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REVIEW OF ECONOMETRIC MODELS USED BY THE AER TO ESTIMATE OUTPUT GROWTH

A REPORT PREPARED FOR CITIPOWER, POWERCOR AND UNITED ENERGY

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1 INTRODUCTION

1.1 Background

In recent Draft Decisions, the AER has determined opex allowances related to the growth in network outputs by weighting four key outputs: customer numbers, circuit length, ratcheted maximum demand and energy throughput.

The weights applied to these four outputs, for the purposes of setting opex allowances, are derived using the results from four econometric models that the AER uses to estimate the relationship between opex and cost drivers (i.e., output variables). These models are:

- A Stochastic Frontier Analysis Cobb-Douglas (SFA CD) model;
- A Least Squares Cobb-Douglas (LSE CD) model;
- A Least Squares translog (LSE TL) model; and
- A Leontief cost function used to determine the output weights used in the AER's Multilateral Partial Factor Productivity (MPFP) model.

These models have been estimated by the AER's advisers, Economic Insights (EI). The AER averages the estimated output weights derived from these four models and then applies these average output weights to all the Distribution Network Service Providers (DNSPs) that it regulates, regardless of their individual circumstances. The standard weights that the AER applies to all DNSPs may not reflect well how CitiPower's, Powercor's and United Energy's mix of outputs may be expected to grow over a particular regulatory control period.

NERA has recently prepared a report for several DNSPs that argues that the AER should give no consideration to the output weight estimates derived using the LSE TL and Leontief models. NERA recommends that the AER should rely on the SFA CD and LSE CD models instead.[1] The AER's advisers, Economic Insights (EI), have prepared a response that seeks to rebut NERA's analysis.[2]

Against this background, Frontier Economics has been asked to provide an independent opinion on the reasonableness of the AER's approach to estimating output weights.

1.2 Key findings

Our main focus in undertaking this review has been on the econometric modelling undertaken by EI for the AER, which forms the basis for the calculation of the output weights. In particular, we have examined the statistical properties of the estimated Leontief cost functions and the statistical reasoning that underpins the AER's use of the translog functions when calculating output weights. On the basis of our review, our key findings are that:

The AER should discontinue its reliance on the Leontief model in the setting of opex allowances

We agree with NERA that the AER should discontinue its reliance on the Leontief model in the setting of opex allowances. We base our conclusion on the fact that there very serious statistical problems

[1] NERA, *Review of the AER's proposed output weightings*, 18 December 2018.

[2] Economic Insights, *Review of NERA report on output weights*, 30 April 2019.

associated with the Leontief models estimated by EI. Of the 52 Leontief cost functions EI estimated for the AER's 2018 Annual Benchmarking Report, more than half of the estimated cost functions do not have a single coefficient that is statistically significant at the commonly used 5% level of significance.[3] Even at the less strict 10% level of significance, 46% of the 52 equations do not have a single statistically significant coefficient. Further, for 25 of the 52 equations, the estimated rate of technical change is so large as to lack any credibility.

The situation is exacerbated by the extreme multicollinearity between the customer numbers, circuit length and the time trend in the estimating equations. For all 13 DNSPs, the correlation between customer numbers and the time trend is 0.96 or higher, and for 11 DNSPs it is 0.99. The correlations between circuit length and the time trend, and between circuit length and customer numbers are also extremely high for 11 of the 13 DNSPs.

EI has stated that:

> *To minimise the risks associated with the limited degrees of freedom per regression and the fixed propositions nature of the Leontief cost function, we then take a weighted average of the derived output cost shares across all the Australian DNSP observations, where the weights are the DNSPs' opex shares in total distribution industry opex.*[4]

However, in our view, the statistical problems with the estimated equations are so severe that they cannot be overcome by taking weighted averages. It is hard to overstate how poor the statistical properties of the estimated Leontief functions are. In our view, it is not possible to derive credible estimates of the relative contributions to opex of different outputs from such poorly estimated models.

Since the same output weights are used in the construction of the Multilateral Total Factor Productivity (MTFP) and MPFP productivity indices, the same conclusion applies to those indices.

Based on the statistical evidence, energy throughput is not a material driver of opex

In its rebuttal of NERA review of the AER's proposed output weightings, EI has stated that the reason for including energy is that:

> *Economic Insights uses a functional output specification in its economic benchmarking, ie outputs reflect the key services provided to and valued by consumers while their weights reflect the relative costs of providing those services.*[5]

However, the AER is using the Leontief cost models to forecast DNSPs' opex over a regulatory control period, not to determine how much customers value different outputs. Hence, the pertinent issue is whether energy throughout contributes materially to opex.

Our review of the statistical properties of Leontief cost functions estimated by EI for the 2018 Annual Benchmarking Report finds no statistical evidence that energy throughput has any material impact on opex. In only one case did energy make a statistically significant contribution to opex. For all the other DNSPs the contribution of energy to opex is statistically highly insignificant.

[3] We note that the 2019 Annual Benchmarking Report did not use updated Leontief output weights. Hence, the AER's latest estimates of Leontief output weights are those used in the 2018 Annual Benchmarking Report.

[4] Economic Insights, *Review of NERA report on output weights*, 30 April 2019, p. 9.

[5] Economic Insights, *Review of NERA report on output weights*, 30 April 2019, p. 9.

