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Deregulation, efficiency and policy determination: An analysis of Australia's electricity distribution sector

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ABSTRACT

In 1998, the Australian electricity distribution was deregulated with the aim of promoting competition and reducing retail prices. However, since then these outcomes have not transpired, which raises the question of whether there may be underlying causes leading to inefficiencies within the power distribution industry. To assess the performance of the electricity distribution system and sources of (in)efficiency since deregulation, we employ Simar and Wilson's (2007) double bootstrap data envelopment analysis truncated regression approach. The results suggest that most distributors were operating well below efficient levels for the period concerned. In the second-stage analysis, the results indicate that reliability promotes efficiency suggesting that a focus should be placed on the continuous supply of energy. Specifically, inefficient distributors can improve network reliability by replacing aged poles and the expansion of market size could encourage healthy competition.

1. Introduction

Australia's National Electricity Market (NEM) covers the east and south-eastern states of Queensland, New South Wales, Victoria, South Australia, Tasmania and the Australian Capital Territory. It was developed during the 1990s to create competitive wholesale and retail electricity markets, and to raise the productivity and efficiency of regulated monopoly networks through increased output and lower prices. For most of the NEM's first 20 years of operations, wholesale and retail markets performed well. Of considerable interest to policymakers, however, had been the performance of regulated monopoly networks (see, for example, Mountain and Littlechild 2010; Simshauser and Akimov 2019). A series of material policy changes including a tightening of reliability standards in two NEM jurisdictions in 2005 led to sizable increases in the capital stock and associated resourcing (Simshauser 2014). These policies remained in force until the early 2010s when it became clear that i). demand was contacting due to the rising uptake of solar PV and energy efficient appliances, and ii). the tightened standards were beginning to drive sharp increases in network tariffs. Our interest is therefore in analyzing sectoral performance during and after these policy changes.

At a retail level, price controls in Victoria were removed in 2009, in South Australia in 2013, in NSW in 2014, and in South East Queensland in 2016. Throughout much of this period however, regulated network charges increased. Thus, even with the introduction of competition, retail-level electricity prices still rose (Wood et al. 2013). As noted by the ACCC (2018, p. 155), "….network, environmental and retail supply chain costs all make a significant contribution to electricity prices faced by consumers". These price rises related to regulated networks and to the multi-billion outlays on infrastructure, some of which may have been made redundant due to falling consumption. Higher prices exacerbated falling consumption with consumers switching to alternative sources that were cheaper, such as rooftop solar PV (Abban and Hasan 2020), and more energy efficient appliances (Swinson et al. 2015). Importantly, contracting demand for electricity in Australia had not, overall, led to falling electricity prices. This has been blamed on the high level of expenditure on electricity infrastructure - namely the poles, wires and substations. Under these conditions, all stakeholders within the electricity industry - especially within the distribution network – have had to improve their management efficiency in order to operate effectively.

For their part, regulated network utilities claimed rising expenditure was justified, given the ageing infrastructure – poles, wires and substations require high levels maintenance or replacement which leads to rising costs and Regulatory Asset Base. Other costs include fixing faults and damaged power lines due to severe storms and bushfires which might have otherwise caused supply outages. In addition, there are

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repairs to related infrastructure such as electricity meters that are located at every house and business all of which add to costs. These issues raise a key concern over whether the electricity distribution networks are operating efficiently.

However, under the regulatory environment network businesses are regulated monopolies and therefore not subject to usual market forces (Wood et al. 2013; Productivity Commission, 2013). There are a number of inefficiencies that have developed within the electricity network which have been discussed in detail, for example, by Simshauser (2019) and Simshauser and Akimov (2019) and others, but not determined using distribution network data to provide evidence of the extent of the problem while also identifying some of the causes. The purpose of this article is to rectify this void in the literature. In doing so we also highlight some of the dilemmas that exist, and various issues that policy decision makers need to consider while making systems more efficient and also keeping electricity retail prices low at a time when behind-the-meter substitutes are becoming widely available and affordable.

With this in mind, this article examines to what extent electricity distribution networks have been efficient in Australia's NEM jurisdictions. For this purpose, a Data Envelopment Analysis (DEA) approach is adopted using panel data for the period, 2009–2019 representing 14 electricity distribution network businesses which cover the entire NEM plus Australia's Northern Territory and determine the sources of (in)efficiency.

Our analysis confirms that many of the distributors are operating below required efficient levels. The individual distributors are identified. The results show that, except for years 2013 and 2015, more than 70% of distribution network businesses were operating inefficiently. One of the key sources of inefficiency was the reliability of distribution. However, addressing this issue while reducing inefficacy in distribution requires the allocation of even more resources which will ultimately reach a point of being counter-productive – an issue analysed in prior work in the field (see, for example, Simshauser, (2019); Simshauser and Akimov (2019). The results of the DEA highlight the dilemmas that exists in Australia's distribution networks. The work raises the question of whether Australia's incentive-based regulation system is suitably framed. On the one hand, inefficient distributors can improve the reliability of their network by allocating capital and operating costs where needed, and not before it is needed, to improve efficiency and sustainability of the network. Also, given an increasing number of customers is shown to improve efficiency, it suggests a larger coverage could induce better results (e.g. consolidations, mergers and acquisitions of these regulated monopolies, as was done in Queensland during 2017). Growth in demand for grid-supplied electricity has not been strong during the preceding decade, but electricity prices have remained elevated (save for cost-of-capital induced step reductions in network tariffs). Consequently, elevated tariffs encourage end-users to seek cheaper behind-the-meter (partial) substitutes. On the other hand, and as one reviewer noted, an output-based regulatory framework may better target improvements in service quality. However, this does not necessarily solve issues related to delivering cheaper retail-level electricity and maintaining a stable level of grid-supplied consumer demand. These issues are not restricted to Australia. As many countries witness a surge in renewable energy and see the need for network restructure and become more efficient, this article provides valuable insights to the issues that are faced by electricity regulators and policy decision-makers around the world. There are lessons to be learnt and some pitfalls to avoid.

The remainder of the article is organised as follows. Section 2 provides a brief background to the NEM. Section 3 presents the methodology and a review of the literature on its application to the electricity industry. Section 4 describes and discusses the data and explains the reasons for choosing the inputs and outputs. Section 5 presents a discussion of the results and sources of inefficiencies leading to policy recommendations. Section 6 concludes with a summary of the main findings and future possible research extensions based on findings of this study.

2. Background to the NEM

Prior to the 1990 reforms, vertically integrated monopoly electricity utilities were public assets built-up within state boundaries. *State Electricity Commissions* were non-taxpaying entities, responsible to their State Government owners vis-à-vis system planning, investment, system operations, reliability of supply and tariffs. As with many vertical utilities around the world, during the 1980s and early-1990s the status of the monopoly power generation industry in South-Eastern Australia was bordering on critical due to excess capacity. Microeconomic reform of Australia's power industry can be traced back to 1991 when the Commonwealth Government initiated a national inquiry via one of its economics agencies, the Productivity[1] Commission. Australia's east-coast electricity market was progressively deregulated (Nelson et al. 2019). What evolved was a recommendation to restructure, deregulate and establish a 4-state interconnected grid covering east and south-eastern Australia; viz. Queensland (QLD), New South Wales (NSW), Victoria (VIC) and South Australia (SA). The island state of Tasmania (TAS) would later be interconnected by an undersea HVDC cable. Western Australia and the Northern Territory could not be connected due to geographical distances.

