	1.94
AGG	2010	1.26	1.55	1.33	1.78	OGC	2010	4.67	5.31	4.78	6.02
AGG	2011	1.00	1.38	1.07	1.47	OGC	2011	4.50	5.00	4.60	5.61
AGG	2012	1.10	1.25	1.13	1.37	OGC	2012	4.29	4.77	4.38	5.32
AGG	2013	1.20	1.44	1.25	1.62	OGC	2013	5.70	6.69	5.84	7.56
AGG	2014	1.38	1.67	1.44	1.89	OGC	2014	3.50	3.81	3.53	4.24
AGO	2010	4.57	5.27	4.72	5.89	OMH	2010	1.93	2.10	1.96	2.31
AGO	2011	1.92	2.18	1.96	2.43	OMH	2011	2.16	2.51	2.23	2.84
AGO	2012	2.25	2.57	2.32	2.86	OMH	2012	1.92	2.28	2.00	2.57
AGO	2013	2.06	2.40	2.09	2.73	OMH	2013	2.07	2.27	2.10	2.51
AGO	2014	1.20	1.50	1.26	1.70	OMH	2014	1.91	2.21	1.96	2.52
AQP	2010	3.39	3.62	3.43	3.94	OZL	2010	2.40	2.81	2.45	3.23
AQP	2011	1.58	1.76	1.62	1.94	OZL	2011	3.42	4.03	3.50	4.59
AQP	2012	2.37	2.70	2.41	3.05	OZL	2012	4.22	5.06	4.35	5.70
AQP	2013	4.63	5.22	4.76	5.84	OZL	2013	6.51	7.36	6.64	8.20
AQP	2014	3.75	4.00	3.80	4.31	OZL	2014	3.45	3.93	3.52	4.48
BHP	2010	3.07	3.33	3.11	3.67	PAN	2010	1.90	2.02	1.92	2.14
BHP	2011	2.59	2.80	2.62	3.08	PAN	2011	2.26	2.42	2.29	2.57
BHP	2012	2.90	3.15	2.93	3.50	PAN	2012	2.51	2.69	2.55	2.86
BHP	2013	3.04	3.29	3.07	3.64	PAN	2013	3.40	3.61	3.45	3.85
BHP	2014	3.67	4.18	3.74	4.70	PAN	2014	3.06	3.22	3.09	3.43
EVN	2010	2.52	2.64	2.54	2.80	PNA	2010	2.94	3.21	2.98	3.56
EVN	2011	5.73	6.74	5.86	7.58	PNA	2011	3.19	3.44	3.22	3.79
EVN	2012	2.13	2.39	2.17	2.67	PNA	2012	3.71	4.20	3.80	4.69
EVN	2013	1.59	1.80	1.62	2.02	PNA	2013	4.66	5.39	4.75	6.06
EVN	2014	1.72	2.01	1.75	2.31	PNA	2014	5.60	6.31	5.69	7.09
FMG	2010	1.45	1.58	1.47	1.73	RIO	2010	2.15	2.25	2.17	2.39
FMG	2011	1.24	1.33	1.26	1.44	RIO	2011	2.30	2.44	2.33	2.61
FMG	2012	1.34	1.43	1.36	1.55	RIO	2012	2.81	3.03	2.85	3.28
FMG	2013	2.04	2.17	2.06	2.34	RIO	2013	2.79	2.99	2.82	3.25
FMG	2014	2.64	3.02	2.72	3.34	RIO	2014	3.09	3.30	3.12	3.60
GRR	2010	2.81	2.96	2.84	3.15	RND	2010	1.68	1.91	1.72	2.12
GRR	2011	3.34	3.71	3.42	4.10	RND	2011	1.44	1.61	1.48	1.75
GRR	2012	3.67	4.11	3.76	4.55	RND	2012	1.58	1.77	1.61	2.01
GRR	2013	2.52	2.78	2.58	3.03	RND	2013	1.00	1.22	1.05	1.36
GRR	2014	2.38	2.51	2.40	2.68	RND	2014	1.18	1.38	1.21	1.55
IGO	2010	1.40	1.56	1.44	1.68	RSG	2010	2.54	2.67	2.57	2.84
IGO	2011	2.14	2.32	2.19	2.47	RSG	2011	3.08	3.30	3.12	3.58
IGO	2012	3.42	3.69	3.48	3.98	RSG	2012	2.34	2.49	2.36	2.70
IGO	2013	2.22	2.40	2.26	2.55	RSG	2013	1.87	1.98	1.89	2.11
IGO	2014	1.58	1.69	1.61	1.80	RSG	2014	2.37	2.49	2.39	2.64

Table 6.8 (continued): Bootstrap DEA efficiency estimates – Model I (general model)

Firm	Year	Original	Bootstrap	Lower bound	Upper bound	Firm	Year	Original	Bootstrap	Lower bound	Upper bound
ILU	2010	4.66	5.13	4.71	5.72	SAR	2010	2.25	3.00	2.35	3.57
ILU	2011	2.94	3.34	3.00	3.73	SAR	2011	1.00	1.32	1.05	1.56
ILU	2012	2.02	2.32	2.06	2.62	SAR	2012	1.13	1.37	1.17	1.57
ILU	2013	3.64	4.09	3.74	4.56	SAR	2013	1.84	2.16	1.92	2.41
ILU	2014	4.12	4.57	4.18	5.11	SAR	2014	1.78	2.06	1.85	2.29
KCN	2010	2.51	2.75	2.56	3.01	SBM	2010	2.26	2.40	2.29	2.55
KCN	2011	5.00	5.86	5.14	6.53	SBM	2011	2.07	2.20	2.10	2.34
KCN	2012	3.89	4.56	3.96	5.21	SBM	2012	1.47	1.56	1.49	1.68
KCN	2013	4.13	4.78	4.20	5.48	SBM	2013	2.07	2.17	2.09	2.30
KCN	2014	5.13	6.09	5.29	6.80	SBM	2014	2.32	2.45	2.35	2.60
MBN	2010	4.56	5.15	4.65	5.76	SLR	2010	2.15	2.27	2.17	2.41
MBN	2011	3.41	3.84	3.49	4.28	SLR	2011	2.30	2.41	2.32	2.55
MBN	2012	4.93	5.99	5.07	6.85	SLR	2012	1.73	1.82	1.75	1.93
MBN	2013	4.91	6.06	5.20	6.83	SLR	2013	3.59	3.99	3.64	4.43
MBN	2014	1.00	1.53	1.06	1.83	SLR	2014	2.48	2.71	2.51	2.97
MCR	2010	4.26	4.72	4.33	5.28	TBR	2010	1.10	1.34	1.13	1.57
MCR	2011	6.68	7.37	6.76	8.22	TBR	2011	1.25	1.47	1.29	1.65
MCR	2012	4.60	5.21	4.73	5.85	TBR	2012	1.31	1.54	1.34	1.77
MCR	2013	5.07	5.73	5.18	6.43	TBR	2013	1.00	1.27	1.06	1.44
MCR	2014	4.86	5.40	4.96	6.03	TBR	2014	1.25	1.54	1.30	1.77
MGX	2010	1.32	1.57	1.37	1.73	TRY	2010	2.83	3.32	2.95	3.71
MGX	2011	1.20	1.40	1.25	1.55	TRY	2011	2.50	2.89	2.60	3.22
MGX	2012	1.00	1.50	1.06	1.73	TRY	2012	1.40	1.65	1.44	1.86
MGX	2013	2.74	2.90	2.76	3.13	TRY	2013	1.46	1.83	1.52	2.09
MGX	2014	2.57	2.71	2.59	2.90	TRY	2014	1.67	2.06	1.72	2.40
MLX	2010	2.41	2.54	2.43	2.70	WLC	2010	2.15	2.37	2.19	2.62
MLX	2011	1.28	1.35	1.29	1.43	WLC	2011	1.85	2.04	1.89	2.22
MLX	2012	4.27	4.58	4.33	4.96	WLC	2012	1.36	1.68	1.42	1.90
MLX	2013	2.27	2.39	2.29	2.54	WLC	2013	2.99	3.35	3.09	3.62
MLX	2014	1.57	1.68	1.59	1.82	WLC	2014	9.75	10.73	9.98	11.69
MML	2010	1.31	1.41	1.32	1.55	WSA	2010	1.53	1.73	1.57	1.93
MML	2011	1.12	1.21	1.14	1.33	WSA	2011	1.24	1.40	1.28	1.55
MML	2012	1.54	1.76	1.60	1.94	WSA	2012	1.52	1.74	1.56	1.93
MML	2013	1.84	2.03	1.86	2.26	WSA	2013	1.37	1.56	1.42	1.72
MML	2014	3.18	3.81	3.29	4.28	WSA	2014	1.60	1.81	1.65	2.00
NCM	2010	2.09	2.21	2.11	2.36	ZIM	2010	2.28	2.41	2.30	2.58
NCM	2011	3.73	4.26	3.83	4.74	ZIM	2011	2.22	2.50	2.29	2.76
NCM	2012	3.52	4.03	3.64	4.49	ZIM	2012	2.58	2.92	2.67	3.23
NCM	2013	2.09	2.42	2.16	2.72	ZIM	2013	3.09	3.45	3.17	3.82
NCM	2014	1.00	1.37	1.04	1.62	ZIM	2014	3.47	3.71	3.51	4.04

Source: Author's calculations

Table 6.9: Bootstrap DEA efficiency estimates – Model II (natural resource basis model)

Firm	Year	Original	Bootstrap	Lower bound	Upper bound	Firm	Year	Original	Bootstrap	Lower bound	Upper bound
ABY	2010	1.67	1.77	1.69	1.86	NGF	2010	3.09	3.41	3.16	3.64
ABY	2011	1.79	1.91	1.82	2.02	NGF	2011	1.06	1.28	1.08	1.46
ABY	2012	1.65	1.76	1.67	1.87	NGF	2012	2.38	2.58	2.42	2.74
ABY	2013	1.76	1.89	1.78	2.02	NGF	2013	1.33	1.45	1.35	1.56
ABY	2014	2.17	2.31	2.20	2.44	NGF	2014	1.48	1.61	1.51	1.72
AGG	2010	1.00	1.23	1.02	1.45	OGC	2010	2.12	2.30	2.16	2.46
AGG	2011	1.00	1.35	1.02	1.66	OGC	2011	2.34	2.58	2.39	2.76
AGG	2012	1.00	1.23	1.02	1.41	OGC	2012	2.38	2.63	2.43	2.84
AGG	2013	1.00	1.22	1.02	1.42	OGC	2013	2.16	2.39	2.19	2.57
AGG	2014	1.10	1.30	1.12	1.53	OGC	2014	1.59	1.67	1.61	1.75
AGO	2010	2.80	3.10	2.84	3.37	OMH	2010	1.57	1.67	1.60	1.78
AGO	2011	1.22	1.38	1.24	1.50	OMH	2011	1.70	1.87	1.72	2.07
AGO	2012	1.27	1.42	1.29	1.54	OMH	2012	1.57	1.80	1.60	2.01
AGO	2013	1.21	1.37	1.23	1.55	OMH	2013	1.72	1.87	1.75	2.02
AGO	2014	1.00	1.27	1.02	1.48	OMH	2014	1.50	1.69	1.52	1.87
AQP	2010	1.89	2.02	1.91	2.11	OZL	2010	1.00	1.16	1.02	1.24
AQP	2011	1.21	1.33	1.25	1.44	OZL	2011	1.30	1.46	1.32	1.58
AQP	2012	1.82	2.03	1.86	2.24	OZL	2012	1.49	1.64	1.51	1.77
AQP	2013	2.14	2.29	2.17	2.43	OZL	2013	2.71	3.19	2.76	3.59
AQP	2014	2.65	2.88	2.69	3.07	OZL	2014	1.43	1.61	1.46	1.75
BHP	2010	1.07	1.26	1.09	1.47	PAN	2010	1.53	1.62	1.55	1.71
BHP	2011	1.00	1.21	1.02	1.41	PAN	2011	1.84	1.97	1.87	2.09
BHP	2012	1.00	1.18	1.03	1.37	PAN	2012	2.05	2.19	2.09	2.33
BHP	2013	1.00	1.21	1.02	1.39	PAN	2013	2.56	2.72	2.60	2.88
BHP	2014	1.02	1.19	1.04	1.39	PAN	2014	2.24	2.40	2.28	2.54
EVN	2010	2.46	2.75	2.51	2.99	PNA	2010	1.44	1.52	1.46	1.59
EVN	2011	2.80	3.03	2.85	3.23	PNA	2011	1.61	1.70	1.63	1.78
EVN	2012	1.34	1.48	1.37	1.61	PNA	2012	1.57	1.66	1.59	1.74
EVN	2013	1.00	1.12	1.02	1.22	PNA	2013	1.69	1.80	1.71	1.92
EVN	2014	1.11	1.25	1.13	1.41	PNA	2014	2.09	2.26	2.13	2.41
FMG	2010	1.11	1.31	1.13	1.55	RIO	2010	1.00	1.25	1.02	1.44
FMG	2011	1.00	1.20	1.02	1.40	RIO	2011	1.00	1.20	1.03	1.36
FMG	2012	1.00	1.25	1.02	1.44	RIO	2012	1.03	1.16	1.05	1.33
FMG	2013	1.01	1.20	1.02	1.35	RIO	2013	1.00	1.13	1.02	1.29
FMG	2014	1.00	1.27	1.02	1.46	RIO	2014	1.13	1.29	1.15	1.48
GRR	2010	2.10	2.22	2.13	2.35	RND	2010	1.68	1.98	1.71	2.21
GRR	2011	1.87	2.03	1.90	2.16	RND	2011	1.44	1.68	1.46	1.85
GRR	2012	2.14	2.35	2.18	2.53	RND	2012	1.58	1.95	1.60	2.36
GRR	2013	1.79	1.97	1.82	2.14	RND	2013	1.00	1.32	1.02	1.55
GRR	2014	1.94	2.05	1.96	2.16	RND	2014	1.18	1.36	1.20	1.51
IGO	2010	1.34	1.50	1.36	1.63	RSG	2010	1.85	2.01	1.89	2.12
IGO	2011	1.81	1.98	1.84	2.11	RSG	2011	1.84	1.97	1.87	2.06
IGO	2012	2.46	2.68	2.51	2.88	RSG	2012	1.38	1.48	1.41	1.54
IGO	2013	1.79	1.92	1.82	2.05	RSG	2013	1.47	1.59	1.50	1.71
IGO	2014	1.30	1.38	1.32	1.46	RSG	2014	1.78	1.94	1.81	2.07

Table 6.9 (continued): Bootstrap DEA efficiency estimates – Model II (natural resource basis model)