Note, however, that the output weights calculated by EI are based on the Leontief equations for all inputs, not just opex. In the vast majority of cases, specifically, in 42 out of the 52 estimated Leontief equations, the estimated impact of energy on input costs was not only statistically insignificant, but the t-values were 0.000. For these 42 cases, the models imply that the probability that energy has zero impact on opex is 100%. We cannot think of any statistical reason why energy should be included in these equations.

We also note that in the estimation dataset, energy and opex often moved in opposite directions. In 50% of cases, either real opex decreased when there was a year-on-year increase in energy, or real opex increased when there was a decrease in energy. This is consistent with the lack of statistical evidence and casts further doubt on EI's contention that energy is an important driver of opex.

The fact that EI has been able to derive a weight for energy of 0.12 from the Leontief analysis should not be interpreted as evidence that energy is an important driver of input costs. This result is driven by the very few cases where the coefficient for energy is significant. The proportion of significant coefficients for energy is no better than if the energy data were replaced by a set of random numbers.

EI itself has recognised that DNSPs' costs are unlikely to be influenced significantly by changes in energy throughput:[6]

> *The value of the throughput output would be revenue multiplied by its cost share, which we would expect to be relatively small* ***given that costs are not likely to be greatly influenced by small variations in throughput****. [Emphasis added]*

The AER has also previously acknowledged that energy throughput is unlikely to be a material driver of DNSPs' costs:[7]

> *Energy delivered may not be an ideal output variable for DNSPs because it may not significantly affect the costs of providing distribution services..……Turvey notes that the amount distributed is not decided by the DNSP. In the short-run a load alteration will not affect the size of the network and will and only trivially affect operating and maintenance costs.*

EI's and the AER's acknowledgment that energy throughput is not a material driver of DNSPs' costs is borne out by the statistical evidence presented in our review.

If the AER wishes to use econometric models to forecast DNSPs' opex over a regulatory control period, those econometric models should include *relevant* opex drivers, not outputs that have little influence over costs. However, the AER has not done that. Instead, the AER has used, for the purposes of forecasting opex over a regulatory control period, models containing a variable that both EI and the AER have acknowledged has little impact on DNSPs' costs. The resulting models are mis-specified and, therefore, unreliable for the purposes to which they have been put by the AER.

[6] Economic Insights, *Economic Benchmarking of Electricity Network Service Providers*, 25 June 2013, p. iv.

[7] AER, *Expenditure forecast assessment guidelines for electricity distribution and transmission*, Issues Paper, December 2012, p. 78.

The translog cost function should only be considered for determining output weights if translog-derived weights are evaluated at output levels that are relevant to the Australian DNSPs

In EI's methodology, the output weights derived from the Cobb-Douglas and translog cost functions are obtained by normalising the elasticities implied by these functions so that they sum to 1. An important feature of the translog cost function that distinguishes it from the Cobb-Douglas cost function, is that it allows for elasticities to vary as output levels change rather than imposing constant elasticities across all DNSPs. When deriving elasticities from the translog cost function, a decision has to be made about the levels of the outputs at which the elasticities should be evaluated.

The approach adopted by the AER is to evaluate the elasticities at the geometric average output levels of all DNSPs in the international sample. However, these average output levels are vastly different to the output levels of Australian DNSPs. The output levels chosen by EI for evaluating the translog cost function elasticities have no economic or statistical justification. In our view, these elasticities should be evaluated at output levels that are reflective of the operating characteristics of the Australian DNSPs.

However, if the AER believes that the elasticities *are* constant across all utilities in the sample, then it would be statistically more efficient to estimate these constant elasticities using the Cobb-Douglas cost function.

2 MODELS USED BY THE AER TO ESTIMATE OUTPUT WEIGHTS

2.1 Use of output weights in determining opex allowances

As described in the AER's Expenditure Forecast Assessment Guideline,[8] the allowable opex in each year of a regulatory control period is obtained using a 'base-step-trend' approach.

Under this approach, a nominated year from the previous regulatory period is determined to be the 'base year' from which allowable opex for the upcoming regulatory period is rolled forward for each DNSP. The formula for obtaining the allowable opex in year t can be written as:

(1) $Opex_t = [(Y_b - efficiency\ adjustment) \times \prod_{i=1}^{t}(1 + percentage\ change_i)] \pm step\ changes_t$

where:

- The expression (Y_b - *efficiency adjustment*) represents target opex in the base year, where:
  - it is assumed that the base year is $t = 0$; and
  - Y_b is the proposed opex in the base year.
- *efficiency adjustment* is the adjustment that needs to be applied to proposed opex in the base year to bring it in line with the target opex in the base year.
- $percentage\ change_i$ is a combination of the changes in real prices and in output, as well as any productivity change in year i.
- $step\ changes_t$ represents any step changes that may be applied to allowed opex in year t to account for efficient expenditures not captured in the target base year opex or the rate of change.

In this formula, the percentage change in output in year i refers to output as a single aggregate measure of output. The output weights are used to derive this aggregate output measure as a weighted average of the individual outputs. The impact of output growth on opex, as measured by this aggregate output measure, is a key input in determining network opex allowances.

2.2 AER's approach to estimating output weights

In recent Draft Decisions, the AER has determined the output weights used to calculate the aggregate output measure by weighting four key outputs: customer numbers, circuit length, ratcheted maximum demand and energy throughput.[9, 10]

The weights applied to these four outputs, for the purposes of setting opex allowances, are derived from four econometric models that the AER uses to estimate the relationship between opex and cost drivers (i.e., output variables). These models are:

- A Stochastic Frontier Analysis Cobb-Douglas (SFA CD) model;
- A Least Squares Cobb-Douglas (LSE CD) model;

[8] *AER Expenditure Forecast Assessment Guideline for Electricity Distribution*, AER, November 2013.