There were four key steps to reform:

1. State-owned monopoly Electricity Commissions were 'corporatised' (i.e. commercialised). These entities became businesses incorporated under Australian Corporations Law, were given a commercial mandate and profit motive, and subsequently exposed to a taxation equivalence regime.
2. Corporatised monopoly utilities were then vertically restructured into three segments; generation, transmission and distribution/retail supply, within existing state boundaries. This corporatisation process proved to be a critical step in levelling the playing field and removing any residual unfair advantage that would otherwise exist.
3. Competitive segments of generation and retail supply were horizontally restructured into a number of rival entities within each region. Transmission and distribution networks, as natural monopolies, would be subject to economic regulation. The form of regulation would be based on Littlechild's (1983) incentive-based *RPI-X*.
4. Some businesses were privatised but the timing of this final stage varied considerably across NEM due to regional political agendas.

3. Methodology

3.1. Data envelopment analysis

Data envelopment analysis (DEA) was developed by Charnes, Cooper and Rhodes (CCR) (Charnes et al. 1978) under the assumption of constant returns to scale (CRS) and later modified by Banker, Charnes and Cooper (BCC) under the variable returns to scale (VRS) assumption in 1984 (Banker et al. 1984). It builds on the frontier efficiency concept first elucidated in Farrell (1957). It is a non-parametric method that measures the efficiency of decision-making units (DMUs) and does not require the specification of a specific functional form relating inputs to outputs or the setting of weights for the various factors. DEA thus optimizes for each observation an efficient frontier either based on an input-oriented measure or output-oriented measure. For a general overview of DEA, see Coelli et al. (2005).

We employ both CRS and VRS DEA models and assume an input-orientation model. The output CRS DEA model (CCR model) is expressed as:

$$\hat{\theta}_i = \max_{\hat{\theta},\lambda}\left\{\theta_{i0} > 0|\hat{\theta}_i y_i \sum_{i=1}^{n} y_i\lambda; x_i \geq \sum_{i=1}^{n} x_i\lambda; \lambda \geq 0\right\} \tag{1}$$

[1] The Productivity Commission was actually then known as the Industry Commission.

where y_i is a vector of outputs, x_i is a vector of inputs and λ is an I x 1 vector of constants. The value obtained for $\hat{\theta}_i$ is the technical efficiency (TE) score for the *i-th* DMU. A measure of $\hat{\theta}_i = 1$ indicates that the DMU is technically efficient, whereas it is inefficient if $\hat{\theta}_i < 1$. This linear programming problem must be solved *n* times, once for each DMU in the sample. To obtain the VRS DEA model (BCC model), we simply impose the convexity constraint, $\Sigma\lambda_0 = 1$ (i.e. sum of the intensity variables, λ's, equal to one). The BCC model is expressed as:

$$\hat{\theta}_i = \max_{\hat{\theta},\lambda}\left\{\theta_{i0} > 0 | \hat{\theta}_i y_i \sum_{i=1}^{n} y_i\lambda; x_i \geq \sum_{i=1}^{n} x_i\lambda; \sum_{i=1}^{n}\lambda = 1; \lambda \geq 0\right\} \quad (2)$$

In this study, we employ an input-oriented model under both CRS and VRS to derive TE scores. Studies such as Çelen (2013) and Arcos-Vargas et al. (2017); and the literature reviewed in their studies noted that the input-oriented model was most widely used. As pointed out by Jamasb and Pollitt (2003), an input-oriented specification is appropriate because demand for distribution network services is a derived demand that is beyond the control of utilities.

3.2. Application of DEA in the electric power industry literature

The literature on the use of DEA in measuring energy (including electricity) and environment is substantial and has been extensively reviewed in Mardini et al. (2017) and Sueyoshi et al. (2017).[2] We describe below some of the findings from these two articles and more recent articles (2017 to 2020) in order to illustrate and specify our model.

The use of DEA is widely used in international studies. Yunos and Hawdon (1997) compared Malaysia's electricity generation with Thailand and United Kingdom using DEA and the Malmquist productivity index. Output data consisted of electricity generated and inputs including installed capacity, labour, electricity losses and thermal efficiency. In another study, Lam and Shiu (2001) used DEA to measure the TE of China's thermal power generation for 1995 and 1996. Inputs are capital (measured in terms of installed thermal generating capacity in megawatts (MW); fuel consumption (coal, oil and gas aggregated and measured in terajoules (TJs)); and labor inputs in terms of number of workers employed in thermal power generation. Output is electricity generated. Chen (2002) measured the TE and cross-efficiency in Taiwan's electricity distribution sector for the period 1997 and 1998 using DEA. The inputs employed are labor, capital equipment (comprising distribution networks and transformers) and general expenses. Output comprises the number of low voltage electricity customers, the number of high voltage electricity customers, low and high voltage electricity supply (MWh). Pacudan and de Guzman (2002) also employed DEA to measure the efficiency of electricity distribution of 15 utilities in the Philippines for the year 1996. Their inputs were comprised of the number of employees, circuit km of network lines and network losses (in GWh). Outputs included the number of customers, service area and electricity sales (in GWh). Korhonen and Syrjanen (2003) used DEA to measure cost efficiency of Finnish electricity distribution. Inputs comprised operational expenditure and cost of capital; outputs comprised distributed energy and quality. Nemoto and Goto (2003) used a DEA dynamic framework to measure the efficiency of 9 electric power production plants in Japan between 1981 and 1995. Inputs comprised variable inputs, fuel and labour. Quasi-fixed inputs were comprised of generation plants, transmission facilities and distribution facilities. Outputs comprised amounts of MWh sold to commercial and industrial use and electricity sold for residential use. Vaninsky (2006) employed DEA to measure United States (US) electricity power generation for the period 1991 to 2004. The outputs comprised utilisation of net capacity and inputs comprised operating expenses and energy loss. Ajodhia (2010) employed DEA to measure efficiency performance of UK and the Netherlands electricity distribution. Inputs comprise total expenditures and customer minutes loss (CML). Outputs comprise energy delivered and the number of consumers.

Besides the use of DEA, some studies included variations of DEA and other complementary models. Sueyoshi and Goto (2001) used slack-adjusted DEA modelling to examine the performance of 10 electric power generation companies in Japan between 1984 and 1993. They employed three inputs - the amount of total fossil fuel generation capacity measured by megawatts, the amount of total fuel consumption (oil, coal, and gas) and the total number of employees working in these fossil fuel plants. Output consisted of the total power generation (GWh) from these plants. Omrani et al. (2015) employed a combination of principal component analysis and DEA to evaluate efficiency of electricity distribution companies in Iran. Inputs comprised transformer capacity (MVA), number of transformers, terrestrial network length, aerial network length, number of employees and area. Outputs comprised energy delivery (MkW), energy consumption of other customers, industrial energy consumption, household energy consumption, number of other customers, number of industrial customers, number of household customers and number of lights of street lighting. Tavassoli et al. (2015) employed a slacks-based measure, strong complementary slackness condition, and discriminant analysis DEA approach to rank electricity distribution companies in Iran. Inputs comprised number of employees, transmission capacity (MVA) and network length. Outputs comprised unit delivery (MWh) and service area (km2). Bongo et al. (2018) employed conventional DEA and super-efficiency DEA to measure the efficiency of an electricity distribution utility in Philippines. The input indicators considered were purchased electricity supply and total length of power lines. Outputs were electricity consumed, number of consumers, and total power losses.

Some studies incorporated bad outputs in the DEA model to assess environmental efficiency. Seifert et al. (2016) employed a metafrontier DEA to measure the performance of the German electricity generating sector. Inputs comprised capital, fuel and labour. Outputs comprised energy output (good output) and CO_2 output (bad output). Bigerna et al. (2019) employed a two-stage DEA and Malmquist productivity model to measure the environmental and energy efficiency performance of the electricity industry of 19 European Union countries. Inputs comprised electrical capacity, input fuels and employment. Outputs comprised good outputs (electricity generation or output measured by total net production) and bad outputs (greenhouse gas emission). Their study also included a regression analysis using explanatory variables such as the overall regulatory index for the electricity sector and environmental policy stringency. Monastyrenko (2017) employed DEA and Malmquist-Luenberger productivity indexes to measure the eco-efficiency of European electricity producers in 2005–2013. The input indicators considered were total installed capacities involved in electricity generation (MW) and total operational expenditures. Outputs were physical amounts of generated electricity (TWh) and total CO_2 emissions from electricity generation.

There are also studies that included a regression analysis to determine sources of (in)efficiency. Besides Bigerna et al. (2019) as described earlier, Saastamoinen et al. (2017) employed DEA to assess the performance of Norwegian electricity distribution from 2004 to 2012. The input indicator is total cost. Outputs are the number of customers, the length of high voltage (HV) lines and the number of network stations. Environmental variables include geo1 and geo 2 which relates to the operating environment, distance to road, forest and share of underground lines in the HV network. Bobde and Tanaka (2018) employed a two-stage DEA with bootstrap estimation to examine the efficiency of electricity distribution utilities in India from 2005 to 2012. Inputs comprised number of employees, distribution line length, transformer capacity and total assets. Outputs comprised number of customers and electricity delivered. Environmental variables for the second stage comprised the tariff ratio, consumer structure, population density, ownership and

[2] Their analysis considers impacts of technology heterogeneities on electricity production (i.e. at the electricity generation stage). Our analysis focuses exclusively on distribution networks.

subsidy. Zhao et al. (2018) employed a three-stage DEA model to assess the operational efficiency of the Chinese Provincial Electricity Grid. Inputs comprised number of employees, fixed assets investment, 110 kV and below distribution line length and 110 kV and below transformer capacity. Outputs comprised electricity sales, number of customers and line loss rate. Environmental variables for the regression analysis comprised GDP per capita, proportion of the second industry added value in GDP and urbanization rate.

Most recently, Navarro-Chávez et al. (2020) employed a network DEA to measure efficiency of the electricity sector of Mexico for the period 2008–2015. They identified four nodes (generation, transmission, distribution and sales) in the network DEA. In node 1 generation, the inputs - plant capacity and the number of electricity generating units - produces the output - electric power generated. Electric power generated in node 2 (transmission) becomes an input and is transmitted via transmission lines (another input) to produce transmitted electric power (the output). The transmitted electric power becomes an input in node 3 and is distributed via inputs (distribution lines and transformation capacity). The distributed electric power becomes an input and together with the number of employees (another input) in node 4 is sold (the output) to customers.

In the case of Australia, there are only a handful of studies using DEA. Zhang and Bartels (1998) used DEA to measure the efficiency of Queensland and NSW electricity distributors. Inputs included the number of employees, total kilometres of distribution lines and total transformer capacity. Output is measured in terms of the total number of customers served. London Economics (1999) assessed the efficiency and productivity performance of NSW electricity distributors using DEA. The inputs were comprised of total operations & maintenance (O&M) expenditures, route kilometres and nameplate transformer capacity. Outputs included total energy delivered, total number of customers and peak demand (measured in MW). Abbott (2006) used the Malmquist productivity (DEA approach) to estimate productivity change of the Australian electricity supply industry from 1969 to 1999 between states. The study used aggregated inputs such as capital stock, energy and labour employed. Outputs were measured in terms of the amount of electricity consumed. The Australian Energy Regulator (AER) (2016) measured the efficiency of 13 electricity distribution network service providers (DNSPs) in the NEM using a TFP index approach. Inputs included operating expenditure and capital stock. Outputs comprised the number of customers, circuit line length, maximum demand, energy delivered and reliability. In addition, the AER (2016) measured the efficiency of five DNSPs in the NEM using the TFP index approach. Inputs included operating expenditure and capital stock. Outputs comprised the line length, energy transported, maximum demand (quantity specified), voltage of entry and exit points and reliability.

The literature above essentially employs DEA and satisfies the model specification of input-output production. Some studies focused only on the transmission process whereas others focused on the distribution component. The only study that focused on the entire network was Navarro-Chávez et al. (2020). With regards to examining sources of (in)efficiency - of particular interest to policy makers - only a handful of studies have attempted this. This study focuses on determining sources of (in)efficiency among Australian electricity distribution networks and provide recommendations for improvement.

3.3. Second-stage – bootstrap regression

DEA, however, has some limitations. There is no error term in DEA suggesting that mismeasurement and misspecification errors are included in the efficiency estimates. DEA scores also provide no conventional measures of statistical significance owing to its nonparametric nature. To overcome this problem, Ray (1991) and Coelli et al. (2005) suggested the use of a two-stage analysis, whereby the first stage derives efficiency estimates, and the second stage performs a regression analysis on the efficiency estimates.

By their nature, DEA efficiency scores are bounded at unity from above, thereby making them a limited dependent variable (McDonald 2009; Ramalho et al. 2010). Econometric modelling of bounded dependent variables—especially non-binary variables with a significant number of observations at the extremes—becomes a challenge because it makes the application of standard linear models inappropriate. The use of logit and probit models - given their strong distributional assumptions for the underlying population - provides only a limited approach to solving the problem. Tobit regressions, on the other hand, are appropriate when the dependent variable is limited either above or below, but is unbounded elsewhere (Ramalho et al. 2010). Simar and Wilson (2007) argued that numerous studies suffer from the problem of serial correlation. That is, these studies adopt a two-stage approach and regress DEA scores on covariates (i.e. environmental variables) without considering an appropriate data generating process. Hence, direct regression analysis is invalid owing to the dependency of the efficiency scores.