Firm	Year	Original	Bootstrap	Lower bound	Upper bound	Firm	Year	Original	Bootstrap	Lower bound	Upper bound
ILU	2010	1.90	2.03	1.93	2.15	SAR	2010	2.25	2.73	2.29	3.27
ILU	2011	1.12	1.19	1.13	1.26	SAR	2011	1.00	1.25	1.03	1.46
ILU	2012	1.34	1.57	1.37	1.78	SAR	2012	1.06	1.22	1.08	1.38
ILU	2013	1.84	2.03	1.87	2.27	SAR	2013	1.60	1.82	1.63	2.01
ILU	2014	1.94	2.14	1.97	2.33	SAR	2014	1.54	1.73	1.56	1.90
KCN	2010	1.78	2.01	1.82	2.18	SBM	2010	1.78	1.89	1.81	1.99
KCN	2011	2.53	2.77	2.58	2.99	SBM	2011	1.63	1.73	1.66	1.82
KCN	2012	1.67	1.81	1.70	1.94	SBM	2012	1.17	1.24	1.19	1.30
KCN	2013	1.80	1.95	1.82	2.09	SBM	2013	1.56	1.68	1.59	1.79
KCN	2014	2.23	2.42	2.27	2.56	SBM	2014	1.82	1.97	1.85	2.12
MBN	2010	2.85	3.21	2.91	3.52	SLR	2010	1.98	2.18	2.02	2.33
MBN	2011	2.24	2.50	2.28	2.74	SLR	2011	2.01	2.18	2.05	2.34
MBN	2012	2.94	3.40	2.99	3.91	SLR	2012	1.53	1.64	1.55	1.75
MBN	2013	4.01	4.82	4.09	5.67	SLR	2013	2.82	3.07	2.88	3.34
MBN	2014	1.00	1.36	1.02	1.71	SLR	2014	1.94	2.08	1.98	2.23
MCR	2010	2.37	2.55	2.41	2.74	TBR	2010	1.10	1.30	1.11	1.52
MCR	2011	3.74	4.16	3.82	4.43	TBR	2011	1.24	1.44	1.26	1.59
MCR	2012	3.13	3.48	3.18	3.84	TBR	2012	1.26	1.48	1.28	1.68
MCR	2013	3.42	3.78	3.46	4.17	TBR	2013	1.00	1.25	1.02	1.41
MCR	2014	2.86	3.10	2.90	3.34	TBR	2014	1.25	1.49	1.27	1.71
MGX	2010	1.00	1.19	1.02	1.33	TRY	2010	2.36	2.70	2.41	2.97
MGX	2011	1.00	1.20	1.02	1.35	TRY	2011	1.77	1.98	1.80	2.17
MGX	2012	1.00	1.33	1.01	1.64	TRY	2012	1.12	1.27	1.14	1.39
MGX	2013	1.49	1.59	1.51	1.68	TRY	2013	1.12	1.29	1.14	1.44
MGX	2014	1.48	1.60	1.51	1.70	TRY	2014	1.38	1.61	1.40	1.81
MLX	2010	2.03	2.18	2.07	2.31	WLC	2010	1.90	2.05	1.93	2.19
MLX	2011	1.17	1.30	1.19	1.40	WLC	2011	1.70	1.86	1.73	2.01
MLX	2012	3.85	4.19	3.93	4.44	WLC	2012	1.36	1.62	1.39	1.84
MLX	2013	2.05	2.23	2.09	2.38	WLC	2013	2.35	2.62	2.41	2.85
MLX	2014	1.36	1.45	1.38	1.52	WLC	2014	7.00	7.66	7.12	8.30
MML	2010	1.14	1.34	1.15	1.50	WSA	2010	1.31	1.48	1.33	1.62
MML	2011	1.00	1.19	1.02	1.33	WSA	2011	1.00	1.18	1.02	1.30
MML	2012	1.35	1.57	1.37	1.76	WSA	2012	1.18	1.35	1.20	1.51
MML	2013	1.27	1.44	1.29	1.59	WSA	2013	1.01	1.16	1.03	1.29
MML	2014	1.73	1.94	1.77	2.12	WSA	2014	1.30	1.49	1.33	1.65
NCM	2010	1.14	1.28	1.17	1.40	ZIM	2010	1.64	1.77	1.66	1.88
NCM	2011	1.37	1.55	1.40	1.72	ZIM	2011	1.72	1.98	1.76	2.21
NCM	2012	1.26	1.42	1.29	1.57	ZIM	2012	1.93	2.20	1.97	2.47
NCM	2013	1.16	1.40	1.19	1.67	ZIM	2013	1.96	2.19	2.00	2.40
NCM	2014	1.00	1.35	1.02	1.69	ZIM	2014	1.89	2.05	1.93	2.16

Source: Author's calculations

6.3 Second-Stage DEA Results

This section presents the results derived from the second-stage DEA model explained in Section 6.2. With the aim of identifying the firm-specific determinants of technical efficiency, the proposed econometric model is developed with respect to major factors influencing mining operations. To overcome the drawback of Tobit or ordinary least square (OLS) models in the presence of serial correlations among DEA efficiency estimates, a truncated regression model is constructed following Simar and Wilson (2007). Their second algorithm is applied to generate bootstrap data and construct the proposed econometric model. The FEAR package (Wilson, 2013) and R codes developed for the current study are used to run the double bootstrap procedure.

The second-stage analysis is conducted for both technical efficiency Models I and II. As explained in Section 6.2, the deviation of the estimates in CRS DEA modelling, compared with those from VRS DEA modelling, is due to the presence of some degree of scale inefficiency. In other words, when considering the general form of technical efficiency modelling which assumes only labour, capital and intermediate inputs are utilised to produce mining operation output, the estimated technical efficiency scores include the effects of operating scale efficiency (the degree of deviation from the optimal operating scale) and pure technical efficiency (the ability of firms in transforming inputs to outputs given their operating scale). Once the natural resource input is included in the technical efficiency model, the presence of the scale inefficiency turns out to be insignificant. There are negligible variations among VRS estimates derived from Model I and Model II; furthermore, VRS estimates in Model II are very close to the CRS estimates in this model. Hence, in the second-stage analysis, the DEA estimates under the CRS assumption are used. CRS DEA estimates provide greater discriminatory power in the second stage to evaluate the significance of firm-specific factor effects on technical efficiency in each model. In addition, the CSR DEA estimates are significantly different between two models; these deviations facilitate the understanding of differences in the role of firm-specific factors in the efficiency performance once applying different model specifications for Models I and II.

6.3.1 Second-Stage DEA in Model I

Table 6.10 shows the empirical results obtained from the second stage truncated regression equation constructed for Model I. The parameters of the constructed econometric model are estimated according to the second algorithm in Simar and Wilson (2007), with 2000 iterations for bias correction of efficiency estimates and 2000 iterations to obtain confidence intervals for parameters of the truncated regression model.

This study's truncated regression model includes 15 regressors: ownership ratio of substantial shareholders (OWNER), firm size (SIZE), firm age (AGE), ratio of PP&E assets to total assets (PPE), financial leverage (LEV), dummy variables for main product as iron ore (IRON) and gold (GOLD), dummy variable for product portfolio diversification (DIV), dummy variables for growth factors including change pace (CH_PACE) and change direction (CH_DIR), dummy variable for location of operations (LOC_OPS) and four year dummies (2010, 2011, 2012, 2013 and 2014).

Following Simar and Wilson (2007, 2011) confidence intervals obtained from the bootstrap truncated regression model are used to test whether the estimated coefficients are statistically significant or not. If the value of zero does not fall into the relative confidence interval, the estimated coefficient is statistically significant.

As the Farrell efficiency measure has been employed in this study, the higher efficiency score indicates the lower efficiency of a firm. Hence, in Table 6.10, a positive relationship between the efficiency scores and the firm-specific factor represents the negative effect of the factor on the firm's efficiency performance.

(i) Types of Product

First of all, the results show the importance of product portfolio on the efficiency gains. At the 1% level, iron ore mining as the main activity (IRON) has a positive effect on firm efficiency. The scale of iron ore mining projects is significantly larger than other mining activities. Companies focusing on iron ore mining benefit from economies of scale and consequently they gain higher efficiency performance. In addition to the significant effect of iron ore mining on efficiency, gold mining (GOLD) contributes to higher efficiency gain. Gold has been a major mining product in the past two centuries in Australia. As such, the gold mining life cycle is mature, utilising advanced technology compared to other mining activities. Moreover, economies of scale are another contributor of higher efficiency gain in gold mining, as exemplified in a study by Asafu-Adjaye and Mahadevan (2003). They reported the cost efficiency ratio in gold mining being greater than other mining sectors in Australia over the period 1968-69 to 1994-95. This sector has maintained its high efficiency in the following decades; however, iron ore has moved to first place in recent years due to the significant increase in the economic demonstrated resources as well as production of iron ore since the early 2000s. In 2014-15, iron ore consisted of 74 per cent of total metal ore mining industry value added in Australian. The iron ore mining contributed to 38 per cent of total mining industry value added in this year (ABS, 2016).

Table 6.10: Bootstrap truncated regression results for Model I

Variables	Estimates	90% Conf. Int.		95% Conf. Int.		99% Conf. Int.	
		LB	UB	LB	UB	LB	UB
Constant	-0.23	-7.01	5.84	-8.46	7.08	-11.14	9.20
Substantial shareholder (OWNER)	-0.05***	-0.07	-0.03	-0.08	-0.03	-0.09	-0.02
Firm size (SIZE)	0.38	-0.01	0.81	-0.08	0.90	-0.21	1.08
Firm age (AGE)	-0.02**	-0.04	-0.01	-0.04	0.00	-0.05	0.00
PP&E assets ratio (PPE)	-0.01	-0.04	0.02	-0.04	0.03	-0.06	0.04
Financial leverage (LEV)	-0.04	-0.61	0.47	-0.74	0.55	-1.08	0.73
Iron ore production (IRON)	-2.59***	-4.41	-1.05	-4.90	-0.78	-5.95	-0.29
Gold production (GOLD)	-1.77***	-2.74	-0.89	-2.96	-0.70	-3.42	-0.37
Product diversification (DIV)	-1.95***	-3.35	-0.80	-3.62	-0.62	-4.22	-0.30
Change pace (CH_PACE)	0.31	-0.58	1.20	-0.73	1.36	-1.11	1.70
Change direction (CH_DIR)	-1.62***	-2.61	-0.72	-2.80	-0.58	-3.22	-0.29
Location of operation (LOC_OPS)	-0.47	-1.33	0.38	-1.55	0.55	-1.95	0.91
Year 2011 (Y2011)	-0.52	-1.73	0.67	-1.98	0.91	-2.43	1.41
Year 2012 (Y2012)	-0.36	-1.62	0.87	-1.94	1.09	-2.27	1.68
Year 2013 (Y2013)	0.27	-0.92	1.46	-1.18	1.73	-1.57	2.16
Year 2014 (Y2014)	-0.02	-1.19	1.14	-1.44	1.48	-2.09	2.13
Truncated regression standard error	2.06	1.73	2.46	1.69	2.54	1.62	2.75

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

(ii) Product Diversification

Similar to product portfolio, product diversification (DIV) is statistically related to mining firms' efficiency. In contrast with findings in the existing literature, the current study's findings show that diversification increases firm performance. In a study centring on the manufacturing industry, Chakrabarti et al. (2007) found that that diversification improves performance only in the least developed institutional environments; otherwise its impact is negative. Nath et al. (2010) also found that logistics firms achieve higher performance if they concentrate on a narrow portfolio of products/services while diversifying their geographical market. Differences in the mining industry compared to other sectors may explain the contrasting results found in the current study. The mining industry heavily depends on capital investment. Once investment occurs, any changes in the market and production cannot be followed by some changes and adjustments in capital in the short term. Hence, through product diversification, mining companies could achieve the economics of scope and utilise the available productive capacity and operation capabilities. With respect to the significant variation of mining commodity prices in recent years, such a diversification strategy could enable mining companies to reduce the business risk that arises from falling prices.

(iii) Growth Status

The Australian mining industry has experienced a significant growth in the exploration and extraction activities since the early 2000s. The number of mining companies listed on the ASX increased sharply in recent years, reaching around 700 companies. Despite the overall growth in the industry, many mining companies have experienced both growth and decline in their investment and operations. What's more, the change rates vary across mining companies. Some companies could maintain more stable production while others experienced significant fluctuations in their operations. To study the effects of growth status, two variables were incorporated into the econometric model presented in Chapter 5. Change direction dummy shows if a company's production increased or decreased in each year. Furthermore, change pace dummy indicates if a company's change has been substantial or gradual.

The results from the second-stage analysis confirm that the presence of rapid growth in total firm's output has an adverse effect on efficiency; however, this effect is not statistically significant. Direction of output changes has a significant influence on the mining firms' efficiency, implying that generally mining companies are not agile enough to optimise their inputs consumption in the decline stage. Such conclusion is highly expected as companies cannot adjust and optimise their available long-term (non-current) assets with the same pace of output changes. While short-term cost reduction strategies may help companies to adjust operating expenses relative to declined production, companies need to adopt long-term strategies to minimise the impact of operating under capacities during downturn periods (Mitchell and Steen, 2014).

(iv) Ownership

The coefficient for indicator OWNER is found to be negative and significant at the 1% level. This suggests that among the Australian listed mining companies, those with higher ownership concentration achieve higher efficiency. In the literature, the empirical evidence on the relationship between ownership concentration and firm performance is mixed. This finding is in line with a number of studies that have found positive associations between ownership concentration and firm performance among private companies (see e.g. Boubakri et al., 2005; Omran, 2009; Ma et al., 2010; Cabeza-García and Gómez-Ansón, 2011). Under Australian law, a high level of protection is provided to shareholders in comparison with other countries (Anderson et al., 2012). Hence, the minority shareholders are protected from the influence of large shareholders colluding with managers to expropriate their benefits (tunnelling). On the other hand, large shareholders have the power and 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.

(v) Firm Size

Size, which is measured here by natural logarithm of total productive assets, has a negative impact on the efficiency of fully operational mining companies. However, this adverse effect is not statistically significant. While the significance of size in firms' efficiency could not be identified, the findings in the existing literature are ambiguous. Diaz and Sanchez (2008) explained that due to the complexity of larger firms in organisational and managerial control, they tend to be less efficient than small and medium companies. In contrast, Badunenko (2010) found that small firms are less efficient and Schiersch (2013) reported a U-shaped relationship meaning smallest firms are almost as efficient as the largest ones while most SMEs are among the least efficient companies.

In the context of the mining industry, it was expected that larger firms would be better off due to the advantage of economies of scale. However, the sector-level studies in Australian mining productivity have addressed two main issues that induce the significant deterioration of productivity growth (see e.g. Topp et al., 2008; Zheng and Bloch, 2014; Syed et al., 2015). The first issue results from the decline in the quality of natural resource, while the second issue arises from the lags between capital investments and the production response to these investments. Both effects can cause higher growth in a firm's assets, which is the proxy for firm size, than the growth in production. Companies experiencing more decline in the quality of their natural resources need to invest more in exploration expenditure. Moreover, during the mine development phase, firms can aim to increase their assets to enhance the production capability; however, three to five years lag is expected before achieving full production from the invested capital. Over the period of the current study, the Australian mining capital index increased sharply (ABS, 2018a). Hence, the adverse effect of capital-production lags as well as the resource depletion effects could offset the positive effect of economies of scale on the technical efficiency of mining firms.

(vi) Firm Age

Firm age with a P-value of less than 5% is a significant contributor of efficiency gains in mining firms. Focusing on profitability, Loderer and Waelchli (2010) found a negative relationship between firm age and profitability performance; however, as Majumdar (1997) explained, older firms may be less profitable but they are more productive. That is, old companies can leverage their experience to utilise their resources more efficiently. In the context of the Australian mining industry, this study's finding implies that most young firms have severe efficiency challenges. This conclusion is well expected while field research revealed that a lack of skills and expertise is a major drawback in the sector (Lumley and McKee, 2014), and newer formed companies have considerably less knowledge, expertise and resources to manage booming operations. Along with the growth in global demand for mining commodities in the 2000s, newly established mining companies also increased sharply. Many of these newcomers were on the ASX to attract their required capital; however, capital was not their only need, these companies suffered mainly from the lack of mining business knowledge and required skills.

(vii) Capacity Utilisation

The obtained results do not confirm the significance of the capacity utilisation effect on the efficiency of Australia's mining sector. Both Topp et al. (2008) and Zheng and Bloch (2014) have presented comprehensive explanations regarding the effect of investment-production lag on the Australian mining sector's productivity. Since the efficiency model of the current study is constructed comprising utilised capital service with a selection of total asset depreciation as the capital service proxy, the undesirable effects of non-operational capital is removed from the estimated efficiency. Hence, the obtained efficiency estimates are not biased due to the investment-production lag phenomenon. Lumley and McKee (2014) argued that non-optimised capacity and asset utilisation can be owing to inefficient utilisation of established infrastructure and equipment in the Australian mining firms. This current study's results suggest that the capacity utilisation for ongoing mining operations is not a driver of inefficiency. Instead, the new capital investment and the depletion of natural resources are more significant, leading to inefficiency in mining companies. Non-operational assets forming during exploration and development phases are mainly responsible for lowering the mining sector's efficiency and productivity.

(viii) Financial Risk

The second-stage results show a negative but insignificant effect of business risk, measured using financial leverage, on mining firms' efficiency. Mining firms use funds from lenders to accelerate the progress of their exploration and development projects. The results of the econometric model confirm that such a risk-increasing approach neither impacts the firm's economic performance adversely nor induces performance gain. Therefore, mining firms can adjust their lending strategies independent from their economic performance goals. The existing literature provides vague conclusions on the association of financial risk and firm performance. For instance, Yazdanfar and Ohman (2015) and Vatavu (2015) found a negative relationship between firm performance and financial risk, while El-Sayed Ebaid (2009) found no significant relationship. It is worth noting that, to best of this researcher's knowledge, no study has examined the relationship between efficiency and financial risk in the mining industry. Moreover, in the existing literature, various firm performance and financial risk measures have been applied. Hence, due to differences in the capital structure in mining companies with companies from other sectors, as well as differences in the investigated measures, this study's results may not be necessarily comparable with other studies.

(ix) Location of Operations

Although product diversification is related to the efficiency of mining firms, the 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. This result may also be related to the project portfolio status of mining companies. That is, in recent years, Australian mining firms have been attracted to investment beyond its borders. Many overseas projects have not reached their full production scale, while investments in Australia are in general more mature. With such differences among the development status of domestic versus overseas mining projects, those involved in foreign investment projects may be affected by a stronger impact of capital-production lag, offsetting their benefit from lower operating costs.

Australian mining has been the focus of many domestic and international business investors over the past two decades. The Fraser Institute's investment attractiveness index (Stedman and Green, 2018; Jackson and Green, 2015) shows that Australian states, with a higher position than other mining regions across the globe, have experienced rises and declines in their rankings in recent years. But for Queensland and South Australia, other Australian states' rankings have declined since 2013. Hence, it is not surprising that Australian mining firms tend to expand their activities toward emerging and attractive mining regions outside Australia.

(x) Year Dummies

Finally, the results show that the year dummies are insignificant, suggesting that the efficiency performance of the Australian mining companies did not significantly change over the period of study. This finding from the second-stage analysis is in line with the results derived from the first-stage analysis, implying that no significant changes of efficiency gains occurred during the period 2010-2014.

Earlier studies including Asafu-Adjaye and Mahadevan (2003) and Syed et al. (2015) reported improvements in the efficiency of mining industry; however, the current study presents results that do not support extant findings. As previously discussed in this chapter, the differences in the study period, the applied techniques and the study scope can drive such differences in efficiency improvements.

6.3.2 Second-Stage DEA in Model II

The empirical results of the second-stage truncated regression analysis, based on the technical efficiency specifications of Model II, are presented in Table 6.11. Similar to the second-stage analysis of Model I, the second algorithm in Simar and Wilson (2007) with 2000 replications is used to obtain the bias-corrected efficiency estimates as well as confidence intervals for truncated regression parameters. FEAR package and the researcher's own developed R codes are used to generate the second-stage results of Model II.

Since the efficiency model specifications of Model II vary from Model I, it is possible to achieve different results in the second-stage analysis of Model II from those of the second stage of the general model of technical efficiency. Sections 6.2.1 and 6.2.2 previously explained that accounting for the natural resource input in the efficiency estimation of mining firms leads to a higher efficiency performance among mining companies. Mining companies utilise more resource in their operations when facing depletion in the natural resource inputs. To maintain their economic operations, mining companies assign part of their financial resources to exploration expenditures. The aim of such expenditures is to enable them to extract mining product from less accessible or low grader mining fields or even to start mining operations in new fields. In this study's second model of efficiency estimation, the natural resource input is proxied by a mixed index which is calculated based on the average value of two defined ratios: the exploration expenditure expenses to operating expenses ratio, and the capitalised exploration expenditure to total assets ratio. Such index reflects extra resource consumptions in mining activities due to resource depletion.

A lack of consideration for the natural resource input in mining operations leads to biased estimations of efficiency scores. For instance, if Company A owns better ore reserves in terms of ore quality or accessibility than those own by Company B, keeping all other factors constant, Company B consumes more labour, capital and intermediate inputs than Company A to produce the same amount of output. Therefore, Company B appears to be less efficient than Company A; however, the presence of higher inefficiency in Company B is due to the natural resource input effect, not the capability of this company in the transformation of inputs to desired outputs. By controlling for this adverse effect, the resulting efficiency scores are the correct representation of mining companies' technical ability in producing maximum outputs given a certain level of inputs.

Accounting for the natural resource input in formulation of technical efficiency in mining companies is also important for the second-stage analysis. Indeed, by removing the effects of resource depletion on the estimated efficiency scores, one can examine the driving factors directly associated with technical ability of mining firms in the transformation of their utilised inputs in production of their desirable outputs.

Results from stage one and stage two of the analysis based on Model I are important as they present the overall efficiency performance and its driving factors regardless of reserves characteristics. Such results may be of interest to key stakeholders in the global mining industry and particularly shareholders, whereas the overall performance (with consideration to both exogenous and endogenous factors) is admissible for their decision making. However, the results of such modelling are ambiguous while the evaluation of mining firms' technical capabilities is under investigation.

The results derived from Model II satisfy the requirements for investigating the driving factors of technical efficiency in the mining sector. The adverse effect of natural resource characteristics on efficiency performance is removed in Model II by adding the introduced natural resource quality index to mining operation inputs. The second-stage results from Model II are presented in Table 6.11.

Table 6.11: Bootstrap truncated regression results for Model II

Variables	Estimates	90% Conf. Int.		95% Conf. Int.		99% Conf. Int.	
		LB	UB	LB	UB	LB	UB
Constant	12.59***	8.48	16.97	7.79	18.22	6.17	20.68
Substantial shareholder (OWNER)	-0.01***	-0.02	-0.01	-0.03	-0.01	-0.03	0.00
Firm size (SIZE)	-0.51***	-0.78	-0.26	-0.85	-0.22	-1.00	-0.12
Firm age (AGE)	-0.02***	-0.03	-0.01	-0.03	-0.01	-0.04	-0.01
PP&E assets ratio (PPE)	0.02	0.00	0.03	0.00	0.04	-0.01	0.04
Financial leverage (LEV)	0.34**	0.09	0.59	0.04	0.65	-0.07	0.74
Iron ore production (IRON)	-0.95**	-1.84	-0.14	-2.06	-0.02	-2.53	0.22
Gold production (GOLD)	-1.06***	-1.54	-0.62	-1.65	-0.54	-1.86	-0.40
Product diversification (DIV)	-0.32	-0.90	0.25	-1.04	0.36	-1.27	0.56
Change pace (CH_PACE)	0.48*	0.05	0.92	-0.03	1.01	-0.25	1.23
Change direction (CH_DIR)	-1.17***	-1.69	-0.68	-1.80	-0.61	-2.04	-0.45
Location of operation (LOC_OPS)	-0.47*	-0.88	-0.06	-0.98	0.03	-1.14	0.16
Year 2011 (Y2011)	-0.34	-0.97	0.26	-1.10	0.37	-1.41	0.54
Year 2012 (Y2012)	-0.26	-0.87	0.37	-1.01	0.47	-1.25	0.75
Year 2013 (Y2013)	0.05	-0.52	0.65	-0.62	0.74	-0.82	0.92
Year 2014 (Y2014)	-0.20	-0.80	0.40	-0.93	0.48	-1.18	0.75
Truncated regression standard error	0.98	0.83	1.16	0.80	1.19	0.76	1.27

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

(i) Types of Product

Similar to the Model I results, the second-stage results of Model II show that the product portfolio is a key firm-specific factor driving the efficiency of mining firms in Australia. At the 1% level, companies with gold mining activities (GOLD) are more efficient than companies active in other mining extraction activities. The economies of scale are a main contributor to higher efficiency gains in gold mining. More importantly, the experience and maturation in gold mining over the past two centuries has promoted this sector to best-in-class in the Australian mining sector and even across the globe.

Well-established mining activities along with the utilisation of advanced technology have resulted in a high level of efficiency gain among Australian mining firms involved in gold exploration and extraction projects. Australian gold mining companies provide a range of best practices and are considered the benchmark in strategy, process and performance for gold mining companies around the world. Moreover, companies involved in other mining activities can benefit from the best practices of gold mining companies to improve the organisational capabilities toward enhanced economic performance.

Firms heavily involved in iron ore mining (IRON) are also more efficient than their counterparts. Iron ore mining companies benefit from large-scale operations, resulting in a lower production cost per unit of production. However, the significance level of coefficient relative to iron ore production dummy variable increased to 5% in Model II from 1% in Model I. This indicates that iron ore mines are less depleted in comparison with other ore resources in Australia; not surprising, given that iron ore deposits have significantly higher grades than other mining reserves in Australia (Mudd, 2010). Iron ores contain hematite (Fe_2O_3) and magnetite (Fe_3O_4) with almost 70 and 20-30 per cent ore grades respectively. More than 90% of extraction and export of iron ore in Australia is high-graded hematite (Geoscience Australia, 2017).

(ii) Product Diversification

Unlike the Model I results, product diversification (DIV) appears to be statistically insignificant in influencing the mining firms' efficiency gains under the Model II specifications. Considering the natural resource input to mining operations, the expansion of mining activities to broader range of mining production does not provide much advantage in gaining higher technical efficiency performance. This finding supports the results from Chakrabarti et al. (2007) and Nath et al. (2010) concerning the independency of economic performance from the product diversification approach.

The differences between the operational versus organisational advantage of product diversification are evident when comparing the results of Models I and II. While product diversification does not provide operational advantage in optimising mining production given a set of utilised inputs, this strategy is important from an enterprise perspective. That is, the long-term success of a mining firm relies on its success in business risk reduction. Product diversification can outweigh the adverse effects of market shocks, whereas the adjustment of capital inputs is not practical in the short term in response to output demand fluctuations. A diversified product portfolio enables mining companies to leverage their unutilised capacities in the production of mining commodities not affected by adverse market shocks.

(iii) Growth Status

The results reported in Table 6.11 confirm that the presence of volatile growth of total firm output (CH-PACE) exerts significant negative effects on efficiency. This finding is not in line with the findings from Model I, confirming that no significant correlation is evident between growth rate and efficiency gains. The results from Model II suggest that companies with a stable or gradual growth pace in their output experienced higher efficiency among mining firms. The total output of mining activities for each company depends on the stage of their life cycle. During exploration, development and mine closure phases, no operating revenue is typically expected. Ineffective and unbalanced portfolio management leads to unstable production and operating revenue in mining companies. In the short run, a steep increase in production results in paying higher premiums for hiring labour and service capital; furthermore, a sharp decline in production output does not allow mining businesses to adjust their fixed assets. Similar to Mitchell and Steen (2014), the current study's findings suggest that companies enjoy higher efficiency gains when they maintain a gradual pace in growth. This steady progress can be achieved through effective portfolio management and having a balanced set of projects in the portfolio.

In addition, the results of Model II confirm that the direction of output changes has a significant effect on mining firms' efficiency. The considerable challenge facing mining firms is being agile enough to optimise their consumed inputs during downturns. Mining companies adopt short-term plans to accommodate declining production through operating cost reduction programs. However, they may have limited success in implementing such plans due to business environment factors such as contractual commitments, regulations or companies' future strategies. Hence, mining companies need to adopt long-term strategies toward asset utilisation and minimising the impact of operating under capacities during downturn periods.

(iv) Ownership

Another explanatory variable in this study is ownership concentration. The results in Table 6.11 show a negative coefficient for ownership concentration at the 1% significance level, suggesting a strong positive relationship between ownership concentration and firm performance. These findings are in line with that of Boubakri et al. (2005), Omran (2009), Ma et al. (2010), Cabeza-García and Gómez-Ansón (2011), all of which emphasise the significant role of ownership concentration on higher firm performance. Ownership concentration may result in adverse outcomes for minority shareholders since the dominating influence of a few major shareholders could be against minority shareholder benefits. Shleifer and Vishny (1997) argued that with adequate legal protection provided to shareholders, higher ownership concentration results in better corporate governance and economic performance. Australian law provides a high level of protection for shareholders in comparison with other countries (Anderson et al., 2012). Hence, while the minority shareholders are protected from the influence of large shareholders colluding with managers to expropriate their benefits, known as 'tunnelling', they benefit from the large shareholders' power and incentives to monitor management performance and prevent expropriation or asset stripping by managers.

(v) Firm Size

The coefficient for indicator SIZE, measured by natural logarithm of productive assets, is found to be negative and significant at 1% level. This suggests that among the Australian listed mining companies, those with a larger operating scale achieve higher efficiency. Derived from the Model I results, this finding does not identify a significant association between firm size and firm efficiency. As discussed in Sections 6.2.1 and 6.2.2, the efficiency estimates from Model I show a considerable level of scale inefficiency among Australian mining firms. Many observations in the sample exhibit decreasing returns to scale condition.

The results from Model II efficiency estimates revealed that the major driver of such sizable scale inefficiency is declines in natural resource input. Taking into account the natural resource input to mining operations proxied by formulated exploration expenditure index, most Australian mining firms operate close to their optimal scale. The results from stage one and stage two explain that larger mining companies benefit from economies of scale and, as a result, achieve higher efficiency performance. However, such efficiency gains are masked by resource depletion effects. Once the efficiency model controls for resource depletion, the direct effects of operating scale on efficiency performance is observed to be significant and positive. In the mining industry, larger companies are able to run larger mining projects with relatively less overhead cost per unit of production, to share unutilised capacities in other projects and business units, to more easily fund new investments and to hire better managers and professionals. Moreover, from a market point of view, they have better control and penetration in the market.

(vi) Firm Age

As illustrated in Table 6.11 and consistent with results from Model I, there is a significant association between firm age and firm performance at the 5% significance level. This implies that old mining companies outperform the younger firms. In the existing literature, the relationship between firm age and firm efficiency has produced mixed results (see e.g. Majumdar, 1997; Loderer and Waelchli, 2010; Le and Harvie, 2010). The positive relationship between firm age and firm performance is mainly associated with the learning-by-doing phenomenon. The accumulation of knowledge and skills over time is a key factor to boost the efficiency performance at the resource-scarcity time of booming. During the recent boom in the Australian mining industry, talent shortages led to recruiting less skilled labour to operate mining equipment, which consequently caused a further downward effect on the productivity of mining companies (Mitchell et al., 2014; Lumley and McKee, 2014). The current study's results reveal that newer formed companies had more challenges in achieving the required knowledge, expertise and resources to manage booming operations.