[9] For example, SA Power Networks 2020-25 Draft Decision, October 2019, Attachment 6.

[10] Energy throughput is only considered in the Leontief cost function approach to estimating output weights.

- A Least Squares translog (LSE TL) model; and
- A Leontief cost function used to determine the output weights used in the AER's Multilateral Partial Factor Productivity (MPFP) model.

These models have been estimated by the AER's advisers, Economic Insights (EI). In the most recent draft determinations, the AER averages the estimated output weights derived from the above four models and then applies these average output weights to all the DNSPs that it regulates, regardless of their individual circumstances.

The econometric models do not provide estimates of the output weights directly. For the CD and LSE models, the estimated cost function enables the elasticities of opex with respect to each output to be derived. These elasticities typically do not sum to 1, as one would expect for a set of weights. Hence, EI normalises the elasticities to ensure that the weights do add to 1. For the Leontief cost function, the estimated coefficients in the model are input-output ratios, that is, the amount of input required to produce one unit of a given output. These input-output ratios have to be transformed into output weights.

We note that in the AER's 2019 Benchmarking Report,[11] a Stochastic Frontier Analysis translog (SFA TL) model is also included in the set of models used in the benchmarking. In the past, whether or not a particular TL model was included by the AER/EI when calculating the average output weights depended on the dataset used in the estimation of the models. For some datasets the estimated TL model produced violations of the so-called monotonicity condition that EI considered to be unacceptable. In such cases, the AER excluded the model from consideration when calculating output weights. Our conclusions on the AER's use of the TL cost function in estimating output weights apply across all the TL models that EI has estimated at various times.

[11] AER, *Annual Benchmarking Report: Electricity Distribution Network Service Providers*, November 2019.

3 OUTPUT WEIGHTS DERIVED FROM LEONTIEF COST FUNCTIONS

3.1 Overview of approach

Specification of the Leontief model

The output weights used by the AER in its MTFP and MPFP analysis are derived econometrically by estimating Leontief cost functions. In recent Draft Decisions, the AER has also used these output weights in determining base year target opex.

The Leontief function used by EI includes four outputs:[12]

- energy throughput;
- ratcheted maximum demand;
- customer numbers; and
- circuit length.

For each DNSP, EI estimates a separate Leontief cost function for each of the four input variables in EI's input index (the denominator of the MTFP and MPFP calculations). The four input variables are:

- real opex;
- overhead lines (MVAkms);
- underground cables (MVAkms); and
- distribution transformer capacity (MVA) plus the sum of single stage and the second stage of two-stage zone substation level transformer (MVA).

Algebraically, the Leontief model estimated by EI for each DNSP and each input can be written as:[13]

(1) $$x_{it} = \sum_{j=1}^{4} \left(a_{ij}\right)^2 y_{jt}(1 + b_i t) + e_{it}$$

where x_{it}, $i = 1, \ldots 4$ represents the value of the i^{th} input at time t, y_{jt}, $j = 1, \ldots 4$ represents the value of the j^{th} output at time t, and e_{it} represents the residual term in the model. The coefficient a_{ij} in this model has been squared to ensure that an increase in any of the outputs has a non-negative impact on inputs. The terms, $\left(a_{ij}\right)^2(1 + b_i t)$, can be interpreted as input-output coefficients, that is, the amount of input i required at time t to produce one unit of output j. The coefficient b_i is interpreted by EI as the rate of technological change.[14]

[12] Our review of the use of the Leontief models to estimate output weights is based on Economic Insights, *Economic Benchmarking Results for the Australian Energy Regulator's 2018 DNSP Benchmarking Report*, 9 November 2018, and associated files published on the AER's website. These are the estimates that the AER has relied on in its 2019 Annual Benchmarking Report.

[13] We have not included a separate subscript to represent different DNSPs. There is a separate set of four input equations for each of the 13 Australian DNSPs included in EI's benchmarking analysis.

[14] Economic Insights, *Economic Benchmarking Results for the Australian Energy Regulator's 2018 DNSP Benchmarking Report*, 9 November 2018, p. 109.

Estimation of the models

For each of the 13 DNSPs, each of the four input variables (real opex, overhead lines, underground cables, and transformer capacity) is regressed separately against four output variables (energy, ratcheted maximum demand, customer numbers, and circuit length) and a time trend as specified in equation (1). This means that in total 52 Leontief regression models are estimated (i.e., 13 DNSPs x 4 inputs).

The data used by EI to estimate the Leontief regression models for the AER's 2018 DNSP Benchmarking Report covers the 12-year sample period 2006-2017.

We can see from the specification in equation (1) that there are five parameters that need to be estimated in each of the 52 regressions. The data used to estimate these five parameters in each equation uses the 12 observations of data available for the particular DNSP being modelled.

Estimation of cost shares

Once the 52 Leontief cost functions have been estimated, an output cost share can be estimated for each output j and for each DNSP and year as described in the following paragraph.

If w_{it} is the input price for input i at time t, then the input cost of input i in producing y_{jt} units of output j is $w_{it}\left(a_{ij}\right)^2 y_{jt}(1+b_i t)$. This can be estimated for each DNSP, each input and each output by substituting the estimated values of the parameters in the Leontief cost function—i.e., by $w_i^t\left(\widehat{a_{ij}}\right)^2 y_j^t(1+\widehat{b_i}t)$. Summing across the four inputs and normalising then leads to an estimate of the share that each output j contributes to the total cost of inputs for each DNSP and each time period t:

$$(2) \qquad h_{jt} = \frac{\sum_{i=1}^{4} w_{it}\left(\widehat{a_{ij}}\right)^2 y_{jt}(1+\widehat{b_i}t)}{\sum_{j=1}^{4}\left[\sum_{i=1}^{4} w_{it}\left(\widehat{a_{ij}}\right)^2 y_{jt}(1+\widehat{b_i}t)\right]}.$$

For each DNSP this produces 4 x T output shares where T represents the number of years of data available for analysis, 12 years in the present case.

Finally, the output cost shares used in the MTFP analysis and to estimate output growth are derived by taking a weighted average of the cost shares across all DNSPs and years, where each cost share is weighted by the corresponding cost as predicted by the estimated regressions.

3.2 Assessment of estimated Leontief output weights

3.2.1 Statistical properties of the parameter estimates

Very few parameter estimates are statistically significant

Since the main purpose of the Leontief regressions is to obtain estimates of the relative importance of different outputs as drivers of the particular input being modelled, a reasonable expectation would be that at least two of the input-output coefficients in any equation be estimated with acceptable precision, the usual criterion being that the estimated coefficient be statistically significant at the 5% or the 10% level of significance. For the vast majority of the 52 equations this expectation is not met.

Out of the 52 Leontief equations estimated by EI for the AER's 2018 Annual Benchmarking report, 27 equations (52%) have not a single estimated coefficient that is statistically significant at the most commonly used level of significance of 5%. If we use the less stringent 10% level of significance, there are still 24 equations (46%) that do not have a single statistically significant coefficient.

It is difficult to see how one can draw any meaningful inferences from regression models that do not have any significant coefficients. Applied econometricians/statisticians would commonly dismiss a regression model that has no statistically significant parameter estimates as saying anything useful about the relative importance of the different explanatory variables.

Unexpected values for the time trend

The coefficient on the time trend variable in the model, b_i, has been interpreted by EI as the rate of technological change.[15] There is a different rate of technological change for each DNSP and for each input. However, the rate of change is kept constant across outputs.

One would expect the rate of technological change to have values lying in a small range around 0, perhaps from -0.10 to +0.10, representing annual rates of technological change of between -10% and +10%. This expectation is met by some of the 52 Leontief equations estimated by EI. However, for 25 of the 52 equations, the values fall well outside this range, with values above 24 and rising as high as 1,411. If these were interpreted as rates of technological change, this would translate to going from 2,400% to 141,000%. Clearly, for these 25 equations something else is driving these results, not technological change. The estimates of the other parameters in the model would also be affected by these unexpectedly large values for the time trend. It is hard to see how any meaning may be attached to the other parameter estimates for these equations.

The results for energy throughput are particularly bad

Table 1 below lists the t-values (a measure of statistical significance) for the energy throughput output variable in each of the 52 Leontief models estimated by EI. A commonly used rule-of-thumb for a meaningful t-value is that it should be equal to or greater than 2 in absolute value. Out of the 52 t-values in Table 1, only four t-values meet that criterion. Indeed, if we use the 10% critical for the appropriate t-distribution[16] for this case, $t_{7,\,0.05}$ = 1.895, we find that these same four t-values are the only t-values in the table that are significant at the 10%. Having four out of 52 parameter estimates being significant at the 10% level is no better than what one would expect if energy throughput were replaced by a set of random numbers. This indicates that there is no statistical evidence that energy throughput has any influence on any of the input variables.

EI has argues that it:

> *uses a functional output specification in its economic benchmarking, ie outputs reflect the key services provided to and valued by consumers while their weights reflect the relative costs of providing those services.*[17]

However, the task at hand is not to assess how much customers value different outputs, but rather how much each output contributes to opex. And as Table 1 shows, in only one case, for the second DNSP, does energy make a statistically significant contribution to opex. For all other DNSPs the coefficient on energy is highly insignificant.[18] However, the output weights calculated by EI take into

[15] Economic Insights, *Economic Benchmarking Results for the Australian Energy Regulator's 2018 DNSP Benchmarking Report*, 9 November 2018. p. 109.

[16] Since there are 5 parameters in the model and 12 observations used in the estimation, there are 7 degrees of freedom. We have selected the 2-tailed 10% critical value, since the estimated coefficients can be both positive and negative.

[17] Economic Insights, *Review of NERA report on output weights*, 30 April 2019, p. 9.

[18] We have focused on t-values rather than coefficients when discussing the regression results, since, as we argue in section 3.2.2, the coefficients depend on the choice of the base year for the time trend and they are difficult to interpret.

account the estimated Leontief equations for all inputs, not just opex. In the vast majority of cases, the estimated impact of energy on input costs is not only statistically insignificant, but the t-values are 0.000. It is hard to think of a statistical reason why energy should even be included in these equations.