To overcome this problem, they proposed an alternative estimation and statistical inference procedure based on a double-bootstrap approach. We employ this approach in our analysis.[3] The novelty of the second-stage bootstrap regression is that the approach allows one to omit the nondiscretionary inputs from the initial DEA and introduce them in sequential non-DEA stages as proposed by Ray (1991) and Mũniz (2002). In doing so, one can explicitly identify environmental variables that would allow policy makers to address. If nondiscretionary variables were incorporated in the first stage DEA, the results will not provide sufficient information for policy-makers to work with. In addition, the second-stage bootstrap regression of Simar and Wilson (2007) is a novel approach because it performs bootstrap replications to increase the sample size (for example $n = 2000$) and provides statistical inferences in the form of confidence intervals. This is especially useful for studies with small sample size such as the current study. Nonetheless, Simar and Wilson's (2007) DEA bootstrap approach is only applicable for cross-sectional data and hence we employed DEA on each year. While one could attempt using multi-factor productivity such as Malmquist, it is proven by O'Donnell (2011, 2014) that Malmquist is multiplicatively incomplete and fails the transitivity property. Alternatively, one could employ the Färe-Primont productivity index, which satisfies all economically-relevant axioms in the index number theory (O'Donnell, 2011, 2014). Incorporating Simar and Wilson's (2007) bootstrap regression within the Färe-Primont productivity index framework is a worthwhile task but would have to be a future endeavour due to the magnitude of research to be undertaken.

By combining DEA with bootstrapping techniques, we successfully generate a set of bias-corrected estimates of the DEA efficiency scores (denoted $\widehat{\widehat{\theta}}_i$) and confidence intervals that help resolve this problem. In the second stage of our analysis, we regress the bias-corrected efficiency scores derived from the bootstrap algorithm on a set of environmental variables using the following regression model:

$$\widehat{\widehat{\theta}}_i = a + Z_i\delta + \varepsilon_i, i = 1, \ldots, n \tag{3}$$

where $\varepsilon_i \sim N(0, \delta_\varepsilon^2)$ is an error term with left-truncation at $1\text{–}Z_i\delta$, a is a constant term and Z_i is a vector of specific variables for school i expected to influence school efficiency. Simar and Wilson (2007, 2011) detail the bootstrap truncated regression algorithm, which is also described step-by-step in Barros and Assaf (2009). For brevity sake, we refer the interested reader to these studies for details.

We use the software package rDEA version 1.2–4 developed by Simm and Besstremyannaya (2016) to carry out the DEA and double-bootstrap estimations.

[3] Hoff (2007), Simar and Wilson (2007, 2011), McDonald (2009) and Ramalho et al. (2010) review the various models used for explaining efficiency scores using regression analysis.

4. Data

The data used for deriving efficiency scores are drawn from the AER website https://www.aer.gov.au/networks-pipelines/network-performance. Benchmark efficiency comparisons for 2009 to 2019 are based on data from the Electricity network performance report 2020, the respective distributors' Economic benchmarking RIN-Templates response documents and Category Analysis RIN-Templates response documents for age of poles. As noted by Economic Insights (2014), the AER's economic benchmarking RIN data provides the most consistent and thoroughly examined DNSP dataset yet assembled in Australia. We use panel data for fourteen electricity distributors (the entire NEM and Northern Territory), shown in Table 1 covering the period 2009–2017. The study does not include Western Australia (WA) due to data limitations.

4.1. Inputs and outputs

The definition of inputs and outputs used in this study follow those adopted by annual benchmarking reports and are defined below. The input variables used are Operating Expenditure (OpEx), x1, the network capacity measured in mega volt amp (MVA), x2, and the length of the distribution line in km, x3. OpEx is expenditure on operating and maintaining a network. Network capacity is the total amount electricity which is converted from the high voltage transmission network into medium and low voltages and transport electricity from points along the transmission lines to residential and business customers. These inputs are then used to deliver electricity via electrical cables. Hence, we identify one output – electricity delivered in GWh, denoted by y1. A review of 20 benchmarking studies by Jamasb and Pollitt (2001) showed electricity delivered and number of customers were two outputs widely used. We adopted electricity delivered as an output because it satisfies our production model. However, we argue that number of customers, as an output, is more likely to be determined by factors such as price, which are not included in our input set. This suggests that the production model of price "producing" numbers of customers is not directly related to the production model of OpEx.

Besides determining the input and output in the production model, there is also the issue of determining the number of inputs, outputs and DMUs. As noted in Sarkis (2007), the choice and number of inputs and outputs and DMUs determines the quality of discrimination that can exists between efficient and inefficient firms. Table 2 presents a select list of studies that recommend a rule of thumb regarding the minimum number of DMUs required in order for the analysis to provide sufficient discrimination.

Cook et al. (2014, p. 2) however argue that "such a rule is neither imperative, nor does it have a statistical basis, but rather is often imposed for convenience". Nonetheless, they feel that it is still important to consider all relevant inputs and outputs for DEA studies. As our model considers 3 inputs, 1 output and 14 DMUs, it therefore satisfies the minimum condition in the studies listed in Table 2 and the condition that the productivity model should provide sufficient discrimination.

Table 1
Distributors in the NEM and Northern Territory.

Region		Distributors
ACT/NSW	1	Evoenergy
	2	Endeavour Energy
	3	Essential Energy
	4	Ausgrid
QLD	5	Energex
	6	Ergon Energy
SA	7	SA Power Networks
VIC	8	CitiPower
	9	Powercor
	10	United Energy
	11	Jemena
	12	AusNet Services
TAS	13	TasNetworks
NT	14	Power and Water

Table 2
Select studies and the rule of thumb.

	Rule of thumb	Min. no. of DMUs
		$(x = 3, y = 1)$
Boussofiane et al. (1991)	$X \times Y$	3
Golany and Roll (1989)	$2(X + Y)$	8
Banker et al. (1989); Bowlin (1998)	$3(X + Y)$	12
Friedman and Sinuany-Stern (1998)	$(X + Y) < n/3$	$4 < 4.66$
Dyson et al. (2001)	$2(X \times Y)$	6

4.2. Environmental variables

The bias-corrected TE scores are regressed against three determinants:

- Reliability
- Average age of poles
- Number of customers[4]

Reliability measures the extent to which networks are able to maintain a continuous supply of electricity. Three measures of reliability identified by the AER include system average interruption frequency index (SAIFI), customer average interruption duration index (CAIDI) and system average interruption duration index (SAIDI). SAIFI measures the frequency of outages, which essentially shows the number of supply interruptions each customer experienced in a year when averaged over all customers on the distribution network. CAIDI reflects the duration of outages for each customer. It also captures the firm's ability to respond and implement repairs or switching when faults do occur. SAIDI measures the average length of time each customer was without supply when averaged over all customers in the distribution network. In regard to our model, we use SAIDI because we focus on the reliability of the network which would be best measured in terms of duration rather than in terms of customer average or number of supply interruptions. As the value of SAIDI shows the average length of time customers are without supply, we therefore take the reciprocal of this value to reflect reliability. *Average age of poles* (pole age) is the average age of all poles that have been inspected and treated, starting from when the pole was installed. *Number of Customers* is a demand factor and beyond the control of the distributor. We hypothesise that the greater the number of customers, the greater the improvement to economies of scale and therefore the greater the efficiency.

