Memorandum

From: Denis Lawrence and Tim Coelli **Date:** 30 April 2019

To: AER Opex Team

Subject: Review of NERA report on output weights

We have been asked to review the NERA (2018) report on the output weightings used in the AER's 'base/step/trend' method for assessing opex proposals of electricity distribution network service providers (DNSPs). The NERA (2018) report was prepared for CitiPower, Powercor, United Energy and SA Power Networks (hereafter 'CP Group').

Base/step/trend method

The base/step/trend method for calculating the efficient future opex allowance for regulated DNSPs starts by determining the efficient level of opex use in a base year (usually the second last year of the preceding regulatory period). It then rolls efficient base year opex forward each year by the forecast rate of change in opex input prices plus the forecast rate of change in output minus the forecast rate of change in opex partial factor productivity (PFP). The idea is that over time more opex allowance will be required if opex input prices increase relatively rapidly and if output increases (as more inputs are required to supply more output). But increases in opex partial productivity over time will normally reduce the quantity of opex required per unit of output, all else equal. Positive or negative step changes may be added to reflect changes in DNSPs' recognised responsibilities over time.

AER (2018) sets out the AER's preferred method for weighting forecast growth in individual outputs to form a measure of overall output change for use in the base/step/trend method's rate of change. This involves averaging the weights obtained from four of the AER's economic benchmarking models: the Stochastic Frontier Analysis Cobb Douglas (SFACD) model, the Least Squares Econometrics Cobb Douglas (LSECD) model, the Least Squares Econometrics translog (LSETLG) model and the opex partial factor productivity (opex PFP) model. Weights are applied to four outputs – customer numbers, circuit length, ratcheted maximum demand (RMD) and energy throughput. Based on the latest economic benchmarking results in Economic Insights (2018), customer numbers would receive weights of around 70 per cent in the SFACD and LSECD models, around 50 per cent in the LSETLG model and 30 per cent in the opex PFP model. Energy throughput is only included in the opex PFP model and so receives zero weight in the three econometric models.

NERA (2018) findings

NERA (2018) makes three broad criticisms of the AER (2018) approach to forming output weights. These criticisms cover:

- the opex PFP model: NERA (2018, pp.ii–iii) argues the derivation of weights used in the opex PFP model is not transparent, its 'drivers' are based on 'tariff structure', its weights are ‘artificially constrained’ to be positive and ‘very little data’ is used to estimate the weights

- the use of energy throughput: NERA (2018, p.iii) argues that changes in throughput do not affect DNSPs’ costs, the growth of embedded generation has disrupted the link between throughput and peak demand and overseas regulators are tending to ‘delink’ tariff structures from throughput, and
- the LSETLG model: NERA (2018, p.iii–iv) argues that the translog model’s second order coefficients produce counter–intuitive relationships, its results violate required cost function monotonicity properties, translog models have been rejected by a key UK regulator and the second order coefficients are not included in forming weights when they should be.

NERA (2018, p.iv) recommends that the AER form its output weights from an average of those in two of the econometric models only – the SFACD and LSECD models.

We now address each of the NERA (2018) criticisms and recommendations.

Opex PFP model

Transparency

The first criticism NERA (2018, pp.13–14) makes of the opex PFP models is:

> ‘While [Economic Insights] and the AER have set out the process through which they used the MPFP modelling to benchmark DNSPs’ efficiency, they have published little detail on the approach they used to estimate the weights.’

This is incorrect. Economic Insights (2013, pp.22–28) contains a detailed discussion of the options considered for estimating output cost shares for use in the productivity index number models. This discussion covers deriving weights from the estimation of econometric cost function models, the use of results from econometric cost function models in similar industries and the collection of relative output cost information directly from DNSPs. It is noted that a disadvantage of using the results of modelling from other industries is that the choice of outputs would be constrained to that used in previous studies. And the discussion of what would be involved in trying to source relative output cost information directly from DNSPs illustrates the difficulties involved and the burden it would impose on DNSPs. This leaves the direct estimation of cost functions from the available Australian DNSP data as the preferred option.

Economic Insights (2013, pp.22–28) detailed the previous econometric cost function approaches used to derive output cost shares in energy distribution productivity index number studies, including the Leontief cost function approach and the more flexible translog cost function approach. 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. The first option was adopted for the cost function–based efficiency assessments in Economic Insights

(2014) by incorporating data for New Zealand and Ontario DNSPs while the second approach (as outlined in detail in Economic Insights 2013) was adopted for the productivity index number models which used only Australian data.

Consistent with the approach commonly adopted in regulatory applications and discussed in Economic Insights (2013, pp.22–28; 2018, pp.1–3), the output cost shares estimated for the productivity index number models in Economic Insights (2014) were left in place for the 2015, 2016 and 2017 annual benchmarking reports. This allows changes in annual productivity results to be attributed to DNSPs' operations and not to changes in estimated output shares. However, it is appropriate to periodically update the output cost share estimates as more and better data become available and as circumstances change. This was done in Economic Insights (2018). These estimated output cost shares were recommended to be left in place for the next five years. Despite the infrequent periodic updating of the output cost shares, we have continued to describe the methodology used in all relevant economic benchmarking reports.

NERA (2018, pp.13–14) goes on to state:

> 'An appendix to the [Economic Insights] annual benchmarking report gives a half–page description of the approach, but does not report the input variables used or show any statistical results that could be used to appraise the reliability of the weights.'

Although the Leontief cost function methodology is relatively simple, it involves the estimation of 52 separate regressions – 4 input demand equations for each of the 13 DNSPs. Each regression contains five parameters to be estimated – 4 input/output coefficients and a time trend coefficient. The most efficient way of presenting this volume of material is to provide the econometrics program output file which is what we have done. This file provides the standard statistical information for each regression. Because the Leontief methodology involves fixed proportions of inputs (and hence cost) being allocated to each output, it does not include any substitution parameters or elasticities which would be the items of most interest in more sophisticated cost functions.

Not only do we provide the regression output files accompanying Economic Insights (2018), we also provide the regression data files and regression input files. This allows anyone with a basic familiarity with quantitative methods to undertake their own sensitivity analyses and, if desired, additional interrogation of the results. This extreme degree of transparency in the presentation of quantitative modelling material supporting regulatory decisions is near unprecedented. It is incorrect to describe it as 'opaque' as NERA (2018, p.13) does.

Furthermore, Economic Insights (2018, p.2) undertakes additional analysis which corroborates the output cost share estimates obtained from the Leontief methodology. We note:

> 'The expanded Australian DNSP database now also supports estimation of a translog cost function across the whole sample. While the sample size and degree of data variation across DNSPs is still at the lower end of that required, the derived output cost shares are broadly similar to those obtained from the Leontief

> cost functions. The translog cost function methodology is also outlined in appendix A.'

And the translog regression output file, input file and data file accompany the report, again demonstrating our adherence to maximum transparency.

Finally, NERA (2018, p.14) argues that we have not described or assessed 'the reliability of the output weights as a means of keeping allowances in line with efficient opex in the rate of change calculation'. This is incorrect. Economic Insights (2013, pp.6–28) provides a lengthy discussion of the basis for choosing outputs to include in economic benchmarking and of alternative methods of deriving output weights under a building blocks regulatory regime. This will be covered in more detail below but it is sufficient here to note that we observe that outputs need to be measured in a way similar to the range of deliverables and performance standards the regulator bases their revenue requirement decisions on. We also note that the weight given to energy throughput would be expected to be relatively small given that marginal changes in throughput will not have a large impact on DNSP costs. We furthermore note that the large majority of DNSP costs are relatively fixed in nature and relate to providing the infrastructure to connect and supply customers and to provide adequate (but not excessive) system capacity. Outside these broad expectations regarding output weights, the exact size of the output weights is a matter for empirical determination. The output weights estimated using the Leontief methodology in Economic Insights (2014) and the Leontief and translog methodologies in Economic Insights (2018) are consistent with these expectations of what would be required to allow DNSPs to recover efficient opex costs.

Basis for choosing outputs included in opex PFP

NERA (2018, p.ii) claims that Economic Insights:

> 'chose drivers to include in the MPFP model on the basis that they were drivers of revenue and hence reflected the design of regulated tariffs.'

This is incorrect. In fact, nothing could be further from the truth. Economic Insights (2013, pp.6–22) presents a detailed discussion of whether outputs should be selected on a 'billed' basis (ie only including those things that are directly charged for) or on a 'functional' basis (ie reflecting the key service dimensions provided to customers, regardless of whether these are directly charged for or not). Economic Insights (2013, p.6) notes:

> 'Under building blocks regulation there is typically not a direct link between the revenue requirement the DNSP is allowed by the regulator and how the DNSP structures its prices. Rather, the regulator typically sets the revenue requirement based on the DNSP being expected to meet a range of performance standards (including reliability performance) and other deliverables (or functional outputs) required to meet the expenditure objectives set out in clauses 6.5.6(a) and 6.5.7(a) of the National Electricity Rules (NER). … in the case of building blocks, it will be important to measure output (and hence efficiency) in a way that is broadly consistent with the output dimensions implicit in the setting of NSP revenue requirements. This points to using a functional rather than a billed outputs specification, a proposition universally supported by stakeholders during consultation.'

Economic Insights (2013, pp.6–7) went on to state that a set of selection criteria would be needed to choose the appropriate set of functional outputs:

> ‘The AER (2012.., p.74) proposed the following criteria for selecting outputs to be included in economic benchmarking:
>
> 1) the output aligns with the NEL and NER objectives
> 2) the output reflects services provided to customers, and
> 3) the output is significant. ….
>
> ‘Stakeholders at the first workshop agreed that the AER (2012a) criteria above provided a reasonable basis on which to select outputs for use in economic benchmarking studies.’

This set of selection criteria has been the basis of our choice of outputs for economic benchmarking.

With regard to the first two selection criteria Economic Insights (2013, p.7) noted:

> ‘The first selection criterion states that economic benchmarking outputs should reflect the deliverables the AER expects in setting the revenue requirement which are, in turn, those the AER believes are necessary to achieve the expenditure objectives specified in the NER. The NER expenditure objectives for both opex and capex are to:
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> - meet or manage the expected demand for *standard control services*
> - comply with all applicable regulatory obligations or requirements associated with the provision of standard control services
> - maintain the quality, reliability and security of supply of standard control services, and
> - maintain the reliability, safety and security of the distribution system through the supply of standard control services.
>
> ‘If the outputs included in economic benchmarking are similar to those the DNSPs are financially supported to deliver, then economic benchmarking can help ensure the expenditure objectives are met at an efficient cost.
>
> ‘The second selection criterion is intended to ensure the outputs included reflect services provided directly to customers rather than activities undertaken by the DNSP which do not directly affect what the customer receives. If activities undertaken by the DNSP but which do not directly affect what customers receive are included as outputs in economic benchmarking, then there is a risk the DNSP would have an incentive to oversupply those activities and not concentrate sufficiently on meeting customers’ needs at an efficient cost.’ (emphasis added).

Economic Insights (2013, p.7–22) then goes on to evaluate a range of both billed and other functional outputs for inclusion in economic benchmarking but first noted the following:

> ‘Most economic benchmarking studies to date have included either all or a subset of billed outputs in their output coverage. However, the weights applied to billed

> components have typically varied between studies adopting a billed outputs only approach and those adopting a broader functional outputs approach. Those studies that have adopted the broader functional outputs approach have included additional outputs such as system capacity and reliability …'

In an earlier detailed technical report for the New Zealand Commerce Commission, Economic Insights (2009) demonstrated that, under incentive regulation, billed outputs should be included as a subset of overall functional outputs and the shadow prices applied should reflect the differences between marginal costs and prices charged. This points to the inclusion of energy throughput but that it should receive a relatively small weight.

Economic Insights (2013, pp.8–9) went on to discuss the pros and cons of including energy throughput as one of the overall functional outputs in economic benchmarking – it is the inclusion of this output which NERA (2018, p.ii,14–15) objects to and about which it makes incorrect statements. We noted that some DNSPs argued against the inclusion of energy throughput on the grounds that it had little direct effect on DNSP opex but others noted that because throughput is what customers see directly and pay for, it should not be ignored. In other words, energy throughput scores highly on the second selection criterion because it reflects a major service provided to customers but it would likely receive a low weight on a cost reflective basis. We noted that other reasons supporting the inclusion of energy throughput were precedent from previous studies (allowing more direct comparisons) and the fact that DNSPs have very robust data on this variable (from charging records). These were secondary considerations but important ones nonetheless.

Another issue regarding the inclusion of energy throughput as an output is also noteworthy. NERA (2018, pp.14–15) appears to view the NER objectives as being solely related to DNSPs' fixed costs and that this should be the only criterion for inclusion of outputs. We note that the overarching objective of regulation is to advance the long term interests of consumers. It is difficult to assess whether consumers' long term interests are being advanced if one of the main outputs they consume is not being included in the assessment of efficient costs. And, we note that the first of the NER objectives is to 'meet or manage the expected demand for *standard control services'* (emphasis added). In this context we note that AER (2018, p.9) defines the first of its standard control services, direct control services, as follows:

> '… this grouping relates to *the conveyance or flow of electricity through the network* for consumers (and includes activities that relate to maintaining network integrity)' (emphasis added).

Thus, energy throughput is recognised directly as a standard control service and, all else equal, should be included as an output based on the first selection criterion in Economic Insights (2013) (ie that relating to the NER objectives) as well as the second and third selection criteria (which are expressed more directly in terms of services provided to consumers).

Squaring of opex cost function output coefficients

NERA (2018, p.15) states the following:

> '[Economic Insights'] attempt to calculate weights with a translog function actually found that opex was *negatively* correlated with some of the outputs. To

correct for this shortcoming, [Economic Insights] instead estimated a non–linear regression in which the coefficient on each output is squared … This approach guarantees that each estimated squared coefficient … is positive. … Therefore, even if the true relationship between an output and opex is non–existent or indeed negative, [Economic Insights'] approach would assign positive weight to that driver. Indeed, the fact that [Economic Insights'] first attempt found negative first order coefficients … suggests that some of the relationships included in the MPFP model may be inappropriate, and arbitrarily forced to be positive.'

Nearly all the statements in this section of NERA (2018) are incorrect. Firstly, NERA confuses negative correlation with the inability to obtain robust estimates due to lack of variation in the Australian data and multicollinearity issues. Economic Insights (2014, p.28) notes:

> 'We first examined the scope to estimate an opex cost function using only the AER's economic benchmarking RIN data on 13 DNSPs over an 8 year period (104 observations in total). However, this produced econometric estimates that were relatively unstable. … We observed that small changes in variable sets (and methods and functional forms) could have a substantial effect on the output elasticity estimates obtained and the subsequent efficiency measures derived from these models. … After a careful analysis of the economic benchmarking RIN data we concluded that there was insufficient variation in the data set to allow us to reliably estimate even a simple version of an opex cost function model … In essence, the time series pattern of the data is quite similar across the 13 DNSPs. Hence, in this case, there is little additional data variation supplied by moving from a cross–sectional data set of 13 observations to a panel data set of 104 observations. As a consequence we are essentially trying to use a data set with 13 observations to estimate a complex econometric model. The 'implicit' degrees of freedom are near zero or even negative in some cases, producing model estimates that are relatively unstable and unreliable.'

As already noted above, we adopted two different strategies to address this issue. In the case of obtaining output cost shares for use in the Australian DNSP–only opex PFP analysis, we moved to using a very basic Leontief cost function estimated on a DNSP–by–DNSP basis. In the case of the opex cost function–based efficiency scores we supplemented the Australian DNSP data with comparable overseas DNSP data to introduce more variation in the overall data set.

The second problem encountered in estimating opex cost functions across the whole data set was multicollinearity. Economic insights (2014, p.32) notes:

> 'It was observed that the estimated coefficients of either *Energy* or *RMDemand* were generally insignificant in these models. Upon investigation it was found that the sample correlation coefficient between these two variables was larger than 0.99 and the behaviour of their coefficients was almost certainly a consequence of multicollinearity problems (ie these variables are so closely related that the model is not able to distinguish their effects). We hence decided to drop *Energy* from the

> model and re–estimated … including three output variables (*CustNum*, *CircLen* and *RMDemand*).'

Thus, no reliance could be placed on the output shares estimated from the Australian DNSP database as a whole and the NERA (2018, p.15) statement that the 'translog function actually found that opex was *negatively* correlated with some of the outputs' is incorrect.

Next, it has always been our practice to estimate the Leontief cost function model with squared output coefficients. In fact, we have never estimated this model without squared output coefficients as negative coefficients are at odds with the underlying economic theory. However, this does not 'guarantee' that 'each estimated squared coefficient … is positive' nor that 'even if the true relationship between an output and opex is non–existent or indeed negative' a positive weight would be obtained as NERA (2018, p.15) claims. Rather, it simply means that the overall output coefficient will be non–negative. If the relationship in the database is non–existent then the regression will return a zero estimate for the output coefficient. If the relationship in the database is negative then the regression will force the estimated coefficient to zero as it is the least cost way it can satisfy the non–negativity constraint that is being imposed.

To put this another way, NERA (2018) appears to be under the misapprehension that the regression coefficients are first estimated and then subsequently squared to produce a positive number. That is not the case. Rather, in a non–linear regression of this type, the coefficient is estimated taking the imposed constraint into account. In this case, if the underlying relationship in the data were negative and we imposed a non–negativity constraint on the estimation process, then the regression would produce a zero coefficient as that would be the most efficient solution to satisfying the non–negativity constraint. The fact that we observe a positive rather than near zero share for all the outputs in the Leontief results indicates that the model has in fact found a positive relationship between opex and all the included outputs.

Finally, as noted earlier, Economic Insights (2018, p.2) reported that the Australian database running to 2017 now better supports estimation of a translog opex cost function across the Australian sample as a whole. However, despite a 50 per cent increase in annual observations for each DNSP, the degree of data variability across DNSPs is still at the lower end of that required. As can be seen from the output file accompanying Economic Insights (2018), the translog opex cost function produces output shares of 30 per cent for customer numbers, 29 per cent for circuit length, 26 per cent for RMDemand and 16 per cent for energy throughput. This compares closely to the Leontief cost function–based estimates of 30 per cent for customer numbers, 29 per cent for circuit length, 28 per cent for RMDemand and 12 per cent for energy throughput. Because the significance levels of coefficients in the translog model are not yet as strong as we would prefer, we have again based our opex PFP output shares in Economic Insights (2018) on the Leontief results.

Precision of estimates

NERA (2018, p.iii) claims:

> 'The MPFP weights are estimated with very little data, suggesting the weights are estimated imprecisely: [Economic Insights] estimates a separate regression for

> each company, so each has only 12 data points. This is unlikely to be enough data to calibrate the relationship between costs and drivers accurately.'

As discussed above, the Australian database contains less variability across the 13 DNSPs than is required to produce fully robust parameter estimates from an econometric opex cost function. