Image by nedu503 from Pixabay

Economic impact assessment (EcIA) is an essential part of a broader environmental impact assessment (EIA). While EIA is meant to help policy makers to decide whether the proposed project should be granted an approval to move forward, it is typically used for the information and not being determinative in decision making (Wood & Jones, 1997 & Cashmore et al., 2004). Jay et al. (2007) noted a growing dissatisfaction over the EIAs influence on approval decisions. There is a limited interaction between EIA and planning theory, reducing the efficiency of the EIA process (Lawrence, 2000). Furthermore, McDonald & Brown (1995) stated that providing passive advice to decision-makers is inefficient and ineffective, with EIA not leading to solutions. They emphasized the need of aligning EIA to policy and planning.

The problem is that EIA is not designed to stop bad projects, for several reasons including insufficient scope, vested interests, and poor governance, especially where development is equated with economic growth and jobs (Laurence & Salt, 2018). Fonseca & Gibson (2021) noted that projects are rarely rejected in EIA. For example, in Australia, only 18 projects out of 824 projects (2.2% of projects that required approval) have been denied environmental approval since 2000 (Milman & Evershed, 2015).

Economic policy is an important factor in regional development. In Australia, in general, mining is considered as an activity that brings prosperity to the regions. While the concept of the ‘economic base’, with its focus on export activities, is the most popular among the theories of regional development, most recent theories emphasise the importance of diversification, government intervention and investment in infrastructure, and education in order to facilitate economic growth and reduce regional uneven development (Hadjimichalis & Hudson, 2014 &, Alicja, 2009).

EcIA as a part of EIA can help select the projects that increase the long-term sustainable growth in regions (Williams, 2020). However, in practice, it is usually used to justify the project and reports mostly basic information such as employment and income. Regional sustainability and social equality can be measured using a range of indicators such as income distribution, but those indicators are rarely used in impact assessment. As a result, regional areas are often found to be behind South East Queensland metropolitan region in many socio-economic indicators including health, teenage unemployment, low educational attainment, and high domestic violence (Richards 2016, ABS 2021).

Measuring the efficiency of economic policy that is focused on expansion of mining activities (and therefore, mining project approvals) can play an important role in adjusting such policy and achieving improvements in regional performance. The variations among regions in terms of distance from the efficient benchmark can be identified by using data envelopment analysis (DEA). DEA[1] is a non-parametric technique that can be used to analyse the efficiencies of the regions where projects were approved and compare these regions to other regions in order to identify the best practice performance in the use of resources and to highlight where the greatest gains can be made from improvement in efficiency. Typically, regional infrastructure, and the population of a region are used as inputs, and income distribution, employment rate, labour productivity as outputs (Galiniene & Dzemydaite, 2012; Singh-Peterson et al. 2016 & Rabar, 2013). DEA allows social and economic impacts to be modelled in addition to environmental impacts, thus providing a comprehensive assessment of the proposed project at the regional level.

This paper illustrates the use of DEA with various socio-economic indicators to compare mining and non-mining regions efficiencies in Queensland (one of the mining states in Australia). Higher efficiency in mining regions would mean that the policy encouraging mining investments resulted in better utilised resources and higher outputs.

Queensland is the third largest economy in Australia but the average unemployment in Queensland local government areas (LGAs) was higher and mean wages lower than the national average in 2016-17 (ABS, 2019). The income distribution coefficients showed a large disparity in values among LGAs ranging from 0.18 to 0.42. Figure 1 illustrates the income for 2016 and change in coal mining employment in Queensland between 2006 and 2016.

The purpose of EIA in Queensland is to improve the information (often with recommendations) available to government resulting in the overwhelming majority of proposed projects being approved. One of the compelling reasons for approvals of mining projects is that they bring employment (figure 1) and relatively higher incomes to mining workers compared to other industries. That, though, can add to the already existing income inequality in the region. Income inequality is found to be associated with several negative socio-economic outcomes including age specific mortalities, smoking, violent crime, higher expenditure on medical care and police protection (Kaplan et al. 1996). Kawach et al. (1997) suggested that income inequality would result in fewer investments in social capital, while Hill et al. (2012) found a negative association between income inequality and employment resilience.

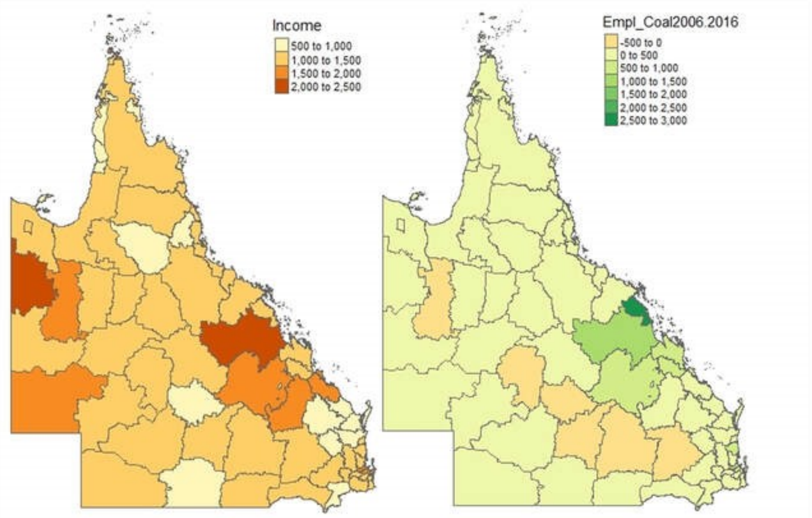

Figure 1. Income (Aus$/week) disparity in Queensland and change in coal mining employment (count of persons aged 15 years and over) in LGAs between 2006 and 2016.

In Queensland, economic impacts of mining outside of EIA process have been examined at local, regional and state levels (e.g. Williams & Nikijuluw, 2020a, 2020b; De Valck, et al, 2020; Rolfe et al, 2007). The overall results showed that the mining industry created both positive and negative impacts for regional Queensland. Importantly, once externality costs were included, the net present value of coal mining became negative while grazing and conservation options remained positive.

A typical DEA constructs the best practice production frontier [2], which is then used to evaluate relevant efficiency of different units (Farrell, 1957). DEA can have several inputs and outputs in the non-parametric analysis. LGAs are used as units of analysis. An LGA is considered to be inefficient if it generates less output than LGAs with similar resource endowment (Schaffer, et al, 2011). Inefficient LGAs can be thought of the ones that do not utilise resources fully and more focus should be directed to these regions to achieve more efficient outcomes [3].

Inputs and outputs for the study are chosen in line with the regional efficiency literature. This study focuses on income, unemployment, and selected socio-economic indicators such as housing affordability, percent of low-income families and the index of relative socio-economic disadvantage (IRSED) as outputs. In terms of inputs, variables that reflect the resource endowments have been used such as region-specific human capital and infrastructure. Contextual variables are used to account for heterogeneity in regions and include the share of mining and share of agriculture in an LGA's industry structure, population density, industry diversity and population over 65 years old. Summary statistics for the input, output, and contextual variables for the Queensland LGAs are presented in Table 1.

Table 1. Descriptive statistics of variables

	Variable	Mean	Std. Dev.	Min	Max
Inputs	Labour force, FTE	32,265	10,198	47	676,993
	Roads, km	1,950	176	18	7,526
	Secondary education, %	71	1.6	25	100
	Access internet, %	71	1.4	35	88
Outputs	Median family income, $/week	$1,401	$48	$678	$2,777
	Unemployment, %	11	1.2	2.3	50.0
	Low income, %	19.7	1.9	4.4	75.2
	Children in jobless, %	19.6	1.8	0.01	70.6
	Mortgage stress, %	7.3	0.9	0.01	66.7
	Rent stress, %	19.3	1.2	0.01	41.1
	IRSED	886	18	404	1,064
	Over 65 yo, n	8,797	2,389	13	140,681
Contextual variables	Share of mining, %	4.7	0.9	0.0	42.0
	Share of agriculture, %	13.1	1.5	0.0	49.0
	Population density, p/km^2	41.3	14	0.003	842
	Industry diversity, index	0.66	1.09	0.01	6.05

It is interesting to note that the higher percentage of employment in mining does not translate to the higher efficiency for all mining regions (Figure 2). That means that regions can be efficient in utilising their resources without reliance on mining. According to figure 2, some of the most efficient regions have very small percentage of mining employment compared to total employment in LGAs. On the other hand, there is a large proportion of non-mining regions with the efficiency less than average of 0.78. Mining regions tend to have a higher average efficiency (0.84) although not being the most efficient regions.

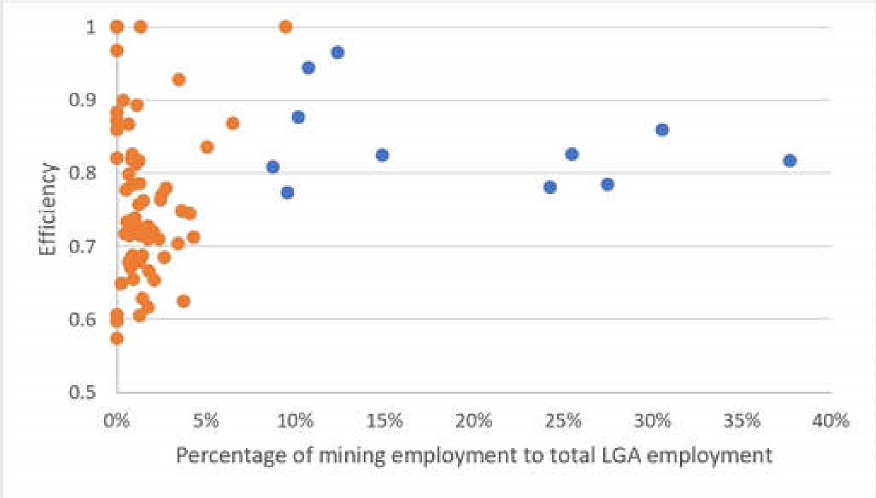

Figure 2. Productive efficiency and mining employment in Queensland LGAs, base model, (blue dots – mining LGAs).

The results of other models are similar to the base model: the efficiency of coal mining regions vary but tend to gravitate towards higher-than-average efficiency. Adding other socio-economic variables such as population density, and industry diversity does not change the mining regions' performance relative to other regions.

More research is needed to identify factors lowering non-mining regions' efficiency and learn from both mining and non-mining regions with higher efficiency.

It is important to note that mining regions were not the regions with the highest efficiency. Therefore, it would be incorrect to infer that all mining projects that bring employment and income to regions are necessarily improving regions' social and economic indicators and utilise resources efficiently. It is important to understand the factors that influence the regional efficiency discrepancy. The analysis using a regression of bias-corrected efficiency scores against a set of contextual variables shows that industry diversity has a highly significant (at 1% level) positive influence on regional efficiency. That is not a surprising result as industry diversity is widely considered a pre-requisite for regional sustainability. Mining share in total employment is not statistically significant, while share of agriculture in the total employment had a positive effect on efficiency and is statistically significant at the 5% level. The proportion of elderly people in the population has a significant negative effect on efficiency. On the other hand, neither population density nor income distribution have a significant effect on efficiency.

The results indicate that policy aimed at growth of a particular sector such as mining does not necessarily improve efficiency of those regions compared to non-mining regions. Further research and more in-depth analysis are needed to understand the reasons behind low performance in some non-mining regions and how to improve efficiency of other regions exposed to the long-term economic policy aimed at growing mining industry.

This example illustrates the importance of a thorough examination of the socio-economic impacts beyond reporting the employment and income from the project during the impact assessment process. Future research can investigate more variables affecting regional development to assist with designing economic policy which is used for conducting EIAs. For example, more socio-demographic variables such as crime rates, hospital admissions, literacy can be used in order to evaluate regional performance. The overall strategic planning should take into account potential negative consequences of reliance on one industry using inputs from various impact assessments. Policy makers can use this approach to refine economic policy to improve regional efficiency.

Notes

[**1**] DEA is used to measure productive efficiency of decision-making units (DMUs). Since it is a non-parametric method, it does not require ex-ante specification of a production or cost-function and, therefore can compare efficiency based on input and output combinations. Most efficient DMUs (eg. those that maximise outputs with given inputs) form the production frontier against which the rest of DMUs is compared.

[**2**] The efficiency is calculated for each DMU as a ratio of the sum of its outputs to the sum of its inputs. Each DMUs efficiency score is calculated relative to an efficiency frontier. Those firms with score less than 100% have the capacity to improve their performance. DMUs located on the frontier are used as benchmarks (Huguenin 2012).

[**3**] This paper uses output-oriented, variable returns to scale DEA model to assess regional performance. The LGAs are assumed to maximise the outputs while holding inputs constant. For example, in the base model, LGAs are assumed to maximise median income and minimise unemployment using available labour force and infrastructure. To adjust for the extreme values the bias-corrected efficiency scores are calculated using contextual variables. This method yields robust and consistent results (Kneip, et al, 2003 & Simar & Wilson, 1998).

References

ABS. (2019). *Labour force*. Retrieved from Australian Bureau of Statistics, Canberra, Australia

ABS (2021). Census of Population and Housing, General Community Profile. Retrieved from Australian Bureau of Statistics, Canberra, Australia

Alicja, S.-W. (2009). Theories of Regional and Local Development - Abridged Review. *Bulletin of Geography. Socio-economic Series, 12*, 75-90. doi:10.2478/v10089-009-0005-2

Cashmore, M., Gwilliam, R., Morgan, R., Cobb, D., & Bond, A. (2004). The interminable issue of effectiveness: substantive purposes, outcomes and research challenges in the advancement of environmental impact assessment theory. *Impact Assessment and Project Appraisal, 22*(4), 295-310.

De Valck, J., Williams, G., & Kuik, S. (2021). Does coal mining benefit local communities in the long run? A sustainability perspective on regional Queensland, Australia. *Resources Policy, 71*, 102009. doi:https://doi.org/10.1016/j.resourpol.2021.102009

Farrell, M. (1957). The Measurement of Productive Efficiency. *Journal of Royal Statistical Society, 120*, 253-281.

Fonseca, A., & Gibson, R. B. (2021). Why are projects rarely rejected in environmental impact assessments? Narratives of justifiability in Brazilian and Canadian review reports. *Journal of Environmental Planning and Management, 64*(11), 1940-1962. doi:10.1080/09640568.2020.1852073

Hadjimichalis, C., & Hudson, R. (2014). Contemporary Crisis Across Europe and the Crisis of Regional Development Theories. *Regional Studies, 48*(1), 208-218. doi:10.1080/00343404.2013.834044

Huguenin, J. (2012). Data Envelopement Analysis (DEA). A pedagogic guide for decision makers in the public sector. IDHEAP, Lausanne, pp.81.

Jay, S., Jones, C., Slinn, P., & Wood, C. (2007). Environmental impact assessment: Retrospect and prospect. *Environmental Impact Assessment Review, 27*(4), 287-300. doi:https://doi.org/10.1016/j.eiar.2006.12.001

Kneip, A., Simar, L., & Wilson, P. W. (2003). *Asymptotics for DEA estimators in non-parametric frontier models*.

Laurence, W., & Salt, D. (Producer). (2018, 6 March 2023). Environmental impact assessments aren't protecting the environment.

Lawrence, D. P. (2000). Planning theories and environmental impact assessment. *Environmental Impact Assessment Review, 20*(6), 607-625. doi:https://doi.org/10.1016/S0195-9255(00)00036-6

McDonald, G. T., & Brown, L. (1995). Going beyond environmental impact assessment: Environmental input to planning and design. *Environmental Impact Assessment Review, 15*(6), 483-495. doi:https://doi.org/10.1016/0195-9255(95)00077-1

Milman, O., & Evershed, N. (Producer). (2015). Australia has denied environmental approval to just 18 projects since 2000.

Rabar, D. (2013). Assessment of regional efficiency in Croatia using data envelopment analysis. *4*, 76-88. Richards, L. (2016) Challenges to children's well-being in CQ, Health Implications, *Central Queensland Hospital and Health Services,* http://www.livewellcq.org/wp-content/uploads/2015/04/ecdec-presentation_len-richards_health-impacts-of-health-indicators-v3.pdf

Rolfe, J., Miles, B., Lockie, S., & Ivanova, G. (2007). Lessons from the Social and Economic Impacts of the Mining Boom in the Bowen Basin 2004-2006. *The Australasian Journal of Regional Studies, 13*(2), 134-153. Retrieved from https://search.informit.org/doi/10.3316/ielapa.982752523628612

Schaffer, A., Simar, L., & Rauland, J. (2011). Decomposing Regional Efficiency. *Journal of Regional Science, 51*(5), 931-947. doi:10.1111/j.1467-9787.2011.00731.x

Simar, L., & Wilson, P. (1998). *Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models*. Retrieved from https://EconPapers.repec.org/RePEc:cor:louvrp:1304

Williams, G. (2020). Future potential of economic impact assessment. *Impact Assessment and Project Appraisal, 38*(4), 272-277. doi:10.1080/14615517.2019.1684097

Williams, G., & Nikijuluw, R. (2020a). The economic and social benefit of coal mining: the case of regional Queensland. *Australian Journal of Agricultural and Resource Economics, 64*(4), 1113-1132. doi:https://doi.org/10.1111/1467-8489.12401

Williams, G., & Nikijuluw, R. (2020b). Economic and social indicators between coal mining LGAs and non-coal mining LGAs in regional Queensland, Australia. *Resources Policy, 67*, 101688. doi:https://doi.org/10.1016/j.resourpol.2020.101688

Wood, C., & Jones, C. E. (1997). The effect of environmental assessment on UK local planning authority decisions. *Urban Studies, 34*(8), 1237-1257.