Table 1: Energy throughput t-values for different input models and DNSPs

DNSP	REAL OPEX	OVERHEAD LINES	UNDERGROUND CABLES	TRANSFORMER CAPACITY
1	0.000	0.000	0.000	-4.171
2	4.610	0.000	0.000	0.000
3	-0.073	0.000	0.000	0.667
4	0.518	0.000	0.000	0.000
5	0.000	0.000	0.000	-1.210
6	0.000	0.000	0.000	0.000
7	0.000	0.000	0.000	0.000
8	0.000	0.000	0.000	0.000
9	0.000	0.000	0.000	0.000
10	0.000	3.411	0.000	0.000
11	0.000	0.000	0.000	0.000
12	0.058	5.010	0.000	0.000
13	0.211	0.000	0.000	0.000

Source: Frontier Economic analysis of results in the file LCSTFNNLDOT.txt produced by EI for the 2018 Annual Benchmarking Report and available on the AER's website

3.2.2 Other statistical issues with the estimates

Lack of convergence

Since the coefficients of the output variables in EI's Leontief model are represented by the squared terms $\left(a_{ij}\right)^2$ to ensure that the impact of an increase in an output cannot lead to a decrease in any input, the models cannot be estimated by the usual linear regression technique. EI has used a method known as non-linear least squares to estimate the models. This is an iterative procedure, which terminates once a convergence criterion is reached. In practice there is also a limit set on the number of iterations that are carried out before the estimation procedure terminates, even if the convergence criterion has not been met. EI set this limit for the maximum number of iterations at 5,000.

For two of the 52 Leontief regressions estimated by EI, the estimation procedure produced an error code = 3. This indicates the estimation procedure had not converged after 5,000 iterations. That is, the interim estimates after 5,000 iterations did not meet the criteria of the computer package SHAZAM (the statistical software used by EI) for a satisfactory conclusion of the estimation procedure. Normally, one would discard an estimated model that has not converge or modify the estimation procedure to achieve convergence. However, despite the lack of convergence, EI has ignored the lack of convergence and treated these two regression models in the same manner as all the other regression model. No special consideration was given to the regression models that did not converge.

Estimates are dependent on the choice of base year

The estimates of the input-output ratios $(a_{ij})^2$ depend on the base year selected for the time trend. Hence it is possible that for one choice of base year an estimated input-output ratio is constrained to be zero, while for another choice of base year it is positive. The implication is that the output weights derived from the Leontief cost functions are dependent on the choice of base year for the time trend, which is obviously an undesirable aspect of this approach to estimating output weights.

Base year is not specified consistently across DNSPs

The time trend variable in EI's SHAZAM code is created using the command GENR T=TIME(0). According to the SHAZAM manual this "creates a time index so that the first observation is equal to 1 and the rest are consecutively numbered".[19] The effect of this command on the way EI has prepared the data for the analysis, is that for the first DNSP in the dataset the time trend will have values from 1 to 13, for the second DNSP the time trend will have values from 14 to 26, for the third DNSP the time trend will have values from 27 to 39 and so on.

The constraint that the $(a_{ij})^2$ coefficients be non-negative ensures that the input-output coefficient at time t, i.e. $(a_{ij})^2(1+b_i t)$, is positive when $t=0$. Because of the way EI has defined the trend variable, for the first DNSP in the dataset $t=0$ corresponds to the year 2005. Hence, for the first DNSP the constraints ensure that the coefficients are non-negative in 2005. For the second DNSP in the dataset $t=0$ occurs 13 years earlier, in the year 1992. Hence, for the second DNSP the constraints ensure that the coefficients are non-negative in 1992. Similarly, for each successive DNSP in the dataset, $t=0$ corresponds to the year that is 13 years earlier than for the previous DNSP, and the non-negativity constraints are imposed in that year. We can think of no reason why EI has chosen to define the trend variable in this way, but it leads to an inconsistent treatment across the DNSPs of the way the non-negativity constraints are imposed.

Bias

The non-linear estimation procedure that ensures that the estimated coefficients of the output variables in the models cannot be negative leads to biased estimates, if the non-negativity constraints that have actually been imposed hold. Since it seems reasonable to assume that the true parameters are indeed non-negative, the bias will disappear in large samples. However, in the present case, each of the regression models is estimated using only 12 observations of data, which cannot be considered a large sample. Hence these biases remain. Without further analysis, it is not possible to say how large these biases are, and how many parameter estimates have been affected by these biases.

[19] SHAZAM Analytics (2011), SHAZAM Reference Manual: Version 11, p. 82.

3.3 Likely reasons for poor estimates

Small sample size, lack of cross-sectional variation and multicollinearity

One of the reasons why EI decided to adopt the Leontief cost function approach for estimating output weights is that there is insufficient cross-sectional variation in the sample of Australian DNSPs to obtain robust estimates using more complex models [20]

> *Economic Insights (2014, pp.28–29) illustrated how the Australian electricity DNSP data at the time exhibited insufficient cross–sectional variation to support robust parameter estimation for the sample as a whole, including for more complex, second–order cost functions such as the translog. This left two approaches available: either incorporate more cross sectional observations or resort to using much simpler cost function methods such as the Leontief which can be applied on a DNSP by DNSP basis.*

However, it appears that this problem has not been resolved by estimating the Leontief cost function on a DNSP-by-DNSP basis. For each regression there are only 12 observations to estimate five parameters. Even if one were only estimating a mean, 12 observations would be generally be regarded as quite a small sample.