(vii) Capacity Utilisation

The results from Table 6.11 show no significant correlation between capacity utilisation and the efficiency of the Australian mining sector. Mitchell et al. (2014) and Lumley and McKee (2014) both expressed that long lead time between investment and production, over-investment in capitals and poor capital utilisation due to the lack of skills and experience have adversely impacted the capital productivity in the Australian mining sector. Topp et al. (2008) and Zheng and Bloch (2014) also explained the effect of investment-production lag on Australian mining sector productivity during the recent mining boom. In the efficiency model developed for this study, the capital service input to the mining operations is measured using depreciation costs which reflect the costs associated with utilising the productive assets. According to the results, based on such unbiased efficiency estimations at the corporate level, productive assets utilisation is not found to have an additional negative effect on the efficiency gains of

Australian mining firms. In line with Topp et al. (2008), Lovell and Lovell (2013) and Zheng and Bloch (2014), this study emphasises the negative effects of new capital investment and depletion of natural resources as drivers of poor efficiency performance among mining companies in Australia; however, capacity utilisation for ongoing mining operations is not a significant driver of their inefficiency.

(viii) Financial Risk

The second-stage results show a positive coefficient for financial leverage as the proxy defined for financial risk in mining companies. While the general modelling of technical efficiency shows insignificant correlation between leverage and technical efficiency, their association turns out to be positive and significant under natural resource-based modelling of technical efficiency in Model II. In fact, when controlling for resource depletion to formulate the efficiency, a higher debt to assets ratio results in lower technical efficiency. Higher debt to assets ratio is associated with higher borrowing expenses; hence, this increase applies downward pressure on the efficiency gains. This effect was masked by the exploration expenditure effects on the efficiency performance in Model I. To the best of the researcher's knowledge, no previous study has evaluated the relationship between financial risk and efficiency performance in the mining sector. Due to financial constraints, many mining companies finance their project by borrowing from financial institutions which involves significant interest payments over the period of operations. The result derived from Model I is in line with a number of studies that have investigated the association of financial risk or capital structure with firm performance (see e.g. Salim and Yadav, 2011; Yazdanfar and Ohman, 2015; Vatavu, 2015). However, the current study's measure of firm performance is different from those in the existing literature.

(ix) Location of Operations

The second-stage analysis of Model II shows that mining firms operating some exploration and extraction projects outside Australia achieve a higher efficiency than those firms limiting their operations to the mining regions in Australia. The comparison of results of Models I and II reveals that Australian mining companies involved in overseas mining projects had more exploration expenditure than those only active in Australia. Due to resource depletion, mining companies invest more in new projects and, in the case of Australian mining companies, internationally based projects appear to be an efficient solution against declining resource deposits in Australia. The success of such international diversification relies on significantly lower operating expenses in other target countries. Moreover, it proves the potential for Australian mining companies to overcome challenges of incorporating their knowledge and technology in a new business environment and aligning local partners toward companies' goals. This finding is consistent with the earlier findings discussed in Nath et al. (2010), particularly on the positive effects of international diversification on firm performance.

(x) Year Dummeis

Similar to the results in Model I, the year dummies are insignificant, indicating that the distribution of exploration expenditure has not changed over the 2010-2014 period. These findings confirm the results achieved in the first-stage analysis which show no significant changes occurring over the study period. Regarding the bias-corrected CRS efficiency estimated from Model II, on average, 47 per cent inefficiency was observed among the major listed mining companies in Australia over the period 2009-10 to 2013-14. With an almost consistent pattern over this period, the efficiency performance was influenced by firm-specific factors including ownership concentration, firm size, firm age, product portfolio, financial risks, growth status and overseas operations.

6.4 Summary

Chapter 6 applied the empirical models developed in Chapter 5. In the first stage, two efficiency models – including a general model of technical efficiency, denoted as Model I, and a natural resource-based model of technical efficiency, denoted as Model II – were utilised to estimate the efficiency scores of 34 Australian mining firms over 2009-10 to 2013-14 period. Using a bootstrap DEA method, the original and bias-corrected estimated were derived for both efficiency models.

The results from the stage-one analysis showed that the variable specification of the technical efficiency model is crucial to efficiency analysis in the Australian mining industry. Unlike most industries with renewable resources, the depletion in non-renewable resource deposits is adversely affecting the economic efficiency performance of mining companies. Model I, which has ignored the natural resource input, shows the presence of significant inefficiency in both components of technical efficiency performance, namely pure technical efficiency and scale efficiency. However, the Model II results revealed that pure technical inefficiency is the main source of inefficiency among mining companies while most mining companies operate at their optimum scale. In fact, the presence of scale inefficiency in the results of Model I reflected the extra resources consumed by mining companies due to natural resource depletion. Considering the natural resource input to mining operations, the scale inefficiency effects almost disappeared. The results from the first-stage DEA confirmed the findings of Topp et al. (2008), Zheng and Bloch (2014) and Syed et al. (2015), who addressed the issue in conventional productivity measurement of the mining sector and emphasised the role of resource depletion as a major contributor to the declining productivity performance of the Australian mining sector in recent years.

Further to the estimation of technical efficiency, Chapter 6 examined and discussed the effects of firm-specific factors on the efficiency estimates from Models I and II. Applying the bootstrap truncated regression methods introduced by Simar and Wilson (2007, 2011) with 2000 iterations, the coefficient estimates and their 90%, 95% and 99% confidence intervals were obtained for 15 variables representing firm-specific factors and apportion years. Such firm-specific factors include ownership concentration, firm size, firm age, capacity utilisation, financial risk, product type, portfolio diversification, growth status and location of operations. To solve the bootstrap DEA and the truncated regression models in this study, FEAR package (Wilson, 2013) in conjunction with the R codes developed by the researcher are used.

The outcomes of the second-stage analysis of both Model I and Model II exhibited similar significant effects for factors including ownership concentration, firm age, product portfolio and change direction. These factors have been dominating the efficiency performance of mining firms regardless of the consideration of mining characteristics. Table 6.12 presents a summary of second-stage tests on the significance of estimated coefficients of the study variables at 5 per cent significance level. In both models, it was found that higher ownership concentration contributes to higher efficiency gains. This result confirmed that once adequate legal protection is provided to shareholders, ownership concentration benefits shareholders and management through enhanced economic efficiency.

What's more, the results of the second-stage truncated regression analysis of both models showed that there is 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 accelerate the process of technology and knowledge acquisition when entering a booming industry.

In addition, both models confirmed that mining firms involved in exploration and extraction of iron ore and gold mines are more efficient than other mining companies in the sample. These outperforming results for iron ore and gold mining companies are the consequence of large operating scales, established organisations, and the utilisation of advanced technology in these two mining activities in Australia.

Also both models presented a strong relationship between growth status and efficiency performance. Mining firms have achieved higher efficiency gains in years with growing production output. In contrast, their efficiency gains have declined when mining companies have reduced their production output. Although this finding seems to be rather expected in most production processes including mining activities, it explains the challenge facing mining firms to adjust their consumed inputs during business downturns.

Product diversification is the only factor that turned out to be insignificant after redefining the input variables in Model II from the initial setup of Model I. The results showed that while product diversification has been a successful strategy in improving the economic performance of mining companies, it has illustrated limited control in increasing the technical capability of mining firms in transforming the consumed inputs to produced outputs.

Unlike the results of Model I, the coefficients of firm size, financial leverage, location of operations and change of pace have been reported to be significant under the Model II specifications. A positive correlation between firm size and firm technical performance displays the importance of economies of scale in mining activities. Also, the specific results obtained from Model II include the positive association between technical performance and operating outside Australia. This association is dominantly cost-driven, rather than technically motivated. Moreover, even though most Australian mining firms utilise advanced technology, the availability of adequate skills to operate mining equipment is another drawback in

Australia. In Model II, financial leverage has a negative impact on firm technical efficiency. The direct interest expenses and also any potential agency costs have resulted in greater monetary value of inputs to mining operations, while the expected return associated with the related borrowings has not offset the effect of such increased inputs on technical efficiency. Finally, considering natural resource input to mining operations in Model II revealed that maintaining a stable or gradual growth of mining operations is important to achieve higher technical efficiency. This finding is in line with operational reports in the Australian mining sector which have advised implementing strategies that lead to balanced set of developing and operational projects in mining companies (Mitchell and Steen, 2014; Lumley and McKee, 2014).

Table 6.12: Comparison of second-stage results between Model I and Model II

Variables	Model I	Model II
Substantial shareholder (OWNER)	Sig.	Sig.
Firm size (SIZE)	Insig.	Sig.
Firm age (AGE)	Sig.	Sig.
PP&E assets ratio (PPE)	Insig.	Insig.
Financial leverage (LEV)	Insig.	Sig.
Iron ore production (IRON)	Sig.	Sig.
Gold production (GOLD)	Sig.	Sig.
Product diversification (DIV)	Sig.	Insig.
Change pace (CH_PACE)	Insig.	Insig.
Change direction (CH_DIR)	Sig.	Sig.
Location of operation (LOC_OPS)	Insig.	Insig.
Year 2011 (Y2011)	Insig.	Insig.
Year 2012 (Y2012)	Insig.	Insig.
Year 2013 (Y2013)	Insig.	Insig.
Year 2014 (Y2014)	Insig.	Insig.

Source: Author’s calculations
Note: “Sig.” and “Insig.” indicate whether the estimated coefficient is statistically significant or insignificant at 5%.

7 Discussions and Policy Implications

7.1 Introduction

The previous chapter provided the detailed results for the first stage and the second stage of the efficiency analysis among the Australian mining companies. According to the empirical results, a significant degree of inefficiency exists among the Australian mining firms. Moreover, the results revealed that the role of natural resource inputs in the efficiency performance of mining companies is significant. Further analysis in the second stage showed the factors contributing significantly in the mining companies' efficiency. It was confirmed that the efficiency performance highly depends on the characteristics of mining companies. While the results in Chapter 6 aimed to achieve the first and the second research objectives in this study, this chapter targets the third objective by providing insight into the observed results and recommending policy options to improve the efficiency performance of mining companies.

Thus, first, Section 7.2 of this chapter discusses the results from the efficiency estimation in stage one to address the challenges and gaps in the performance of mining companies. Then in Section 7.3, it explores the findings from the second-stage analysis to identify the determinants of efficiency performance. Each contributing factor is reviewed, and the implications of the results are discussed. The knowledge of efficiency determinants is important; however, it does not directly guide mining businesses and the governments toward relevant policy and programs. Hence, to answer how to improve efficiency, Section 7.4 introduces a set of policy and program recommendations in relation to the significant efficiency drivers. These policies and programs are not necessarily limited to each specific determinant; in fact, most programs are multidimensional and linked to multiple factors. Finally, Section 7.5 summarises the chapter discussions.

7.2 Efficiency Performance of Mining Firms

The first stage of analysis in this study involved the estimation of an output-oriented measure of Farrell technical efficiency for 34 Australian mining firms listed on the ASX over the period

2009-10 to 2013-14. Unlike most production environments, mining operations rely on non-renewable natural resources. The availability, accessibility and quality of natural resources decline over time. One consequence of such resource depletion is that a greater amount of inputs such as labour, capital or intermediate inputs are consumed over time to maintain the same amount of production outputs. Hence, even if the technical capability of a firm is unchanged, the firm's productivity declines due to resource depletion. In conventional reports on the mining sector's productivity, this depleting effect is commonly ignored. This study constructed two efficiency models: the first model (Model I) followed the common input/output specifications and the second model (Model II) was modified to include the natural resource inputs. Model I consisted of variables including labour (input), capital service (input), intermediate inputs (input) and production (output). Model II included the natural resource input in addition to other variables from Model I.

Further to the original DEA estimates in both Models I and II, the bootstrap DEA estimates were also calculated. The bootstrap DEA model used in this study is based on the proposed model by Simar and Wilson (1998, 2000a) which incorporates the statistical properties in the estimation of DEA efficiency scores.

As presented in Table 6.1 in Chapter 6, according to the Model I specifications, the inefficiency among the Australian mining firms is significant. As the output-oriented measure of Farrell technical efficiency is used, a fully efficient firm's score is equal to 1, whereas any scores greater than 1 show a degree of inefficiency. Hence, a lower score represents a better performance. On average, the Farrell technical efficiency score under CRS assumptions is 2.65, representing around 62 per cent overall inefficiency. The average of technical efficiency fluctuated slightly over the period of study with a minimum of 2.50 in 2011 and a maximum of 2.79 in 2013 and 2014. Under VRS assumptions, the average efficiency score is 1.67, representing the presence of 40 per cent pure technical inefficiency in the performance of Australian mining companies listed on the ASX. The variation patterns of the VRS estimates are almost similar to that of the CRS estimates; 2011 has the best performance with around 37 per cent inefficiency while the 2014 average performance is 43 per cent. Regardless of the observed year-on-year variations in the average performance, the Friedman test did not confirm any significant changes over the period of study in both CRS and VRS models.

The difference between CRS and VRS estimates is associated with the presence of inefficiency in the operating scale. On average, 37 per cent scale inefficiency exists among the mining companies in the sample. Detailed efficiency results in Table 6.3 show that around 90 per cent of observations require a decrease in their operating scale. The decreasing returns to scale phenomenon may be attributable to the nature of mining resources. That is, an increase in production is not necessarily proportional to an increase in exploration expenditure, physical capital and labour when the most accessible deposits are discovered and extracted first (Zheng and Bloch, 2014; Syed et al., 2015). Over time, more inputs are consumed to produce the same amount of output. Hence, it is expected that firms reaching their full operating capacity will have higher efficiency than those with projects in the development phase as well as those with aged operating mines.

The results of Model II are presented in Table 6.2 in Chapter 6. The results show that once accounting for the effects of natural resource inputs, proxied by the exploration expenditure, the average of CRS technical efficiency score shrinks from 2.65 to 1.69, equivalent to 41 per cent overall technical inefficiency. However, the average of VRS estimates changes marginally from 1.67 to 1.64, representing 39 per cent pure technical inefficiency among mining companies. Consistent with that observed in Model I, there is a slight variation among the yearly average CRS efficiency score in Model II with a minimum of 1.59 in 2011 and a maximum of 1.75 in 2014. The same variation pattern exists under VRS assumptions. However, the Freidman test shows no significant changes over the period of study in either CRS or VRS average estimates.

As presented in Table 6.4, with an average scale efficiency score of 1.04, most mining companies were operating close to their optimum scale over the study period under Model II specifications. For those operating slightly below the optimum scale, a combination of increasing returns to scale and decreasing returns to scale is present among observations. These results suggest that the impact of natural resource inputs on the efficiency estimates is substantial. Due to resource depletion, mining companies require higher investment in exploration activities, which in turn results in lower efficiency estimates. Nonetheless, the lower efficiency estimates in such cases are not necessarily related to the poor performance of firms while transforming their consumed inputs to produced outputs; in fact, these lower efficiency estimates are associated with the adverse effect of natural resource inputs. As a result, mining firms increase their labour, capital and intermediate inputs to overcome the impact of natural resource quality. Such an input increase does not result in a proportional increase in production output.

The results from Model II support the arguments in the literature around mismeasurement and misinterpretation of productivity performance in the Australian mining industry (see e.g. Topp et al., 2008; Zheng and Bloch, 2014; Syed et al., 2015). Resource depletion affects the efficiency and productivity of mining companies; hence, any measures of efficiency or productivity performance in mining activities will be biased because of these effects. That is, true reflection of their performance requires accounting for natural resource inputs. In terms of efficiency measurement, resource depletion effects seem to be more on the scale efficiency than the pure technical efficiency. This pattern is well expected as resource depletion forces mining companies to seek new resource deposits and invest in new mining operations. More inputs are consumed over time, but production outputs do not increase proportionally. Therefore, because of greater resource depletion effects, mining firms are moving further away from their optimum operating scale. However, the pure technical efficiency does not change significantly. Pure technical efficiency relates to the ability of mining companies in transforming their inputs to their outputs given the consideration of scale constraints imposed by the resource depletion effects in the mining industry.