Table 3 presents descriptive statistics of the inputs, outputs, and environmental variables for 2017.

5. Results

Table 4 presents the TE scores of each electricity distribution network firm based on the VRS input-oriented DEA model for the period 2009–2019. Only 6 distributors remained efficient throughout the sample period - Evoenergy, Ausgrid, Endeavour Energy, Citipower, Jemena, and Power and Water. However, the efficiency scores under the CRS input-oriented DEA model shown in Table 5 reveal Citipower as the only efficient distributor throughout the sample period. As discussed in Coelli et al. (2005), a firm that is on the VRS frontier (technically efficient) but not on the CRS frontier, is scale inefficient. This suggests that

[4] One Reviewer queried whether CO_2 emissions might be included in these variables. Due to the negligible interaction and impacts of power generation investment decisions on distribution networks, CO_2 emissions have not been incorporated.

Table 3
Descriptive statistics of the inputs, output and environmental variables, 2017.

	Variable	Mean	Min.	Max.	Std. dev.
Inputs	Operating expenditure	227.4	49.0	555.0	149.7
	Network capacity (MVA)	7204.0	1370.9	15,250.6	4434.7
	Length of distribution line (km)	53,235.4	4550.0	192,103.0	57,433.6
Output	Electricity delivered (Gwh)	10,355.8	1780.0	25,669.0	7050.9
Environmental variables	Reliability	0.015	0.004	0.050	0.012
	Average age of poles	32.0	23.7	46.9	6.4
	Number of customers	723.0	85.7	1706.9	464.3

apart from CitiPower and United Energy, and to some extent Ausgrid, all other firms are not operating at the optimal scale of operations and that they either need to increase or decrease their scale of operations. As shown in Table 6, the increasing returns to scale (IRS) for Evoenergy suggest that it needs to increase its scale of operations for all years. Ausgrid exhibited CRS for most years suggesting that it was operating at optimal levels except for 2016 when it should have reduced its scale of operations (represented by decreasing returns to scale (DRS)). The same situation is evident for Endeavour Energy whereby it should have reduced its scale of operations for the years 2009, 2014 and 2016. Jemena Electricity should have increased its scale of operations for years 2011, 2012, 2016, 2017, 2018 and 2019; and Power and Water should have increased its contribution to the NEM. Various studies show that between 2004 and 2018, the Regulatory Asset Base of Australia's electricity network tripled in value, from \$32 billion to \$93 billion. While this has been the result of forecast demand growth and tightening of reliability standards (see, Simshauser and Akimov 2019), demand forecasts proved erroneous. Simshauser and Akimov (2019) also point out that "some networks were characterized by significant investment mistakes in retrospect" (p. 117). Therefore, some of the inefficiencies seen among some of the distributors could be attributed to inefficiencies that have been built into Australia's NEM policies and regulatory structures.

As observed, some distributors are efficient under VRS but not under CRS, which raises the question about the underlying technology and whether it exhibits CRS or VRS. As DEA is a non-parametric method, it relies on convexity assumptions. To test this, we apply Simar and Wilson's (2002) returns to scale bootstrapping statistics test. To formally test whether the technology set *T* from our sample exhibits CRS or VRS, we express our null and alternative hypothesis as follows:

Ho: *T* is CRS

Ha: *T* is VRS

From our test, a false response was returned and indicates that the p-value (0.338) is greater than alpha $= 0.05$. Thus, the null hypothesis (CRS) is not rejected in favour of the alternative (VRS).

As noted by Hughes and Yaisawarng (2004); Avkiran (2007), Tyagi et al. (2009), Liu et al. (2010) and Fallahi et al. (2011), DEA results are sensitive to the number of variables and sample size. A stability test is thus performed by omitting one input variable at a time under CRS

Table 4
Technical efficiency scores (input-oriented VRS) 2009–2019.

		2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
1	Evoenergy	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2	Ausgrid	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3	Endeavour Energy	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
4	Essential Energy	0.606	0.583	0.597	0.624	0.708	0.745	0.759	0.747	0.754	0.761	0.798
5	Energex	1.000	1.000	1.000	1.000	0.910	1.000	1.000	1.000	1.000	1.000	1.000
6	Ergon Energy	0.947	0.943	0.883	0.943	1.000	0.998	0.977	0.946	0.861	0.861	0.891
7	SA Power Networks	0.831	0.854	0.741	0.752	0.747	0.744	0.701	0.771	0.706	0.697	0.696
8	TasNetworks (D)	0.760	0.740	0.769	0.768	0.869	0.883	0.955	0.844	0.770	0.830	0.845
9	AusNet (D)	0.738	0.800	0.776	0.815	0.828	0.854	0.885	0.830	0.852	0.822	0.829
10	CitiPower	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
11	Jemena Electricity	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
12	Powercor Australia	0.918	0.931	0.908	0.939	0.918	0.949	0.934	0.934	0.910	0.891	0.896
13	United Energy	1.000	1.000	0.978	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
14	Power and Water	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Mean	0.914	0.918	0.904	0.917	0.927	0.941	0.944	0.934	0.918	0.919	0.925
	Efficient firms (no.)	8	8	7	8	8	8	8	8	8	8	8

Table 5
Technical efficiency scores (input-oriented CRS) 2009–2019.

		2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
1	Evoenergy	0.762	0.747	0.759	0.787	0.815	0.820	0.815	0.946	0.916	0.829	0.817
2	Ausgrid	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.976	1.000	1.000	1.000
3	Endeavour Energy	0.989	0.986	1.000	1.000	1.000	0.995	1.000	0.998	1.000	1.000	1.000
4	Essential Energy	0.595	0.582	0.572	0.608	0.707	0.741	0.756	0.746	0.747	0.748	0.782
5	Energex	0.886	0.890	0.853	0.870	0.874	0.900	0.891	0.942	0.945	0.891	0.902
6	Ergon Energy	0.935	0.940	0.853	0.925	1.000	0.993	0.974	0.944	0.849	0.848	0.875
7	SA Power Networks	0.777	0.801	0.739	0.752	0.745	0.738	0.695	0.749	0.705	0.684	0.674
8	TasNetworks (D)	0.749	0.713	0.723	0.719	0.760	0.743	0.782	0.825	0.729	0.745	0.734
9	AusNet (D)	0.737	0.786	0.757	0.809	0.817	0.845	0.871	0.825	0.822	0.792	0.792
10	CitiPower	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
11	Jemena Electricity	1.000	1.000	0.974	0.995	1.000	1.000	1.000	0.971	0.976	0.965	0.953
12	Powercor Australia	0.885	0.919	0.906	0.938	0.915	0.926	0.931	0.913	0.905	0.873	0.872
13	United Energy	1.000	1.000	0.967	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
14	Power and Water	0.664	0.680	0.659	0.687	0.681	0.758	0.779	0.792	0.771	0.801	0.745
	Mean	0.856	0.860	0.840	0.863	0.880	0.890	0.892	0.902	0.883	0.870	0.867
	Efficient firms (no.)	4	4	3	4	6	4	5	2	4	4	4

Table 6
Scale efficiency scores (input-oriented) 2009–2019.