For most of the DNSPs, most of the output variables trend up slowly over the 12 years of data. Apart from energy throughput, all outputs are highly correlated with the time trend for the vast majority of DNSPs.[21] This is particularly the case for circuit length and customer numbers, which, for 11 out of the 13 DNSPs have correlations with the time trend exceeding 0.95, and for 9 out of the 13 DNSPs these correlations are equal to 0.98 or higher. The correlations between circuit length and customer numbers follow a similar pattern. These are quite extreme cases of multicollinearity, and it is no surprise that the models have difficulty in producing precise estimates of the separate impacts of each of these output on opex. In the presence of multicollinearity, the individual estimated elasticities used to derive the output weights used by the AER cannot be relied upon.[22]

Outliers

While the right-hand variables in most of the Leontief models estimated by EI generally trend upwards without large changes from year to year, there is more variation in opex, the left-hand variable. Most of the DNSPs have made savings in opex at some point during the estimation period. In some cases the opex savings realised have been quite large. There are no variables on the right-hand side of the equation that can explain such reductions in opex. In such cases, the estimation procedure is likely to rely on accidental co-movements among the explanatory variables to try to achieve as best a fit to the data as possible.

There are, indeed, quite a few cases, where, for a given DNSP, the output variables in a given year are higher than they were in previous years (or, in the case of ratcheted maximum demand, no lower), yet real opex is lower. For example, for each of the 13 DNSP there are 12 years of data; hence we can calculate annual changes in opex and in the output variables for 11 years, making a total of 143

[20] Economic Insights, *Review of NERA report on output weights*, 30 April 2019, p.2.

[21] Our observations are based on the correlations for the logged outputs, since these are the variables used in the regression models.

[22] Multicollinearity is less of a problem for the other econometric models because all DNSPs are used together when estimating those models. As a result, there is cross-sectional variation in the other models, which overcomes the multicollinearity issue.

annual changes for the 13 DNSPs. For 28 of these 143 year-on-year comparisons (20%), there is a decrease in real opex, even though there are no decreases in any of the outputs. These are violations of monotonicity that are incompatible with economic theory. If we consider changes in real opex and outputs across two or more years we find further violations of the monotonicity condition. These violations are also incompatible with constraining the coefficients of the output variables to be non-negative.

Moreover, there were 43 cases (30%) in the 143 year-on-year comparisons where energy for a particular DNSP decreased from one year to the next, yet real opex increased. These observations are incompatible with constraining the coefficients on energy in the Leontief functions to be positive. Taken together with the cases in the previous paragraph, there are 71 year-on-year comparisons, out of 143 such comparisons (50%), where the direction of the annual change in energy (increase or decrease) were in the opposite direction to the direction of the change in real opex. This casts further doubt on the contention by EI that energy is an important driver of opex.

3.4 Conclusions about Leontief cost function output weights

Our analysis of the specification and statistical properties of the estimated Leontief cost functions has identified a number of serious issues with these estimated models, including:

- the lack of any statistically significant parameter estimates for about half the equations;
- the implausibility of about 50% of the estimated rates of technological change;
- the high degree of multicollinearity for all but two DNSPs;
- the lack of any drivers in the model that can explain the sizeable reductions in opex achieved by the DNSPs during the estimation period; and
- the inconsistent specification across the different DNSPs of the base year for the time trend and the dependence of the estimated output weights on the base year selected for the time trend.

Our analysis has not been exhaustive. There may be other issues with the estimated models that should be explored. However, the issues we have identified are serious enough to lead us to conclude that it is not possible to derive credible estimates of output weights from these models.

EI has stated that:[23]

> *To minimise the risks associated with the limited degrees of freedom per regression and the fixed propositions nature of the Leontief cost function, we then take a weighted average of the derived output cost shares across all the Australian DNSP observations, where the weights are the DNSPs' opex shares in total distribution industry opex.*

However, in our view, the statistical problems with the estimated equations are so severe that they cannot be overcome by taking weighted averages. It is hard to overstate how poor the statistical properties of the estimated Leontief functions are. In our view, it is not possible to derive credible estimates of the relative contributions of different outputs to input costs from models with such poor statistical properties.

[23] Economic Insights, *Review of NERA report on output weights*, 30 April 2019, p. 9.

Since the same output weights are used in the construction of the MTFP and MPFP productivity indices, the same conclusion applies to these indices.

Energy as a driver of opex

With respect to the use of energy throughput as a driver of opex, our review finds no statistical evidence that energy throughput has any impact on opex. In only one case did energy make a statistically significant contribution to opex. However, the output weights calculated by EI take account of the Leontief equations for all inputs, not just opex. In the vast majority of cases, specifically, in 42 out of the 52 equations, the estimated impact of energy on input costs was not only statistically insignificant, but the t-values were 0.000. We cannot think of any statistical reason why energy should even be included in these equations.

We also note that in the estimation dataset energy and opex often moved in opposite directions. In 50% of cases, either real opex decreased when there was year-on-year increase in energy, or real opex increased when there was a decrease in energy. This is consistent with the lack of statistical evidence casts further doubt on EI's contention that energy is an important driver of opex.

The fact that EI has been able to derive a weight for energy of 0.12 from the Leontief analysis should not be interpreted as evidence that energy is an important driver of input costs. This result is driven by the very few cases where the coefficient for energy is significant. The proportion of significant coefficients for energy is no better than if the energy data were replaced by a set of random numbers.