Further to the efficiency model specifications discussed in Chapter 6 in the form of Model I and Model II, Section 6.2.2 provided the results from a bootstrap DEA for both models. The original DEA model is non-parametric. Hence, the statistical noise, related to measurement or random errors, is not incorporated in the efficiency measurement. Simar and Wilson (1998, 2000a) argued that a smoothing bootstrap procedure could provide consistent bias-corrected efficiency estimates along with their statistical properties. Table 6.6 and 6.7 provided the summary of the bias-corrected efficiency estimates over the period of study. Similar to the variation patterns observed in the original models, 2011 has the lowest while 2013 and 2014 have the highest efficiency score averages. The significance of these variations has been tested in the second-stage analysis through the inclusion of year-specific dummies into the econometric model.

The bias-corrected estimates are higher than the original estimates, showing that the efficiency performance of the Australian mining companies is lower than what was assumed based on the conventional efficiency modelling. In Model I, the average efficiency estimates under CRS and VRS assumptions increase from 2.65 to 2.97 and from 1.67 to 1.87 respectively. Also, in Model II the average efficiency estimates increase from 1.69 to 1.89 under CRS assumptions and from 1.64 to 1.86 under VRS assumptions. On average, the applied bootstrapping procedure corrected 12 per cent bias among efficiency estimates. The Model I results show that, at 95% confidence level, the efficiency estimates are below 2.0 in only one third of observations, representing sizable inefficiency among most mining companies in the sample. With the inclusion of natural resource inputs in the efficiency model, the ratio of observations with efficiency scores lower than 2.0 increases to almost two thirds. Thus, while there is no specifically defined threshold to identify poor performance in mining companies, by considering an indicative efficiency score of 2.0, the results reveal that one third of observations severely suffer from technical inefficiency. As it is evident from the reported results in Table 6.7, this inefficiency is mainly attributable to pure technical inefficiency as opposed to scale inefficiency. A second-stage analysis is required to shed light on the factors determining the poor technical efficiency of mining companies.

7.3 Determinants of Efficiency Performance

While the first stage of the analysis attempted to evaluate the technical efficiency of the Australian mining companies, the second stage aimed to identify the contributing factors of their efficiency performance. The insight provided by the second-stage results supports the development of appropriate policy recommendations to improve the efficiency performance of mining companies. In the implementation of the second-stage analysis, this study followed the truncated regression method proposed by Simar and Wilson (2007). The main advantage of this method lies in its ability to provide consistent results when efficiency estimates driven from DEA are regressed on some explanatory variables. Simar and Wilson (2007, 2011) show that the application of common techniques in the second-stage analysis, such as OLS and Tobit regression models, leads to inconsistent model parameters and furthermore that the conventional likelihood-based approaches to statistical inference are invalid. These issues chiefly arise due serial correlations among efficiency estimates. The DEA efficiency estimates are calculated based on the distance of each observation from the respective frontier, which is constructed using observations in the sample. Hence, the estimated efficiency scores are correlated by construction in a complicated way. The bootstrap procedure suggested by Simar and Wilson provides valid inference in the second-stage regression.

Section 5.5 in Chapter 5 presents the econometric model used in the second stage. FEAR package (Wilson, 2013) and the author's own developed R codes are used to run this truncated regression model with 2000 iterations to obtain intervals of the estimated parameters. This econometric model consists of bias-corrected efficiency estimates as the dependent variable and 15 exploratory variables. The variable “substantial shareholders” (OWNER) controls for the effect of ownership structure on the efficiency estimates. “Firm size” (SIZE), proxied by natural logarithm of total assets, controls for the effect of economies of scale on efficiency gain. The effect of learning by practice and experience is captured by the variable “firm age” (AGE). The “ratio of PP&E assets to total assets” (PPE) reflects the capacity utilisation. “Financial leverage” (LEV) represents the financial risks in the model. Two dummy variables of “iron ore” (IRON) and “gold” (GOLD) are included in the model to distinguish the effect of production of these two dominating products on the efficiency performance. The effect of economies of scope is represented by a dummy variable for “product portfolio diversification” (DIV). The growth effects on efficiency are controlled by introducing two dummy variables of “change pace” (CH_PACE) and “change direction” (CH_DIR). The “location of operations” (LOC_OPS) also included in the model to test if the running of mining projects beyond Australia’s borders changes the efficiency gain. Finally, to capture any exogenous effects out of control of businesses in each year, four year-specific dummies (2010, 2011, 2012, 2013 and 2014) are added to the model.

The results of the second stage regression are presented in Section 6.3.1 in Chapter 6. As two efficiency models were developed in Chapter 5, the second-stage analysis was implemented separately for Model I and Model II. This section reviews results from both models for each explanatory variable in the econometric model.

7.3.1 Type of Product

Under the efficiency specifications of both Model I and Model II, the production of iron ore and gold, represented by IRON and GOLD dummies respectively, appeared to be a significant contributor of higher efficiency performance. Australia has the world’s largest iron ore economic demonstrated resources (EDR) with 29 per cent of the global total (Geoscience Australia, 2018). Iron ore mining involves large-scale extracting operations. Hence, the companies being mainly active in iron ore mining benefit from the economies of scale. Furthermore, due to the large-scale projects in iron ore mining, leading companies such as BHP, Rio Tinto and Fortescue have employed the most advanced technology in their exploration and extraction activities. Such advantages have resulted in the high technical efficiency of companies active in the iron ore mining.

The high efficiency performance of gold mining companies should not be surprising. Gold mining has been a long-standing activity in the Australian resource sector. Some major economic and social developments in Australia have been attributable to the gold exploration and extraction activities over the past two centuries. According to Geoscience Australia (2019), Australia holds a global first place in gold resources and is among the world's top five gold producers. Furthermore, following iron ore and black coal, gold has been the third largest contributor of mineral export earning in recent years. Rich resource endowment has not been the only success factor of gold mining in Australia. A high-skilled work force, well-established operating processes and advanced technology utilised in its mining operations have made gold mining a successful and efficient industry.

While the results from both models confirm the importance of product portfolio in the efficiency of mining firms, the degree of dependency to product type varies between these two models. In Model I, both iron ore and gold are significant at 0.01 level, while the iron ore has greater coefficient. On the other hand, under Model II efficiency specifications, the coefficient of gold is greater than iron ore. This difference indicates two things: first, the severity of resource depletion in gold mining; and second, it shows that gold mining can serve as best practice for other mining activities in acquisition of enablers toward efficiency improvement.

7.3.2 Product Diversification

Under Model I efficiency specifications, companies with a diversified product portfolio turned out to be more efficient than those focusing on a single or a few related mining commodities. This significant effect was not held under the specification of Model II. The results presented in Table 6.11 in Chapter 6 show a positive but insignificant influence of diversification on technical efficiency. While diversification does not provide advantage in technical efficiency gain, it is a suitable business strategy in reducing costs and economic efficiency for those mining companies facing resource depletion. Resource depletion impacts the profitability and economic efficiency of mining operations. The sustainability of mining companies relies on their timely response to such negative effects. Diversification reduces the risks of depleting resources on the business outcomes. Moreover, diversification aids mining companies to reduce the impact of mineral price fluctuations on business performance. Finally, through diversification, mining companies can leverage their key competencies in production of other mining commodities.

7.3.3 Growth Status

Since the early 2000s, mining businesses have experienced a high degree of changes in their production capacity and production output. Due to strong capital investments over the 2000s and early 2010s, the production of mining commodities increased substantially in the years that followed. However, the general growth pattern has not been similar among all players in the mining sector. While initially rising mining commodity prices followed by increased capital investment lifted the production output, price declines since 2011 as well as ongoing resource depletion have imposed downward pressure on the production volume of some mining companies. Further to the differences in growth direction, the pace of changes has also varied among mining companies. Rapid changes, particularly those related to short-term responses to the commodity price changes, can dislocate the efficient utilisation of resources. If mining companies produce below or higher than the output level for which they were designed, their productivity drops (Tilton, 2014). Thus, in the second-stage analysis, this study looked at the impact of changes and growth on the technical efficiency gain through inclusion of two dummy variables of change pace and change direction in the truncated regression model.

The results presented in Chapter 6 show that under both models, the direction of changes has a significant impact on the efficiency performance. A decline in the production outputs results in a decrease in the firm’s efficiency, showing that mining companies are not agile enough to respond to changes in their production output. In addition, under Model II specifications, it is evident that rapid changes in mining output adversely impact the technical efficiency. While these results are well expected, they highlight the challenges facing mining companies. A sudden change in commodity prices, any changes in regulations or the existing gradual resource depletion, can all significantly influence the technical efficiency of mining companies. As Tilton (2014) outlined, such driving factors are not uncommon in the mining industry. Prices of mining and mineral commodities are highly influenced by national and international changes. Government regulations, particularly in relation to the environmental concerns, are changing from time to time across the world. Finally, the finite natural resource inputs are depleting over time. Therefore, dealing with these factors requires sector-wide and corporate-wide strategies rather than short-term tactical and operational solutions.

7.3.4 Ownership

The economic literature emphasises the importance of ownership in the efficiency and productivity performance of companies. Among the Australian listed mining companies, ownership concentration differs widely. As per Table 5.2 in Chapter 5, ownership of the substantial shareholders varies from a minimum of 5 per cent to a maximum of 95 per cent among the selected sample in this study. The results presented in Chapter 6 revealed that ownership concentration positively drives the technical efficiency. Higher ownership of substantial shareholders results in higher technical efficiency performance. The result is consistent in both efficiency models at 99% confidence level. The substantial shareholders have the power and incentive to monitor management performance and prevent inappropriate or inefficient use of companies' assets. The literature supports the positive effect of ownership concentration on the firms' performance; nonetheless, it expresses concerns regarding the high ownership concentration impact on minority shareholders (see e.g. Shleifer and Vishny, 1997; Boubakri et al., 2005; Omran, 2009; Margaritis, and Psillaki, 2010; Ma et al., 2010; Cabeza-García and Gómez-Ansón, 2011). If adequate legal protection is provided to shareholders, the risk of substantial shareholders' colluding with the business management is controlled. Anderson et al. (2012) discussed that such legal protection has been provided to shareholders under Australian law. Hence, without major concerns in relation to maintaining the shareholder benefits, minority shareholders can benefit from a better control of management performance in companies with high ownership of substantial shareholders.

7.3.5 Firm size

The effects of firm size on the technical efficiency of enterprises are reported ambiguously in the literature. Firm size has been interpreted as a source of organisational costs and inefficiency due to the complexity of larger firms in organisational and managerial control as well as difficulties in managing diversified portfolios in larger firms (e.g. Hansen and Wernerfelt, 1989; Diaz and Sanchez, 2008). On the other hand, some studies found a positive or U-shape relationship between size and firm performance (e.g. Badunenko, 2010; Schiersch, 2013). They claimed that small companies do not benefit from economies of scale but face challenges such as lower managerial skill, limited knowledge and presence in the market, and financial constraints which decrease their efficiency.

In the context of the mining sector, generally it is expected to observe a positive association between size and efficiency. Efficient mining operations require acquisition of advanced technology, a skilled workforce and managerial expertise, whereas most newly formed and small firms suffer from the lack of such capabilities (Lumley and McKee, 2014). This study's findings are quite interesting in terms of the linkage between size and efficiency. Based on the specifications of the general efficiency model, no significant effects from size, measured by the natural logarithm of property plant and equipment (PP&E) assets, were identified. However, based on the specifications of the natural resource-based model of technical efficiency, a larger size is associated with a higher efficiency. These results suggest that increasing physical assets is not necessarily a strategy to increase production output, but a way to overcome the adverse effects of resource depletion.

7.3.6 Firm Age

The second-stage findings presented in Chapter 6 reveal the positive effects of firm age on efficiency performance. Young firms' poor efficiency may be attributable to their challenges in finding the essential knowledge, expertise and resources, particularly in booming cycles (Lumley and McKee, 2014). Following substantial increases in global demand for mining and mineral commodities in the 2000s, a large number of newly formed companies turned to the stock markets to attract their required capital. However, capital was not the only thing they were lacking; the skilled workforce to be able to utilise mining equipment effectively and the managerial expertise to lead fast growing businesses were among the main shortages of young firms. As Tilton (2014) discussed, the lack of such quality among a firm's workforce and leadership can deteriorate its productivity.

The findings in this thesis are consistent with the results in Das (2012), reporting a positive relationship between firm age and TFP of the Indian mining companies in metallic, coal and petroleum sectors. In contrast, the results of this study do not support the mine-level findings in Byrnes and Färe (1987) which reported that the age-efficiency relationship is negative. Such contrast is not surprising; at mine level, in addition to the natural resource quality and accessibility, the performance of capital assets such as mining equipment and machineries declines, resulting in a lower technical efficiency of mining operations over time. Nonetheless, mining companies operate a portfolio of mining activities ranging from mine exploration and development to extracting operations. Therefore, more extensive experience aids mining companies to find the optimum mix of these activities to stabilise their business outcome in the long run.

7.3.7 Capacity Utilisation

Capacity utilisation has been addressed as a severe concern in the Australian mining industry. Mitchell et al. (2014) and Lumley and McKee (2014) argued that over-investment in capitals and poor capital utilisation due to the lack of skills and experience have adversely impacted the capital productivity of mining in Australia. Zheng and Bloch (2014) discussed that capacity utilisation, i.e. production below or above the built capacity, had the largest negative effect on the MFP growth of the mining sector in Australia over 1974-75 to 2007-2008 period. The built capacity in a mining company is in fact its productive assets which are recorded in financial statements as the property, plant and equipment (PP&E) assets. This study looks at the share of PPE assets in total assets of mining companies to examine if a high or low degree of PPE ratio affects the technical efficiency. The results derived from both models presented in Chapter 6 do not suggest any significant influences on efficiency imposed by capacity utilisation.

While the results from this study are not necessarily comparable with those reported in Zheng and Bloch (2014) due to the differences in modelling and proximation, this study's findings show that the asset composition does not seem to be a driving factor of efficiency. In other words, a larger share of productive assets does not mean mining companies perform better or worse.

7.3.8 Financial Risk

The results of Model I show no significant effects of financial risk, proxied by leverage ratio, on the firms' efficiency. However, the Model II results present a negative impact. It is worth noting that the unadjusted technical efficiency can be interpreted as an overall business efficiency measure while the adjusted technical efficiency reflects the technical ability of a firm in transforming the resources into production output. These results suggest that while from a corporate perspective a high degree of leverage does not harm the economic performance, it limits the technical efficiency gain of mining companies through imposing higher costs to the production system. Such costs reduce the available funds for operating expenses which directly affect the production output.

Leverage can serve as an influencing factor of agency cost which arises when the interests of the company's managers and that of its shareholders or debt and equity investors are not perfectly aligned. The agency cost directly influences the firm performance; hence the relationship between leverage and agency cost is equivalent to the relationship between leverage and firm performance. The literature reported both positive and negative associations between leverage and agency cost (or inversely firm performance) (e.g. see Abor, 2005; Zeitun and Tian, 2007; El-Sayed Ebaid, 2009; Margaritis and Psillaki, 2010; Yazdanfar and Ohman, 2015). The expected relationship in this study is in line with the theory of agency cost as discussed in Jensen and Meckling (1976), where leverage reduces the agency cost, resulting in higher efficiency performance. However, this expected association was not proven. Fama and French (2002) explained that excessive debt leads to higher agency costs and equivalently lower firm performance. While providing insight into the capital structure is beyond the scope of this study, the findings here illustrate the importance of financing in firm performance. As mining firms greatly rely on external funding, it is important to understand the short-term and long-term effects of financing (debt or equity) on their economic performance prior to such decisions.

7.3.9 Location of Operations

The location of operations did not appear to be influential to the firm's performance in Model I; however, under Model II specifications, this firm-specific factor turned out to be significant. The intention of including this variable in the second-stage model was to evaluate the geological diversification strategy pursued by some mining companies in Australia. Particularly, major mining companies have expanded their exploration and extraction activities to some projects beyond Australia. More than half of the ASX listed Australian mining companies operate overseas. Africa, Latin America and South East Asia are among the places mostly attracting Australian mining companies and engineering consultants. Through these international operations, mining companies leverage their organisational and technical capabilities to benefit from new market and lower operating costs in host countries, leading to a higher efficiency performance. The comparison of the results between general and natural resource-based models show that mining companies operating overseas are more involved in exploration activities compared to those limiting their operations to the resources inside Australia.

The positive linkage between overseas operation and efficiency shows that Australian mining companies have been successful in managing the new business environment while incorporating their knowledge and technology in efficient overseas mining operations.

7.3.10 Year-Specific Effects

To capture year-specific effects, four dummy variables of Y2011, Y2012, Y2013 and Y2014 are included in the regression model. The results from both models did not present any significant exogenous effects along the period of study. Particularly, 2011-12 represented by Y2012 dummy had two major events; the highest aggregate commodity prices and the introduction of the carbon pricing scheme. The average efficiency performance declines from 2010-11 to 2011-12; however, this decline is not statistically significant. These results confirmed the initial findings from the Freidman test on the mean ranks, displaying no differences among average efficiency scores over the period of study. These results also confirm that the effects on the efficiency performance have been mainly captured by firm-specific factors of ownership concentration, firm size, firm age, product portfolio, financial risks, growth status and overseas operations.

7.4 Policy Implications

Over the past few years, many companies in the mining industry have listed productivity among their top priorities. The vulnerability of the mineral commodity prices since 2012 has encouraged mining companies to take strong steps toward improving productivity (Lumley and

McKee, 2014). However, the question is whether the productivity has improved among mining companies. Conventional sector-level reports show a period of productivity decline during mining boom until 2014 and since then it has been stabilised and improved marginally. The literature has addressed the issues around the productivity trends and related them mainly to the contributing factors of resource depletion, investment-production lag and capacity utilisation. Hence, some scholars in the Australian mining context did not recommend any sector-specific policy beyond general advice for productivity improvement (e.g. see Syed et al., 2015).

It is important to recognise that the aggregate reports do not provide insight into the firm-level performance in the mining industry. Understanding the efficiency and productivity gaps and its determinants at firm level is needed to develop improving strategies and programs. While the results of this study support some sector-level findings, such as the importance of resource depletion or investment-production lags in productivity performance, the results also suggest the need to introduce specific recommendations for productivity improvement among mining companies. The results from the first-stage analysis revealed a significant performance gap against the best practices; and results from the second stage presented the main factors driving the efficiency of mining companies. In line with the discussions in Section 7.2 and Section 7.3, several policy implications drawn from the results of this study are presented in this section. It is worth noting that the recommending policy and programs toward improving the efficiency of mining companies are mostly multidimensional. Therefore, each policy and program category in this section may cover multiple efficiency determinants discussed in the previous section.

Both government and mining businesses can benefit from these recommendations to develop strategies and programs aimed at improving the efficiency and productivity of the mining industry.

7.4.1 Human Capital Development

The mining boom of the 2000s was practically a test of the mining industry's capability in human capital. Due to the increasing demand and prices of most minerals, the existing mining companies vastly expanded their operations; in addition, many new players entered the mining market. The results from this study revealed that fast-growing companies as well as young firms exhibited a low efficiency performance over the period of study. Talent shortage, particularly in the utilisation of advanced mining equipment, has been reported as one of main challenges facing mining companies. In addition to technical skills, leadership and managerial skills also did not match the requirements of a booming sector. These skill shortages, along with a high workforce turnover since the beginning of the mining boom, have had a significant impact on the productivity of mining companies (Mitchell et al., 2014).

While war for talent is more evident during booming periods, talent development should be an ongoing program. Yet, the trends in talent development do not look to be moving toward the desired direction. Undergraduate intakes for most mineral resource higher education disciplines have notably declined since 2012. Following the sharp decline in enrolments, the number of graduates in the mining-related disciplines has also decreased (Minerals Council of Australia, 2018). Such concerning trends require a collaborative approach taken by government, the mining industry and the education sector to develop sustainable programs that address such issues. Further to the need for improving trends in mining education, businesses need to have robust plans for people selection and development of their hired employees. Through selecting the right people, the skill mismatch reduces. Moreover, skill development plans improve the workforce capabilities and individuals' sense of belongingness. This approach leads to improved efficiency of mining operations and also results in reducing the high labour turnover in the mining industry.

7.4.2 Product Portfolio and Diversification

The results from this study showed that technical efficiency depends on the product portfolio. Companies mainly active in the production of iron ore or gold are more efficient than those involved in the production of other mining commodities. From an economy-wide perspective, such results are plausible as iron ore and gold are among the chief mining activities and export earning commodities in Australia. However, from a microeconomic perspective, there are a large number of companies operating in the exploration and extraction of other commodities that require boosts to their technical efficiency. Due to the large capital investment required for iron ore and gold mining, diversifying a product portfolio toward inclusion of gold or iron ore may not be practical for many companies. Furthermore, product portfolio diversification is not necessarily associated with higher technical efficiency gain once accounting for the effect of natural resource inputs. Diversification can be pursued as a business strategy in improving sustainability and economic efficiency, but its effect on technical efficiency improvement is unproven. Although it is not recommended that mining companies necessarily move to production of gold or iron ore to boost their technical efficiency, diversification in general can help mining businesses to achieve sustainable business outcomes such as profitability and economic efficiency.

Further to product diversification, findings in this study shed light on the importance of production stability in efficiency. Companies with more stable production output experienced a better efficiency performance. Such stability in production requires effective portfolio management (Mitchell and Steen, 2014). A balanced set of projects in a firm's portfolio results in the stability of production outputs, thus improving the firm efficiency.

The role of diversification in determining efficiency performance is not limited to the product portfolio; it is also the case for the operations location. This study found that companies with active mining projects outside Australia are more efficient than their counterparts that limit their operations to the mineral resources located in Australia. In most host countries, the operating expenses are less that those in Australia. Therefore, the Australian mining companies can leverage their domestic capabilities such as a skilled workforce and advanced technology in locations with lower operating costs. Such diversification is important from various aspects. Firstly, it helps companies to run their projects more efficiently, resulting in a greater operating profit margin. Secondly, this kind of diversification reduces the business risks attributable to the mine sites located in Australia. The rising social claim in relation to the environmental protection in Australia is an example of domestic changes influencing mining business stability in recent years. Thirdly, due to progressive resource depletion in Australian mineral deposits, and its direct impact on the economic efficiency and profitability of mining companies, expanding mining activities in emerging areas across the world aids companies in maintaining their strong presence in the global market in the long term. In addition to the strategic direction of Australian companies toward expanding their engagement in the global mining production, the Australian Government also needs to expand the mining trade missions toward emerging and new markets. These missions should include both mining exploration and extraction companies and mining equipment and service (METS) companies.

7.4.3 Research, Innovation and Technology Advancement

The results from this study confirmed the sizable effect of natural resource inputs on efficiency performance. The distance from frontier production is mainly attributable to the decline in the accessibility and quality of mineral deposits. Unfortunately, resource depletion will have a continuing adverse effect on mining productivity. Unless any technological progress is achieved, given the finite resource deposits on the earth, a greater amount of inputs is required over time to produce the same amount or the same value of mineral commodities. Advancement in technology is required in all phases of mining activities including exploration, mine development, mine extraction, and mine closure and reclamation.

As per findings in this thesis, gold mining is among the most efficient mining activities in Australia. However, there is no guarantee that the most efficient mining activities can deliver sustainable economic success to the Australian economy. The primary challenge in the gold mining industry is resource depletion. Without any new successful exploration projects or technological advancements in the extraction of currently uneconomic low-grade deposits, all gold-producing deposits have only a resource life of 23 years (Geoscience Australia, 2019). As the results of this study show, such significant resource depletion in gold mining will lead to higher consumption of inputs with lower production output. Unadjusted measures of efficiency are expected to decline in the future. Improvement in economic efficiency performance will require technological advancements that enable the economic extraction from low-grade deposits as well as acceleration in the exploration activities. As gold mining companies have high technical efficiency, maintaining their high performance should be among their priorities.

The Australian mining equipment, technology and services (METS) sector is world-leading in providing specialised products and solutions across the mining value chain including mineral exploration, development, extraction, processing, transport and remediation (Geoscience Australia, 2015). As it is characterised by being internationally competitive and innovative, the Australian METS sector is a benchmark for some global competitors. (CSIRO, 2017). During the recent mining boom, the total output of exploration and mining support services increased significantly. However, since transitioning from the mining development phase to the production phase in 2013, both total services volume and its contribution to mining sector production have declined considerably (ABS, 2017a).

Continued investment in research, innovation and technology advancement is required at both government and sector levels. Maintaining the existing advantages in the METS sector can be achieved through development in organisational capabilities as well as practical research and technology solutions. The METS sector needs to develop the right skills, culture and processes to sustainably manage growth domestically and internationally. Moreover, METS companies need to provide opportunities for their researchers and technologists to gain practical experiences in emerging research areas. Such practical engagement helps to successfully convert leading scientific and technological breakthroughs into differentiated, repeatable and operationally ready solutions (CSIRO, 2017).

7.4.4 Organisational Capabilities in Digital World

The vulnerability of mineral commodity prices in recent years has left an extensive pressure on mining companies to improve their productivity. The recent advancements in information technology have opened new opportunities for mining businesses to use data for real-time decision making. In addition to the technological progress – such as the utilisation of artificial intelligence (AI), machine learning and robots in mine exploration and extraction operations – the emerging digital capabilities can aid leaders in mining businesses and government authorities in their decision-making processes. This study showed that companies experience low efficiency during fast changes in the operating scale. The mis-allocation of resources is a main driver of poor efficiency and productivity in a changing environment. Furthermore, the mine operations analysis has revealed a significant degree of unutilised equipment among Australian mining activities (Lumley and McKee, 2014). Real-time equipment performance monitoring facilitates the efficiency of operations management and equipment maintenance activities. A considerable amount of data is collected in each stage of mining operations; however, mining companies usually use a fraction of their data. Many leaders in mining companies have reported their reliance on monthly or quarterly reports while some managers expressed their concerns about the reliability of such reports (Lumley and McKee, 2014; Durrant-Whyte et al., 2015). To address such concerns, mining businesses need to prioritise the development and execution of their digital strategy. Companies need to move beyond data acquisition and rethink about data analytics and data usage.

While digital transformation seems promising in bringing productivity back to mining activities, this may be an impractical feat for some companies. Large mining companies can invest in big data, machine learning and AI, but SMEs and young mining firms do not have the opportunity to easily develop and utilise organisational capabilities in relation to digital transformation. Based on the results in this study, SMEs and young firms are among the least efficient mining companies in the Australian mining sector. Therefore, the emergence of digital transformation is likely to widen the existing efficiency gap for these companies. To aid small and young mining players, the role of the government and METS sector is critical. The exploration of mineral resources is greatly supported by the Australian Government through providing public access to geoscience information (Geoscience Australia, 2017). Further to this kind of support, the government needs to support professional associations to link mining and IT professionals toward collaborative projects in mining SMEs. The METS sector also needs to develop specific solutions suitable for mining SMEs with limited budgets and organisational capabilities. The findings of this research support the Australian Government's initiative under the Entrepreneurs' Programme to boost business competitiveness and productivity in SMEs. Active engagement of the METS sector in this program in providing advice and customised digital solutions for the mining SMEs and the newcomers can support closing the efficiency gap among these mining companies.

7.4.5 Economic Sustainability

Besides the external market factors, the economic sustainability of mining companies relies on their sustainability in growth and control of business risks. This study discussed the adverse impact of extensive changes in the operating scale on the efficiency of the Australian mining companies, revealing that a sustainable growth is associated with high efficiency gain. However, the vulnerability of mineral prices significantly impacts production output. Hence, despite short-term changes, it is important for mining companies to map their long-term journey in the implementation of all enablers such human capital, product portfolio, technology utilisation and digital transformation. Mining companies have reported their success in the implementation of operational strategies; however, they have not been successful in development and implementation of long-term strategies so far (Lumley and McKee, 2014).

The mitigation of business risks is also critical to economic sustainability. During the mining boom of the 2000s, the Australian mining companies increased their short-term and long-term debts to largely cover their investment expenditure in exploration and development activities. In addition to equity financing, mining companies fund their projects through borrowing from external lenders. Due to the fluctuations in production volume and values, higher leverage imposes higher risk to mining businesses. The results from this study showed that higher leverage is associated with lower efficiency among the Australian mining companies. The borrowing expenses could impact the productive operating expenses; hence, a lower efficiency was achieved by highly leveraged companies. The other finding from this study is the strong correlation between ownership concentration and efficiency. That is, a higher ownership concentration leads to a higher efficiency performance. While these findings do not suggest a high degree of equity financing, which results in lower ownership concentration and consequently lower efficiency, they do not also suggest a high level of debt financing. Therefore, mining companies needs to be wise in their financing strategies by understanding the extent of their short-term and long-term implications.

7.4.6 Environmental Protection and Social Licence

Beyond fulfilling the formal regulatory conditions and obtaining a licence to mine, mining companies need to obtain a social license to operate. Increasing social claims from communities and governments have become a prominent challenge for the mining industry. Various aspects of this challenge include environmental considerations, health and safety requirements, employment, stakeholder engagement and community benefits. Such an intangible licence is required to attain and maintain approval for the entire mining project life, from initial exploration to post-closure phases. Mounting community concerns and the requirements for a social licence to operate can result in increased costs and lower efficiency due to longer lead time to attain exploration and mining approvals and complying with more strict regulations (Penny et al., 2012; Geoscience Australia, 2017). While a social licence to operate imposes unpredicted costs on mining companies, it is highly important that mining businesses understand the costs of social conflicts. Companies with such an insight tend to prioritise and pay more attention to the relationships between companies and local communities (Davis and Franks, 2014).

The environmental concerns and social claims in importing countries also influence the Australian mining companies. Iron ore, as the leading mineral exporting industry, faces new challenges influencing its economic and technical performance. In recent years, the iron ore industry focus has shifted from production quantity to ore quality. The global concerns over climate change and the reduction of greenhouse gas emissions played a key role in this direction change. China, as the main importer of Australia's iron ore, has imposed strict regulations on the operation of inefficient steel mills. In addition, the steel manufacturers across the world increasingly prefer high-grade iron ore. These challenges forced some explorers and developers to discontinue their activities in some projects (Geoscience Australia, 2018). While it is important to comply with global market requirements, it is also important to prioritise domestic environmental protection. Mining companies and government authorities should be aware of the environmental, social and economic effects of any strategic direction changes such as concentration on extracting ore from high graded deposits. Accelerating exploration activities may be the solution to seeking high graded deposits; however, due to the finite nature of mineral deposits, this will not create a sustainable way to deal with the market challenges. Through technology advancement and boosting productivity, the mining industry needs to manage both domestic and global concerns in relation to environmental protection and social claims while supporting economic sustainability in Australia.