		2009		2010		2011		2012		2013		2014		2015		2016		2017		2018		2019	
1	Evoenergy	0.762	irs	0.747	irs	0.759	irs	0.787	irs	0.815	irs	0.820	irs	0.815	irs	0.946	irs	0.916	irs	0.829	irs	0.817	irs
2	Ausgrid	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	0.976	drs	1.000	crs	1.000	crs	1.000	crs
3	Endeavour Energy	0.989	drs	0.986	irs	1.000	crs	1.000	crs	1.000	crs	0.995	drs	1.000	crs	0.998	drs	1.000	crs	1.000	crs	1.000	crs
4	Essential Energy	0.983	irs	0.997	irs	0.959	irs	0.974	irs	0.998	irs	0.994	irs	0.995	irs	0.998	irs	0.990	irs	0.984	irs	0.980	irs
5	Energex	0.886	drs	0.890	drs	0.853	drs	0.870	drs	0.961	drs	0.900	drs	0.891	drs	0.942	drs	0.945	drs	0.891	drs	0.902	drs
6	Ergon Energy	0.987	irs	0.998	irs	0.965	irs	0.980	irs	1.000	crs	0.995	irs	0.997	irs	0.998	drs	0.986	irs	0.985	irs	0.982	irs
7	SA Power Networks	0.935	drs	0.938	drs	0.997	irs	1.000	irs	0.997	irs	0.991	drs	0.992	irs	0.972	drs	0.998	drs	0.982	irs	0.968	irs
8	TasNetworks (D)	0.986	irs	0.964	irs	0.940	irs	0.936	irs	0.875	irs	0.841	irs	0.819	irs	0.977	irs	0.946	irs	0.898	irs	0.868	irs
9	AusNet (D)	0.998	drs	0.981	drs	0.976	irs	0.993	irs	0.988	irs	0.990	irs	0.984	irs	0.995	irs	0.966	irs	0.963	irs	0.955	irs
10	CitiPower	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs
11	Jemena Electricity	1.000	crs	1.000	crs	0.974	irs	0.995	irs	1.000	crs	1.000	crs	1.000	crs	0.971	irs	0.976	irs	0.965	irs	0.953	irs
12	Powercor Australia	0.964	drs	0.987	drs	0.998	irs	0.999	irs	0.997	irs	0.975	drs	0.997	irs	0.977	drs	0.994	irs	0.980	irs	0.973	irs
13	United Energy	1.000	crs	1.000	crs	0.989	irs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs	1.000	crs
14	Power and Water	0.664	irs	0.680	irs	0.659	irs	0.687	irs	0.681	irs	0.758	irs	0.779	irs	0.792	irs	0.771	irs	0.801	irs	0.745	irs
	Mean	0.940		0.941		0.933		0.944		0.951		0.947		0.948		0.967		0.963		0.948		0.939	
	Efficient firms (no.)	4		4		3		5		6		4		5		2		4		4		4	

Notes: irs – increasing returns to scale, drs – decreasing returns to scale, crs – constant returns to scale.

Table 7
Stability test results (2017).

	Non bias-corrected				Bias-corrected			
Input	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
OpEx ($'M)	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Network capacity (MVA)	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Circuit line length (km)	Yes	No	Yes	Yes	Yes	No	Yes	Yes
CRS								
Spearman rho with Model 1	–	0.996	0.682	0.939	–	0.996	0.723	0.930
P-values	<0.00001	<0.00001	0.0072	<0.00001	<0.00001	<0.00001	0.0035	<0.00001
VRS								
Spearman rho with Model 1	–	1.000	0.790	0.869	–	0.969	0.785	0.785
P-values	<0.00001	<0.00001	0.0008	<0.00001	<0.00001	<0.00001	0.0009	0.0009

and VRS models to validate the robustness of the DEA efficiency scores. Two tests are performed; one between non-bias efficiency scores and one between bias-corrected efficiency scores. For each test, four models are considered with model 1 as the principal model. A Spearman correlation test is then conducted for model relative to model 1 to assesses the impact of each variation. From the stability test results in Table 7, the Spearman's rho between model 1 and 2; and model 1 and 4 are high, but less so with model 3. Nonetheless, as the *p*-values are extremely low, we observe a significant positive correlation and that dropping variables are insignificant compared to the results obtained from model 1.

5.1. Radial and slack movements

Using 2017 as an example, Table 8 shows the radial and slack movements for each distributor needed to achieve overall efficiency. In essence, inefficient firms would need to change the amount of inputs and/or outputs to become efficient. Using Evoenergy to illustrate this point, it is peered against Citipower and United Energy with λ (weights) 0.2442503 and 0.1872449, respectively.[5] We note that Evoenergy has to cut back on x1 (OpEx) by $4.11 million to $44.89 million. It also has to reduce network capacity (x2) by 183.385 MVA and circuit length (x3) by 447.14 km (a shift towards the frontier which denotes radial movement) and a further 1276.279 km (movement along the frontier which denotes slack movement).

[5] Note that $\Sigma\lambda_i$is not equal to 1 ($0.2442503 + 0.1872449 = 0.431495$) because of the convexity constraint, $\Sigma\lambda_i = 1$ (i.e. the sum of the intensity variables, λ's, is equal to one) is not imposed in the CRS model, hence the weights (i.e. lambdas (λ)) may not necessarily equal 1.00 (i.e. 100%).

5.2. Determinants of efficiency for electricity distribution networks

To quantify the sources of (in)efficiency, we select 2017 as our year for analysis. Ideally, we would have used the averages of the inputs, outputs and environmental variables for the period 2009–2017 because averaging reduces the effects of noise, such as unexpected cost shocks (Kuosmanen et al. 2013). However, this was not possible due to unavailable data for some distributors for some years.

As the study employs a second-stage regression analysis, the assumption of separability needs to be tested (Daraio et al. 2018). Using Wilson's (2008) FEAR software package version 3.1, we test the separability condition using Daraio et al.'s. (2018) proposed central limit theorem. Using bootstrap replications of 1000 and 2000; and 10 splits as recommended by Daraio et al. (2018), each environmental variable is tested individually, while considering all inputs and outputs. After that, we test all environmental variables as a whole. Table 9 presents the *p*-values greater than 0.05 suggesting that the null hypothesis of separability is not rejected and that the separability assumption holds.

We quantify the determinants of efficiency using Simar and Wilson's (2007) double bootstrap truncated regression based on the maximum likelihood estimation. The estimated specification for the regression is:

$$\hat{\hat{\theta}}_i = \beta_0 + \beta_1 reliability + \beta_2 pole\_age + \beta_3 customers \tag{4}$$

where $\hat{\hat{\theta}}_i$ is the bootstrapped bias-corrected efficiency score.

Table 10 provides the estimated coefficients and 95% confidence intervals for the second stage estimation under VRS and CRS. As the R package rDEA reports, the efficiency scores is the reciprocal of the input DEA efficiency scores, whereby the efficiency scores range from one to infinity. A positive sign for a coefficient thus indicates a negative

Table 8
Radial and slack movement (CRS), 2017.

DMU	Benchmark(Lambda)	Radial movement (x1)	Slack movement	Projection	Radial movement (x2)	Slack movement	Projection
Evoenergy	CitiPower(0.24425403); United Energy(0.1872449)	−4.11	0	44.89	−183.39	0	2003.83
Ausgrid	Ausgrid(1.000000)	0	0	555.00	0	0	15,250.64
Endeavour Energy	Endeavour Energy(1.000000)	0	0	319.00	0	0	10,168.80
Essential Energy	Ausgrid(0.23330466); Endeavour Energy(0.3828848)	−85.38	0	251.62	−2528.28	0	7451.54
Energex	CitiPower(0.92076617); United Energy(2.0278973)	−20.33	0	351.67	−815.13	0	14,099.87
Ergon Energy	Ausgrid(0.519381)	−55.94	−26.80188	315.06	−1406.42	0	7920.86
SA Power Networks	Endeavour Energy(0.1972554); United Energy (0.881907)	−77.37	0	184.63	−2670.59	0	6372.59
TasNetworks (D)	CitiPower(0.09016258); United Energy(0.466536)	−26.59	0	71.41	−1007.91	0	2707.51
AusNet (D)	Ausgrid(0.29892088)	−38.35	−11.75314	177.65	−983.98	0	4558.75
CitiPower	CitiPower(1.000000)	0	0	78.00	0	0	4408.04
Jemena Electricity	Ausgrid(0.13310479); CitiPower(0.14320319)	−2.16	−3.796	88.84	−64.73	0	2661.17
Powercor Australia	Endeavour Energy(0.4933582); United Energy (0.3152759)	−21.11	0	200.89	−691.25	0	6577.98
United Energy	United Energy(1.000000)	0	0	138.00	0.00	0	4951.46
Power and Water	Ausgrid(0.069344)	−17.14	−19.37056	57.86	−313.36	0	1057.53
DMU	Benchmark(Lambda)	Radial movement (x3)	Slack movement	Projection	Radial movement (y1)	Slack movement	Projection
Evoenergy	CitiPower(0.24425403); United Energy(0.1872449)	−447.14	−1276.28	3609.58	0	0	2914.00
Ausgrid	Ausgrid(1.000000)	0	0	41,642.00	0	0	25,669.00
Endeavour Energy	Endeavour Energy(1.000000)	0	0	36,993.00	0	0	16,716.00
Essential Energy	Ausgrid(0.23330466); Endeavour Energy(0.3828848)	−48,667.42	−119,556.25	23,879.33	0	0	12,389.00
Energex	CitiPower(0.92076617); United Energy(2.0278973)	−2937.91	−19,573.40	31,245.69	0	0	21,355.00
Ergon Energy	Ausgrid(0.519381)	−22,993.45	−107,869.47	21,628.08	0	0	13,332.00
SA Power Networks	Endeavour Energy(0.1972554); United Energy (0.881907)	−26,274.41	−43,633.12	19,063.47	0	0	10,215.00
TasNetworks (D)	CitiPower(0.09016258); United Energy(0.466536)	−6164.82	−9925.42	6634.76	0	0	4193.00
AusNet (D)	Ausgrid(0.29892088)	−7972.19	−24,487.15	12,447.66	0	0	7673.00
CitiPower	CitiPower(1.000000)	0	0	4550.00	0	0	5917.00
Jemena Electricity	Ausgrid(0.13310479); CitiPower(0.14320319)	−150.68	0	6194.32	0	0	4264.00
Powercor Australia	Endeavour Energy(0.4933582); United Energy (0.3152759)	−7143.49	−45,520.30	22,457.21	0	0	10,720.00
United Energy	United Energy(1.000000)	0	0	13,342.00	0	0	7844.00
Power and Water	Ausgrid(0.069344)	−1603.47	−2523.89	2887.64	0	0	1780.00

Table 9
Separability test (p-values).

	CRS		VRS	
	n = 1000	n = 2000	n = 1000	n = 2000
Reliability	0.396	0.569	0.907	0.894
Average age of poles	0.575	0.381	0.928	0.922
Customers	0.590	0.333	0.914	0.916
All three environmental variables	0.723	0.740	0.930	0.910

influence on efficiency, whereas a negative sign indicates a positive influence on efficiency.

Results from both tables show that reliability (SAIDI), or network reliability, is significant and positively impacts on efficiency, which suggests a continuous supply of electricity with minimal outages. Average

Table 11
System GMM results (one-year lag), 2015–2019.

	Estimate	Std.Err.rob	z-value.rob	Pr(>|z.rob|)
Efficiency $_{t-1}$	−0.1574	1.1789	−0.1340	0.8934
Reliability $_t$	3.4456	0.2393	14.3970	<0.00001***
Reliability $_{t-1}$	−0.2859	0.1125	−2.5410	0.0111*
Ln_Pole_age $_t$	−0.0128	0.4639	−0.0280	0.9777
Ln_Pole_age $_{t-1}$	−0.1447	0.4447	−0.3250	0.7452
Ln_Customers $_t$	0.8084	2.7387	0.2950	0.7680
Ln_Customers $_{t-1}$	−1.4610	0.1135	−12.8760	<0.00001*
2017	−0.0065	0.1275	−0.0510	0.9593
2018	−0.0514	0.0963	−0.5340	0.5933
2019	−0.0720	0.1541	−0.4670	0.6405

Signif. codes: 0 '***', 0.001 '**', 0.01 '*'.
J-Test (overid restrictions): 12.3 with 7 DF, pvalue: 0.0911.
F-Statistic (slope coeff): 297625.9 with 7 DF, pvalue: <0.001.
Serial correlation test: normal = −0.16116, p-value = 0.872.

Table 10
Truncated regression results (VRS and CRS).

Variable	VRS			CRS		
	Coefficient	95% Confidence interval		Coefficient	95% Confidence interval	
		Lower bound	Upper bound		Lower bound	Upper bound
Constant	1.157069*	0.915511	1.405890	1.249659*	0.995200	1.498057
Reliability	−26.290870*	−37.599920	−10.776280	−18.815340*	−25.775010	−9.298864
Average age of poles	0.011778*	0.004091	0.018814	0.009313*	0.002304	0.016209
Number of customers	−0.000172*	−0.000295	−0.000035	−0.000189*	−0.000298	−0.000059

Note: A positive (negative) sign indicates an increase (decrease) in inefficiency.
* Significant at the 5% level; total number of iterations = 2000.

Table 12
Results of the LSDVC (Blundell and Bond estimator).

	Coef.	Std. Err.	z	P > |z|		95% Confidence interval Lower bound	Upper bound
Efficiency $_{t-1}$	11.6824	0.0630	185.52	0.00000	***	11.5589	11.8058
Reliability	50.7409	5.5248	9.18	0.00000	***	39.9126	61.5692
Ln_Average age of poles	0.8489	0.1417	5.99	0.00000	***	0.5711	1.1267
Ln_Customers	18.2488	0.3071	59.43	0.00000	***	17.6469	18.8506

age of poles is significant and negatively impacts on efficiency. This suggests that older poles require more frequent maintenance and replacement of poles indicating more outages. Number of customers is significant and positively impacts on efficiency suggesting increased demand plays a significant contributor to improving efficiency. However, electricity demand is also influenced by competing substitutes, such as solar uptake. As households demand for solar uptake rises, demand for electricity from the grid will fall. The consequence of this is that the remaining customers will have to bear the burden of higher network tariffs (ie. within retail-level prices) in order to maintain the ageing poles and wires (Simshauser, 2016). This outcome will only worsen as poles and wires age, which also impacts on continuous supply and increases the frequency of outages.

As the above result is based on cross-sectional analysis, we verify the results' robustness by performing tests on endogeneity issues such as omitted variables, reverse causality and fixed-effects.

To handle the potential endogeneity issues like omitted variable bias and reverse causality,[6] we use Arellano and Bond's (1991) two-step dynamic generalised method of moments (GMM)[7] based on the nonlinear moment conditions as proposed by Ahn and Schmidt (1995). As our panel-data was unbalanced covers the years 2015–2019.[8] As noted in Wintoki et al. (2012), system GMM provides consistent estimates in the presence of different sources of endogeneity, namely unobserved heterogeneity, simultaneity and dynamic endogeneity. Using Fritsch et al. (2019) 'pdynmc' R package version 0.9.2, we produce the system GMM results in Table 11.

The GMM results support the second-stage regression findings of Table 10. The results are based on one-year lag because our time-series was limited to 5 years. Using two or more lags will reduce the degrees of freedom and reduce the number of observations, and may generate weaker instruments (Roodman 2009). The J-Hansen test is insignificant and we do not reject the null hypothesis because the test does not provide any indication that the validity of the instruments employed in estimation may be in doubt. The second order serial correlation test does not reject the null hypothesis thus not providing any indication that the model specification might be inadequate.

As noted by Nankervis and Savin (1987), estimating a dynamic panel model with finite time series will lead to poor asymptotic estimates and is prone to type one error. Even using the Least Square Dummy Variable (LSDV) or within-group estimators such as the fixed effects, difference and system GMM, Anderson and Hsiao IV can lead to bias estimates (Nickel, 1981; Kiviet, 1995, 1999). To handle the short-comings of the least square estimator, studies such as Judson and Owen (1999), Hansen (2001), Bun and Kiviet (2003); Bruno (2005), Bogliacino et al. (2012), and Kurennoy (2015) proposed a bias corrected LSDV as it has been found to yield more efficient estimates than the GMM method.[9]

[6] For details on the types of endogeneity issues, see Antonakis et al. (2010); Ketokivi and McIntosh (2017).

[7] Also known as system GMM.

[8] As noted by Arellano and Bond (1991, p. 289), "three cross-sections are lost in constructing lags". As such we considered the period 2015–2019 to meet the minimum requirement for the time-series analysis. Data for 2018 and 2019 were available from the AER website as described at the start of Section 3. 2015 and 2016 were incomplete due to missing data and as such, our 2015–2019 data is an unbalanced panel. Nonetheless, this is still suited for GMM as recommended by Judson and Owen (1999).

[9] Also known as least square dummy variable correction (LSDVC).

We employ the LSDVC with fixed effects and perform Monte Carlo simulations.[10] The LSDVC estimation is initialised using Blundell and Bond (1998) GMM estimator to enable the bias correction (Bun and Kiviet, 2003). We present the LSDVC results in Table 12.

The LSDVC results show reliability and customers as significant and having a positive influence on efficiency. This supports the second-stage regression findings. However, age of poles is significant and positively affects efficiency, which contradicts Table 10. One possible explanation for this is the lagged efficiency having a positive contribution to the next period's performance suggesting that efficiency via improved operations, maintenance and streamlining tasks. On the whole, the LSDVC results supports the second-stage regression results of Table 10.

6. Conclusions

This article addresses to what extent electricity distribution networks are efficient in Australia's restructured market. To do so we use panel data for the period 2009–2019 representing 14 electricity distributors covering the entire NEM plus Northern Territory and determine the sources of (in)efficiency. Our results extend the AER's annual benchmarking report on electricity distribution networks by performing a second-stage analysis based on a bootstrap truncated regression which reveals the sources of (in)efficiency.

The mean DEA efficiency scores for both VRS and CRS showed little variation over the sample period. The number of efficient distributors operating under VRS were greater than those operating under CRS which implied that the latter distributors could improve performance by changing their scale of operations, for example by way of mergers or divestment. Several tests such as the stability test, separability test, and test for endogeneity such as omitted variable, reverse causality and fixed-effects were performed to validate the results robustness and the tests supported the study's findings.

In terms of policy implications, our research provides added evidence that many distribution networks are operating below efficient levels. Except for 2013 and 2015, less than 30% of distribution networks were found to be efficient. Most notably, Essential Energy, SA Power Networks and TasNetworks exceeded efficient input levels by of 25%, 29% and 27%, respectively[11] in 2017.

Our regression analysis reveals that reliability promotes efficiency. This suggests policy should focus on this aspect of distribution networks. However, there is a need to be mindful that greater reliability requires more resources and will ultimately reach the point of being counter-productive. This issue has been highlighted by previous work conducted due to significant investment mistakes in retrospect (see, for example, Simshauser, (2019) and Simshauser and Akimov (2019)).

This raises the question of whether Australia's incentive-based regulation is suitably framed. On the one hand, inefficient distributors can improve the reliability of their network by allocating capital and operating costs where needed, and not before it is needed, to improve efficiency and sustainability. Also, given an increasing number of

[10] Based on the recommendation of Judson and Owen (1999), that a balanced panel is required for the LSDVC. As such, we could only use the years 2017–2019.

[11] Excess use of inputs is the ratio of input reduction (radial movement) over actual inputs used.

customers is shown to improve efficiency, this suggests larger coverage could encourage better results (e.g. consolidations, mergers and acquisitions). Note that from 2010 to 2015, demand in fact contracted. Only from 2015 to 2018 did demand increase (Simshauser and Akimov 2019). On the other hand, and as one reviewer noted, an output-based regulatory framework (cf. the NEM's existing incentive based) may better target improvements in service quality.

In terms of future research there is a clear indication that the linkage between Opex and efficiency should be examined at the micro level, to provide precision to this linkage.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105210.

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