As explained above, EI's main argument for including energy throughput in its econometric models is that energy reflects the key services provided to and valued by consumers. However, the AER is using the estimated econometric models to forecast DNSPs' opex over a regulatory control period. These models are not being used to determine how much customers value different outputs.

EI itself has recognised that DNSPs' costs are unlikely to be influenced significantly by changes in energy throughput:[24]

> *The third recommended output is throughput or energy deliveries. While **throughput has a small direct impact on DNSP costs**, it reflects the main output customers are charged for and maintains consistency with earlier economic benchmarking studies, nearly all of which have included throughput as an output. While the majority of DNSP charges remain on throughput it is important to at least recognise throughput as a functional output DNSPs supply although **it is likely to receive a small weight given its likely small impact of DNSP costs**. Maintaining some similarity in output coverage to earlier studies provides a means of cross checking results. And, throughput data are likely to be the most robust for backcasting purposes. The value of the throughput output would be revenue multiplied by its cost share, which we would expect to be relatively small **given that costs are not likely to be greatly influenced by small variations in throughput**. [Emphasis added]*

The AER has also previously acknowledged that energy throughput is unlikely to be a material driver of DNSPs' costs:[25]

[24] Economic Insights, *Economic Benchmarking of Electricity Network Service Providers*, 25 June 2013, p. iv.

Energy delivered may not be an ideal output variable for DNSPs because it may not significantly affect the costs of providing distribution services. Ralph Turvey suggests that DNSPs act passively in distributing energy along their lines and cables and through its switchgear and transformers. Turvey notes that the amount distributed is not decided by the DNSP. In the short-run a load alteration will not affect the size of the network and will and only trivially affect operating and maintenance costs.

EI's and the AER's acknowledgment that energy throughput is not a material driver of DNSPs' costs is borne out by the statistical evidence presented above.

The problem appears to be that these econometric models were developed originally for the purposes of conducting economic benchmarking of DNSPs. Economic benchmarking involves estimating efficiency by comparing the inputs to production to the outputs from production. To the extent that energy throughput is an output delivered by DNSPs, there may be a case for including energy throughput in models used for the purpose of conducting benchmarking analysis.

However, the AER has repurposed those benchmarking models to forecast opex over a regulatory control period. The objective of that task is different to the task of estimating the efficiency of DNSPs.[26] If the AER wishes to use econometric models to forecast DNSPs' opex over a regulatory control period, those econometric models should include *relevant* opex drivers, not outputs that have little influence over costs. However, the AER has not done that. Instead, the AER has used, for the purposes of forecasting opex over a regulatory control period, models containing a variable that both EI and the AER have acknowledged has little impact on DNSPs' costs. The resulting models are mis-specified and, therefore, unreliable for the purposes to which they have been put by the AER.

[25] AER, *Expenditure forecast assessment guidelines for electricity distribution and transmission*, Issues Paper, December 2012, p. 78.

[26] EI argues that in 2013 some stakeholders argued that "throughput is what customers see directly and pay for, it should not be ignored." (Economic Insights, *Review of NERA report on output weights*, 30 April 2019, p. 9) However, those stakeholders argued in favour of the inclusion of energy throughput in the context of the development of economic benchmarking models, not in the context of the development of econometric models for the purposes of forecasting opex. EI argues that another reason for inclusion of energy throughput is "precedent from previous studies." (Economic Insights, *Review of NERA report on output weights*, 30 April 2019, p. 9). However, this is an irrelevant argument because, as EI itself notes, the previous studies referred to are "economic benchmarking studies" (Economic Insights, Economic Benchmarking of Electricity Network Service Providers, 25 June 2013, p. 9), not studies that develop econometric models for the exclusive purpose of forecasting opex.

4 OUTPUT WEIGHTS ESTIMATED USING TRANSLOG COST FUNCTION

4.1 Overview of approach

Specification of the translog model

The basic form of the translog opex cost functions estimated by EI has three outputs (customer numbers, circuit length and ratcheted maximum demand), the share of circuit length that is underground and a time trend. In algebraic terms, the basic functional form of the models can be written as:[27]

(3) $$ln\, C_{it} = b_0 + \sum_{m=1}^{3} b_m\, ln\, y_{mit}$$
$$+0.5 \sum_{m=1}^{3} b_{mm}\, (ln\, y_{mit})^2 + \sum_{m=1,m\neq l}^{2} \sum_{l=2}^{3} b_{ml}\, ln\, y_{mit}\, ln\, y_{lit}$$
$$+b_{UG}\, ln\, shUG_{it} + b_t t + b_{ONT} ONT + b_{NZ} NZ + e_{it}$$

where ln stands for the natural logarithm, the subscript i indicates DNSP i the subscripts m and l represent different outputs, and t represents the year. The dependent (left-hand) variable in the model is real opex, C_{it}, for DNSP i at time t. The explanatory (right-hand) variables, which are assumed to 'drive' opex, are:

- the outputs, where y_{mit} represents output m for DNSP i at time t;
- $shUG_{it}$, which is the share of DNSP i's circuit length at time t that is underground;
- T which is the time trend variable. The coefficient of the time trend variable, b_t, represents technological change; and
- ONT and NZ which are dummy variables to capture differences between Australian DNSPs and those in Ontario and New Zealand.

The term e_{it} is the residual term in the model.