7.5 Summary

The results from this study showed that efficiency is a major concern in mining industry. The overall technical efficiency of the Australian mining companies shows a sizable gap against the best practice performance. However, a major part of this inefficiency can be explained by the adverse effects of natural resource inputs. Resource depletion highly contributes to low efficiency among mining companies.

Through the inclusion of natural resource inputs in the efficiency model, this study presented a better estimation of true technical efficiency among the Australian mining companies. The results from the first-stage analysis show that while the scale inefficiency is marginal, the pure technical efficiency among mining companies in Australia is significant.

The second-stage analysis revealed that the technical efficiency of mining companies is mainly associated with the firm-specific characteristics. Product portfolio turned to be highly important in efficiency gain. Gold and iron ore mining companies outperformed companies with no such products in their portfolio. Highly skilled work force as well as advanced technology in gold mining and the advantage of economies of scale in iron ore mining are among main causes of such outstanding performance. A diversified portfolio seemed to be a better choice in relation to the overall economic efficiency, whereas it might not provide significant advantage in terms of technical efficiency.

Companies with a positive moderate growth were more technically efficient than those with drastic changes or those experiencing contraction in their operations. Misallocation of resources and long lag in capital input adjustment can explain the poor efficiency in companies with sharp changes or decline in revenue. Due to a better corporate governance, more ownership concentration among the mining companies in Australia led to being more efficient. Smaller companies were less efficient than their larger counterparts potentially due to benefits from the economies of scale. Younger companies fell behind those with more experience chiefly as a result of limitations in attracting required skills and expertise. High financial leverage resulted in lower efficiency gain among the Australian mining firms. Excessive debt financing deteriorated the mining firms' performance. Finally, companies with mining operations outside Australia were performing more efficient than those limiting their operations to the mineral resources in Australia. Mining operating expenses is relatively high in Australia in comparison with many other mining regions across the globe.

The knowledge of efficiency determinants aided this study to identify relevant policy recommendations toward improving efficiency in mining industry. Among various programs potentially support efficiency and productivity improvement activities, this study focused on most relevant policy options addressing the findings from the first-stage and second-stage analyses. First, human capital development should be a critical part of strategies in mining industry. Skill shortage in newly formed companies and those with sharp growth was a main driver of poor efficiency. Mining businesses, government and higher education sector need to collaborate in developing consistent strategy in mining human capital.

Second, diversification in general provides better efficiency performance in mining industry. Diversified products, diversified projects in terms of life cycle stages and diversified geographical locations support better utilisation of resources and capabilities.

Third, research, innovation and technology advancements are critical to the efficiency gain resulting to long-term success of mining companies. The resource depletion remains a continuing adverse effect on the mining industry's productivity and efficiency. Only through research, innovation and technology advancements the negative effects of resource depletion can be offset. Innovations in more efficient mining processes and advancements in technology enabling the extraction from less accessible or lower grade mineral deposits are needed to maintain outstanding position of Australia in the global resource market.

Fourth, mining companies needs to develop their digital capabilities. A large amount of data is collected at each stage of mining operations; however, it is not utilised effectively in the decision-making processes. The insight from mining of big data can aid companies to improve the efficiency of asset utilisation in exploration and extraction activities. In particular, newly formed as well as the small and medium-sized companies can greatly benefit from such insights to overcome their limitations in skills and expertise. Nonetheless, the role of government and METS sector is critical in providing support to these companies.

Fifth, mining companies need to think beyond short-term requirements. Tackling undesirable efficiency associated with issues in relation to product portfolio, diversification, growth, ownership structure, capacity utilisation and financing require long-term strategic plans. Such long-term plans should consider all stage of mining life cycle from exploration to extraction to post-closure phases.

Sixth, sustainability, as a main characteristic of efficient firms, should not be only limited to its economic aspect. Mining companies need to be fully aware of environmental concerns and social claims in relation to the adverse effects of mining operations. They need to be actively engaged with government authorities and local communities to understand the concerns and introduce appropriate policy and programs to address their claims.

8 Conclusions

8.1 Introduction

The mining industry plays an important role in Australia's ongoing prosperity. Its significant role in the nation's GDP growth, new capital investment, export, direct and indirect employment as well as developments in regional and indigenous communities has made this sector beneficial to all Australians. Over the past two decades the Australian mining industry has expanded substantially to respond to the increasing global demand for minerals and mining commodities. Despite the growing economic trends, the Australian mining sector has faced a severe challenge in relation to its productivity performance. Some studies have discussed the productivity challenge in the mining sector at an aggregate level; nonetheless, little is known in terms of efficiency and productivity across Australian mining companies.

This study conducted an empirical investigation into the efficiency performance of Australian mining companies. It aimed to answer the following questions: (i) How do Australian mining firms perform in terms of technical efficiency? (ii) Which factors significantly contribute to the efficiency performance of Australian mining firms? (iii) How can the efficiency performance of Australian mining firms be improved?

Toward answering these questions, this study utilised a frontier approach for evaluating the efficiency performance of mining companies. Focusing on mathematical programming techniques, this study introduced a bootstrap data envelopment analysis (DEA) method to estimate the technical efficiency of major mining companies listed on the Australian Securities Exchange (ASX). Moreover, this research investigated the firm-specific factors influencing the efficiency performance in a second-stage analysis.

Chapter 2 explored in detail the Australian mining industry and its significant changes since 2000. The mining sector's contribution to the Australian economy increased from 5 per cent in 2000 to 9 per cent in 2010-11. The export of minerals and mining commodities reached above 50 per cent of Australia's exports, and the share of mining capital stock and number of employed people in mining industry increased by more than 200 per cent in a decade from

2003-04 to 2012-13. This success mainly relied on the natural resource endowment, the favourable investment environment, a skilled workforce and advanced technology in Australia. Aside from growing trends in exploration and extraction activities, the productivity performance of the Australian mining industry has deteriorated over the past two decades. Multifactor productivity (MFP) declined constantly between 2000-01 and 2012-13.

Chapter 3 reviewed the existing literature in efficiency and productivity analysis in mining industry in general. This review showed that the efficiency and productivity measurement highly depends on the scope of study. Research aims, variables of interest, methodologies and policy implications are different among mine-level, firm-level and sector-level studies. While the existing studies have attempted to answer some questions in relation to the efficiency and productivity of the mining industry, little is known about the efficiency of mining enterprises and what determines their performance. Moreover, there is room for improvement in efficiency modelling given the recent advancements in the frontier techniques.

In Chapter 4, this study presented the frontier techniques in efficiency measurement. This measurement relies on the comparison of observed against optimum values of inputs and outputs relying on the technology frontier. DEA and SFA are the main techniques in the efficiency measurement literature; the former being a mathematical programming method while the latter is based on the econometric modelling. This study used DEA to estimate and analyse the efficiency of Australian mining companies. The main advantage of DEA is its flexibility in the efficiency modelling of a multiple input-multiple output production setup. In contrast to SFA, DEA does not require selection of a pre-defined functional form. To overcome the main drawback of DEA, which is deterministic and does not account for the statistical noise in efficiency estimation, this study applied a bootstrap procedure proposed by Simar and Wilson (1998, 2000a). Furthermore, Chapter 4 explored the literature on techniques for analysing the determinants of efficiency. Among various techniques, this study utilised a bootstrap truncated regression model proposed by Simar and Wilson (2007, 2011) which provides consistent results in DEA efficiency modelling.

In Chapter 5, the scope of the study, the research variables and the empirical models were introduced. This study examined the efficiency performance of Australian mining firms using a sample of 34 listed companies on the ASX over the period 2009-10 to 2013-14. Findings from the existing literature guided this research in the selection of efficiency model variables as well as efficiency determinants in a firm-level study. Following the existing literature, variables of capital, labour, intermediate inputs and production output formed the efficiency model in this study. Depreciation, wage bills and operating expenses were selected from financial statements as three input proxies while revenue was the proxy for output in the efficiency model. This study also considered the effects of natural resource inputs on the mining operation performance by including exploration expenditure as a proxy for the cost of resource depletion. Further to the efficiency modelling, Chapter 5 provided a detailed review of the firm-specific factors potentially driving the efficiency performance. These factors include ownership, size, age, capacity utilisation, financial risk, products, diversification, growth status, location and time. The empirical mathematical programming models of first-stage and the empirical econometric model of second-stage are also introduced in this chapter.

The empirical results presented in Chapter 6 revealed a significant degree of inefficiency among the Australian mining firms. In addition, these results showed the importance of variable specification in the technical efficiency model. The efficiency estimates and the source of inefficiency widely varied between the general model of technical efficiency and the natural resource-based model of technical efficiency. By including resource depletion in the efficiency model, the average technical inefficiency under CRS assumptions shrank from 62 per cent to 41 per cent. Moreover, the results proved the importance of robust techniques in the efficiency measurement. Bootstrap DEA estimates are clearly different from those of the original DEA model. Chapter 6 also presented and discussed the results of the second-stage analysis. The results confirmed the significant role of firm-specific factors in the efficiency performance. Ownership, firm size, firm age, financial risks, product type, change status and location were found to be the main determinants of mining companies' efficiency.

Chapter 7 discussed the empirical findings from stages one and two of the efficiency analysis in this study. This chapter explored the implication of findings in relation to the efficiency determinants and introduced a set of policy recommendations addressing factors associated with inefficiency among mining firms. Human capital development, product strategy and diversification, innovation and technology advancement, development of digital capabilities, economic sustainability as well as environmental and social responsibility are among most relevant policy recommendations toward improving efficiency in the mining industry.

The present chapter elaborates on the key concluding remarks of this study. The rest of this chapter is organised as follows: in relation to the first research question, Section 8.2 provides key findings in the efficiency estimation obtained from first-stage analysis. Section 8.3

summarises the research findings in answering the second research question, i.e. “what determines the efficiency performance of mining companies?” Section 8.4 discusses the policy implications of the findings to respond to the question “how can efficiency be improved?” Section 8.5 outlines the significance and the contribution of this study to the existing literature. Finally, Section 8.6 explains the limitations surrounding this study and proposes an agenda for future studies.

8.2 Key Findings in Estimation of Efficiency

In this study, the first-stage analysis was conducted to estimate the technical efficiency of 34 Australian mining firms listed on the ASX over the period 2009-10 to 2013-14. In this regard, two efficiency models were introduced; the first model was constructed based on common input/output specifications in the production function theory while the second model was developed as a specific model of technical efficiency in the mining industry. The general model of technical efficiency (Model I) included labour input, capital service input, intermediate inputs and production (output). The natural resource-based model of technical efficiency (Model II) included the natural resource inputs in addition to other variables from Model I. This study used DEA to estimate the efficiency scores of observations in the sample. In addition to the original DEA model, this study used a bootstrap procedure introduced by Simar and Wilson (1998, 2000a) with 2000 iterations to derive bias-corrected technical efficiency scores along with their corresponding confidence intervals.

The results from first-stage analysis of Model I, presented in Table 6.1, revealed a significant gap in the efficiency of the Australian mining firms. On average, around 62 per cent overall inefficiency was observed among the Australian mining companies. Pure technical inefficiency by 40 per cent and scale inefficiency by 37 per cent contributed to this sizable overall inefficiency among mining companies. Taking into account the natural resource inputs in efficiency modelling, the results from Model II, presented in Table 6.2, show a large change in the observed overall inefficiency shrinking to 41 per cent. Surprisingly, the pure technical efficiency changed slightly reaching 39 per cent while the scale inefficiency diminished substantially to only 4 per cent.

These results present two facts about mining firms’ efficiency. First, the results confirmed the importance of natural resource inputs in the efficiency performance of mining companies.

Natural resource inputs should be among the primary variables of efficiency modelling. Hence, this study supported the arguments in the literature concerning mismeasurement and misinterpretation of productivity performance in the Australian mining industry (see e.g. Topp et al., 2008; Zheng and Bloch, 2014; Syed et al., 2015). Second, the results showed that resource depletion tends to lead to inefficient operating scale while pure technical efficiency seems to be independent from resource depletion. To address the adverse effects from resource depletion, mining companies typically seek new resource deposits and invest in new mining operations. Higher expenditure in exploration activities is required to search for potential deposits in more remote and unexplored regions. Mining companies enlarge their operating capacity and consume more inputs over time, but production outputs do not increase proportionally.

Further to the findings from the original DEA method, Chapter 6 presented the results from the bootstrap DEA method. Despite the similarity of variation patterns among efficiency estimates from the original and the bootstrap DEA methods, the bias-corrected efficiency estimates are significantly lower than the original estimates. On average, the applied bootstrapping procedure corrected 12 per cent bias among efficiency estimates. In addition to point-estimate efficiency scores, the bootstrap DEA provided the confidence intervals for the estimated efficiency of all observations. The results from Model I presented in Table 6.6 show that, at 95% confidence level, the efficiency estimates are below 2.0 (equivalent to 50 per cent efficiency) in only one third of observations. With the inclusion of natural resource inputs in the efficiency model, the ratio of observations with efficiency scores lower than 2.0 increases to almost two thirds (Table 6.7). It reveals, first, that the true technical efficiency of mining companies is considerably better than that measured using common efficiency model specifications, and second, even after accounting for the effects of natural resource inputs, still one third of observations severely suffer from technical inefficiency. As it is evident from the reported results in Table 6.7, this inefficiency is mainly attributable to pure technical inefficiency as opposed to scale inefficiency.

Overall, findings from the application of the bootstrap DEA displayed the benefit of this method in correction of measurement bias and providing confidence intervals. Also, it showed a significant level of pure technical inefficiency among mining companies that needs to be addressed through identifying its determinants and introducing the improvement programs.

8.3 Key Findings in Determinants of Efficiency

The second-stage analysis was conducted to identify the most firm-specific factors driving the efficiency of mining companies. To improve the consistency of results in stage two, this study applied the bootstrap truncated regression method proposed by Simar and Wilson (2007) as discussed in Chapter 4. The econometric model of stage two consisted of bias-corrected technical efficiency as the dependent variable and 15 explanatory variables including ownership concentration, firm size, firm age, capacity utilisation, financial risk, two dummies for product type of iron ore and gold, portfolio diversification, two dummies of change pace and change direction, location of operations and four year-specific dummies. FEAR package (Wilson, 2013) and the author's own developed R codes were used to run this truncated regression model with 2000 iterations to obtain intervals of the estimated parameters.

As per results presented in Section 6.3.1 in Chapter 6, the product type influences the technical efficiency. Production of both gold and iron ore turned out to be positive contributors to efficiency gain. The finding was consistent between both efficiency models. Companies with iron ore production benefit from the economies of scale due to large-scale operations in iron ore mining. Furthermore, large-scale projects provide the opportunities to economically utilise advanced technology that may not be viable for small-scale mining operations. It is also noteworthy that gold mining companies had superior efficiency performance among mining companies in Australia. The advantage of gold mining in comparison to other mining activities relies on a high-skilled workforce, well-established operating processes and advanced technology utilised in gold mining operations in Australia.

The presented results in Chapter 6 from Model I showed a positive association between portfolio diversification and technical efficiency. However, this linkage was not confirmed under the Model II specifications. These results show that while diversification does not provide advantage in technical efficiency gain, it is an important business strategy in reducing costs and economic efficiency. It seems that diversification reduces the adverse effects of resource depletion on the economic performance of mining companies.

In terms of change effects, the results presented in Chapter 6 show that under both models, the direction of changes has a significant impact on the efficiency performance. In general, companies had higher efficiency during growth periods compared to their performance during downturns. This shows that mining companies are not agile enough to respond to negative changes in their production output by reducing their labour, capital and intermediate inputs. Further to direction change, the results revealed that any sharp growth or decline leads to misallocation of resources and inefficiency. These results show the efficiency challenge facing mining companies due to business environment changes such as extensive changes in commodity prices, regulations or quality and accessibility of natural resource inputs.