The Cobb-Douglas model is a special case of the translog where the coefficients b_{mm} and b_{ml} are all equal to 0 (i.e., the middle line in equation (3) disappears), resulting in:

(4) $$ln\, C_{it} = b_0 + \sum_{m=1}^{3} b_m\, ln\, y_{mit} + b_{UG}\, ln(shUG)_{it} + b_t t + b_{ONT} ONT + b_{NZ} NZ + e_{it}.$$

For the LSE variant of the translog and Cobb-Douglas models, dummy variables are added to the above specifications for each of the Australian DNSPs. For the SFA variant of the models, the residual term e_{it} is split into an inefficiency component and a noise term.

Estimation of the models

EI estimates the various translog models using an international sample of DNSPs that includes distribution businesses from New Zealand and Ontario in addition to the 13 Australian DNSPs in the National Electricity Market. The models are estimated over two time periods, the long period (2006-

[27] Our review of the estimation of the models is based on the models presented in Economic Insights, *Economic Benchmarking Results for the Australian Energy Regulator's 2019 DNSP Annual Benchmarking Report,* 5 September 2019.

2018), and the short period (2012-2018). For the long period there are 881 observations in total in the estimation sample, of which 169 observations (19%) come from Australian DNSPs. For the short period, there are 473 observations in the estimation sample, of which 91 observations (19%) come from Australian DNSPs.

Estimation of cost shares

EI estimates cost shares for the Cobb-Douglas and translog models by taking the estimates of the 3 output elasticities implied by the estimated regression model and normalising them so they sum to 1.

For the Cobb-Douglas models this is an easy task, since, for each output, the elasticity of opex with respect to that output is equal to the estimate of the coefficient b_m in equation (4), which is an output of the econometric package used to estimate the model.

For the translog models the elasticities are not a direct output of the estimation package. The elasticity of opex with respect to output m is given by:[28]

(5) $elast_m = b_m + \sum_{l=1}^{3} b_{ml} \ln y_{lit}.$

Hence, the elasticities depend on the levels of all the outputs.

4.2 Evaluation of translog output weights

To derive the elasticities when calculating translog output weights, EI evaluates the translog elasticities at the geometric mean of that output across all DNSPs and time period used in the estimation sample. **Table 2** lists these geometric means in the last row for the 2006-2018 sample period. The contrast with the corresponding values for Australia is quite stark. Average customer numbers for Australian DNSPs are more than six times larger than for the international sample, circuit length more than eight times larger, and ratcheted maximum demand is more than five times larger. For Australian rural DNSPs the discrepancy in average circuit length is even more extreme, being over 20 times larger than the average used by EI in its calculations. Since the elasticities depend on the levels of the outputs, the elasticities derived by EI do not reflect the operating characteristics of Australian DNSPs.[29]

Since the main motivation for estimating a translog model rather than a Cobb-Douglas model is to obtain flexibility in the estimation of elasticities, it is unclear why the AER/EI do not evaluate the translog elasticities at output levels that are more reflective of the Australian DNSPs. If the AER/EI really do believe that the elasticities are constant across all utilities in the sample, then it would be statistically more efficient to impose these restrictions when estimating the model, which would be the same as estimating the Cobb-Douglas cost function.

There have been suggestions that the elasticities could be evaluated separately for each DNSP, or even for each DNSP and year. We recognise that this is not practicable, since there is likely to be too much variability in the estimated elasticities when evaluating them at that level of disaggregation. However, it would be possible to evaluate the elasticities for the average outputs of a sensible grouping of DNSPs, such as the groupings shown in **Table 2**, for example, the average Australian DNSP, or the average Australian urban or rural DNSP.

[28] When evaluating this expression, one needs to use the fact that $b_{ml} = b_{lm}$.

[29] For this statement to be correct, we second order terms in the TL models also need to be significant. Statistical tests of this assumption for the four TL models presented in EI's benchmarking report of 5 September 2019 shows that they are statistically significant.

Table 2: Geometric averages of output variables for different groupings of DNSPs

DNSPs IN GROUP	CUSTOMER NUMBERS	CIRCUIT LENGTH	RATCHETED MAX DEMAND
Australia - Urban	581,140	14,262	2,218
Australia - Rural	636,309	75,009	2,282
Australia - All	605,982	30,684	2,247
All countries - Urban	93,447	2,056	456
All countries - Rural	92,072	9,819	311
Whole international sample	**92,937**	**3,660**	**396**

Source: *Frontier Economic analysis of data used for EI's report "Economic Benchmarking Results for the Australian Energy Regulator's 2019 DNSP Annual Benchmarking Report, 5 September 2019"*

Note: *These are the geometric averages for the 2006-2018 sample*

4.3 Conclusions about translog function output weights

An important feature of the translog cost function that distinguishes it from the Cobb-Douglas cost function, is that it allows for elasticities to vary as output levels change rather than imposing constant elasticities across all DNSPs. When deriving elasticities from the translog cost function, a decision has to be made about the levels of the outputs at which the elasticities should be evaluated.

The approach adopted by the AER is to evaluate the elasticities at the geometric average output levels of all DNSPs in the international sample. However, these average output levels are vastly different to the output levels experienced by Australian DNSPs. The output levels chosen by EI for evaluating the translog cost function elasticities have no economic or statistical justification. In our view, these elasticities should be evaluated at output levels that are reflective of the operating characteristics of the Australian DNSPs. If the AER believes that the elasticities *are* constant across all utilities in the sample, then it would be statistically more efficient to estimate these constant elasticities using the Cobb-Douglas cost function.

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