The results presented in Chapter 6 revealed that under both efficiency models ownership concentration positively drives the technical efficiency. The substantial shareholders have the power and incentive to monitor management performance resulting in better use of company resources and efficiency. While the higher ownership concentration improves the efficiency performance, the rights of minority shareholders needs to be protected by law to avoid any disadvantages to them resulting from substantial shareholders' colluding with business managers.

The results in this study showed no significant relationship between size and efficiency estimates from the general model of technical efficiency; however, under the natural resource-based model specifications, the results confirmed a significant and positive linkage. In addition to the advantage of larger mining companies in terms of economies of scale, they benefit from the utilisation of advanced technology and a skilled workforce which has been a severe challenge for small and medium-sized companies over the past two decades.

In relation to the association between age and technical efficiency, this study showed that younger firms are less efficient in comparison to their counterparts with more experience. Young firms suffer from the lack of essential knowledge, expertise and resources. Such challenges facing young and newly formed companies were more evident during the recent mining boom when a substantial number of companies entered the market in response to the increasing global demand for mineral commodities.

As presented in Chapter 6, this study's findings do not show a significant association between capacity utilisation and technical efficiency. Looking at the share of productive assets among mining companies, the results show that the asset composition does not seem to be a driving factor of efficiency. In other words, a larger share of productive assets does not mean mining companies perform better or worse.

In terms of financial risk association with technical efficiency, Model I did not show the significance of their relationship. However, the financial risk turned out to be influential on the efficiency performance under Model II specifications. That is, a higher leverage results in a lower technical efficiency. These findings illustrate the importance of financing in firm performance. As mining firms greatly rely on external funding, it is important to understand the short-term and long-term effects of financing (debt or equity) on their economic performance prior to such decisions. High levels of debt-financing may result in lower efficiency among mining companies.

The results from the stage-two analysis also show that the location of operations can determine technical efficiency performance. While the relationship between efficiency scores from Model I and location of operations was not significant, Model II showed the relationship at 0.1 significance level. These results confirm the solid strategic direction of major mining companies to expand their exploration and extraction activities to some projects beyond Australia. Through this international diversification of operations, mining companies leverage their organisational and technical capabilities to benefit from a new market and lower operating costs in host countries, leading to a higher efficiency performance.

This study included year-specific dummies to the econometric model of stage two to capture any significant exogenous effects unobserved in this study. The results from both models did not present significant effects along the period of study. Despite existing variations in the average efficiency performance over the period of study, the second-stage results confirmed the initial findings from the Freidman test on the mean ranks, displaying no differences among average efficiency scores over the period of study. These results also confirmed that the effects on the efficiency performance were largely captured by firm-specific factors of ownership concentration, firm size, firm age, product portfolio, financial risks, growth status and overseas operations.

8.4 Summary of Policy Recommendations

Analysis of estimated efficiency and identified determinants helps to derive the appropriate policy recommendations toward improving the efficiency performance of mining companies. This study suggested a set of policies and programs that support both mining businesses and government authorities to prioritise and introduce efficiency and productivity improvement initiatives in the mining industry. The recommended policy and programs have been derived from the key findings in efficiency estimation and the investigation of driving factors. Hence, recommendations in each policy area may not be necessarily linked and limited to only one investigated factor, but rather most recommended programs relate to several contributing factors of technical efficiency.

The results from this study strongly suggest the importance of human capital development. During the mining boom of the 2000s, a large number of newly formed companies entered the fast-growing market of mining and energy. The lack of required skills and expertise was among the main challenges facing mining companies, particularly young and small businesses. As a result, resource utilisation, especially the utilisation of advanced mining equipment suffered from a sizable inefficiency. Mining businesses and government policy makers need to learn from this experience and invest in human capital as an essential success factor in the industry. Frequent boom and bust cycles in the mining sector result in mismanagement and misallocation of resources and consequently low efficiency. Over the past few decades, investing in human capital has been mainly limited to the booming cycles. Mining companies need to think strategically toward long-term plans in human capital development. However, the challenge cannot be effectively managed without collaboration between the government, the mining industry and the education sector to develop sustainable programs that address the issues.

The results from this study showed that technical efficiency depends on the product portfolio. Being active in the mining of certain commodities provides benefits to the company in terms of technical efficiency. Moreover, diversification in product portfolio and operating locations supports the efficiency of mining companies. Hence, diversification in product and operating location needs to be prioritised by mining companies. Product diversification greatly reduces the risks associated with adverse commodity shocks and also provides the opportunity to use the under-utilised capabilities and resources across the broader mining range. The diversification in the location of operations and engagement in global projects furthermore helps mining companies to achieve lower operating expenses, resulting in higher profitability. A large number of small and medium-sized mining companies in the Australian mining sector are active in one or very few mining commodities. These companies mainly face productivity challenge. While it is not always possible for mining companies, particularly SMEs, to independently approach such a diversification strategy, through merging, joint venture and cooperation, mining companies can engage in a diverse set of projects, securing the sustainability and efficiency of their performance.

The first-stage analysis in this study showed the significant effects of natural resource inputs in efficiency performance. Ongoing resource depletion results in greater consumption of resources to maintain production output. Without any technological advancement, such effects will lead to a constant decrease in productivity in the mining sector. It seems that advancement in technology and innovation in mining operations are only solutions to overcome the increasing impact of resource depletion. Continued investment in research, innovation and technology advancement is required at both government and sector levels. Maintaining the existing advantages in the METS sector in Australia can be achieved through development in organisational capabilities as well as practical research and technology solutions.

This study showed that companies experience low efficiency during fast changes in their operating scale. The misallocation of resources is a main driver of poor efficiency and productivity in a changing environment. Unfortunately, mining and energy markets across the globe are highly vulnerable to severe price changes; therefore, such adverse effects are expected to be present in the future. The recent advancements in information technology have provided new opportunities for mining businesses to use data for real-time decision making. Hence, mining companies will be able to make timely decisions in response to various exogenous and endogenous changes. Developing the digital capabilities of mining companies may include the utilisation of artificial intelligence (AI), machine learning and robots in mine exploration and extraction operations. While the Australian mining companies have invested in digitalisation and information technology advancements which provided them the opportunity to collect a wide range of operational data, most mining managers expressed their concerns in relation to the lack of timely and reliable performance reports. Mining companies need to develop their capabilities in using data in the leadership decision-making process. Along with prioritising the development and execution of their digital strategy, mining companies need to move beyond data acquisition and rethink data analytics and data usage.

The findings from this study suggest that the economic sustainability of mining companies relies on their sustainability in growth and control of business risks. Such sustainability requires a long-term corporate strategy; however, mining companies mostly have been successful in the implementation of short-term and operational plans and have struggled to deploy long-term strategies. Hence, the development and deployment of long-term strategies need to be emphasised by mining companies. Such strategies should cover various critical dimensions including human capital, product portfolio, technology utilisation and digital transformation.

The success of implementing long-term plans relies on the mitigation of business risks. This study showed that financial risk can damage efficiency performance. Due to the fluctuations in production volume and values, higher leverage imposes higher risk to mining businesses. Hence, in relation to the financing direction, mining companies first need to evaluate and understand the short-term and long-term effects of financing – both types of debt and equity – on their economic performance.

Finally, mining businesses need to consider environmental accountability and social responsibility among their top priorities. Resource depletion and adverse effects of expansions in mining exploration and extraction activities can lead to severe environmental impacts. Local communities are also highly influenced by boom and bust in mining activities. Hence, mining companies need to obtain a social license to operate and maintain it over all stages of mining life cycle. The economic sustainability of the mining industry relies on its success in introducing effective environmental and social policy and programs. In recent years, environmental and social concerns have been incorporated among main policy and strategies of major Australian mining companies. It is essential to all mining companies to prioritise their environmental and social programs and collaborate with all stakeholders to implement them effectively. Technology advancement and boosting productivity can aid the mining industry to manage both domestic and global concerns in relation to environmental protection and social claims while supporting economic sustainability in Australia.

8.5 Contributions to the Literature

This thesis provides four major contributions to the existing literature on mining efficiency and productivity analysis. First, this study contributes to the literature through examining the efficiency performance of the Australian mining industry at the firm level during the period of 2009-10 to 2013-14. To this point, no study has examined the efficiency of Australian mining firms using frontier techniques. The detailed review of the existing literature in Chapter 3 showed that the conducted research on the efficiency and productivity analysis of the Australian mining industry is limited to some sector-level studies. Mining companies comprise the largest division on the ASX. Shareholders in Australia benefit substantially from the listed companies in this industry. Many people in Australian also benefit from direct or indirect employment due to the activities of these companies. Most social and economic developments in rural and regional Australia have been due to the mining activities commenced by these companies. Given the importance of mining businesses in the Australian economy, firm-level analysis complements the sector-level studies. It enables policy makers in government and the decision makers in mining businesses to better understand the relative economic performance of mining enterprises against best practices. Such a benchmarking approach in performance measurement assists mining companies in realising their efficiency gaps, learning from best practice and developing improvement programs.

Second, this work introduces a firm efficiency model accounting for the natural resource inputs. A major difference between resource sectors such as mining and other economic sectors is the role of natural resource inputs in the production process. In addition to the production inputs, such as capital, labour and intermediate inputs, the mineral deposits in their natural state contribute to the production of mining and mineral products. However, unlike other production inputs, the natural resource inputs are non-renewable. Hence, mineral production results in resource depletion over time. The consequence of such resource depletion is the consumption of a greater amount of labour, capital and intermediate inputs to maintain the same level of production output and value with a given technology. Sector-level and mine-level studies have discussed the resource depletion effects on productivity performance. Nonetheless, none of the firm-level studies in the literature have discussed the role of natural resource inputs in the efficiency performance of mining companies. While the ore quality and accessibility of deposits determine the production output of mines, it is also important to account for their role in the efficiency performance of mining companies. This study extends this concept to a firm-level analysis through introducing a natural resource-based model of technical efficiency.

Third, this study contributes to the existing literature through examining the determinants of efficiency using a second-stage regression. In addition to evaluating technical efficiency performance, it is important to identify the factors contributing to the firm's performance. This knowledge aids government and mining businesses to develop relevant policy to improve the efficiency of mining companies and mining sectors. The existing literature explains some driving factors behind changes in the efficiency and productivity of mining activities; however, the existing body of knowledge is unable to provide a comprehensive picture describing the causes of economic performance of the mining industry. Very limited studies have examined the contributing factors to mining efficiency and productivity. These studies have reviewed certain variables, though a much broader view is needed to help business management and policy makers in developing effective strategies to enhance mining industry performance. The firm-level studies in the literature have only discussed a handful of firm-specific factors such as ownership, size and age. As a first, this research explores the effects of factors such as portfolio diversification, product type, capacity utilisation, location of operations, financial risks and business stability in the context of mining firms' efficiency.

Finally, from a methodological perspective, this is the first study to employ a two-stage double bootstrap procedure to ascertain statistical significance of the determinants of technical efficiency in mining companies using a non-parametric set up. Despite recent methodological advancements in the application of mathematical programming approaches in efficiency measurement, particularly the statistical foundations in non-parametric techniques, the existing firm-level literature relies on purely deterministic techniques. The non-parametric methods of efficiency measurement do not account for the possibility of measurement error and natural randomness. As the frontier is constructed based on the extreme points in the observed data, the estimation of efficiency scores is highly sensitive to outliers. To overcome the limitation of the deterministic method of DEA in providing statistical inference of efficiency estimates, this study employs the bootstrap DEA technique proposed by Simar and Wilson (1998, 2000a). Thus, the error terms and the confidence intervals of efficiency estimates are calculated through procedures explained in Chapter 4 of this thesis. In addition to the first-stage analysis, this thesis revisited the application of second-stage analysis and applied a consistent regression technique in two-stage DEA. A major problem of the two-stage approach arises from the fact that if the input-output factors used in the first stage are highly correlated with the independent (explanatory) variables in the second-stage econometric model, the results are likely to be biased. Furthermore, as the efficiency scores are dependent on each other due to the nature of DEA problems, the basic regression analysis assumption of independency within the sample is violated. Simar and Wilson (2007) show that these dependency issues lead to invalid results from the OLS or the Tobit regression analysis. This study introduces the bootstrap truncated regression model proposed by Simar and Wilson (2007) to examine the effects of firm-specific factors on efficiency performance.

8.6 Research Limitations and Suggestions for the Future Research

This study analysed the efficiency of the Australian mining companies and attempted to identify the determinants driving technical efficiency performance. This study introduced several theoretical and empirical contributions to the limited literature on the efficiency analysis of mining enterprises. Nevertheless, this study is surrounded by several limitations offering potential work for future researchers.

This study looks at the efficiency performance of 34 major mining companies listed on the ASX. All companies in the sample were operational during the period 2009-10 to 2013-14. While companies in this sample contribute to around 90 per cent of the market capitalisation of mining companies on the ASX, the sample may not be representative of all active mining companies. Small and medium sized companies (SMEs), companies not being fully operational for the whole study period, companies in mine exploration and development phases, as well as non-listed companies are not suitably represented by the sample in this study. More than 600 mining companies are listed on the ASX, while other companies are privately owned and not listed in the securities exchange markets. Further research is needed to explore the efficiency of mining companies to include a broader sample or to focus on certain categories such as SMEs.

Furthermore, this study is limited to Australian mining companies. While half of the companies in the sample are operating in locations outside Australia, the sample cannot serve as the representation of the world's major mining companies. A cross-country study can help shed light on the underlying differences in efficiency performance and its determinants in different countries. Benchmarking the economic performance in the mining industry can benefit countries and communities across the globe to learn from the best practices in the most efficient ways of production from non-renewable mineral deposits.

In terms of efficiency modelling, this study looks at the technical efficiency of mining companies. The efficiency model is constructed using information from the annual reports. Hence, the choice of input/output variables was limited to the availability of data in financial statements. Moreover, the annual reports do not provide separate data for input and output volumes and their associated prices. This limits the investigation of economic efficiency, i.e. revenue, cost or profit efficiency. The agenda for further studies could include seeking other data sources in providing alternative input/output proxies as well as price information in conjunction with volume-based data. In addition, the study of mining companies' efficiency analysis can extend from the efficiency measurement to the analysis of efficiency, technology and productivity changes.

One of the main contributions in this study is the inclusion of natural resource inputs to the efficiency model of mining companies using a non-parametric set up. In this study, the effect of natural resource inputs was captured by constructing a measure based on exploration expenditure, i.e. the cost of resource depletion. To maintain the production volume or value, mining companies need to explore new mineral deposits. While such constructed variable seems to be a sound measure of resource depletion, it is only a proxy and may not function as a perfect substitute of unreported natural resource inputs. Following this initial work, further research is needed to find alternative and practical methods of resource depletion estimation in firm-level studies.

This study applied the mathematical programming approach in efficiency analysis using two-stage bootstrap DEA. The future research could consider the application of econometric techniques and the comparison of results with those from the mathematical techniques. The application of flexible functional forms and semiparametric, nonparametric and Bayesian techniques are among recent advancements in the econometric approach that can be employed in the efficiency analysis of mining companies in future research.

Finally, in the second-stage analysis, this study investigated the contribution of multiple firm-specific factors to the technical efficiency of mining companies. Future research can include a broader range of variables, potentially influencing the firms' efficiency. In addition to firm-specific factors, it is interesting to examine the macroeconomic and business environment factors in the second-stage modelling. The econometric modelling of the second stage can also extend beyond the truncated regression analysis employed in this study.

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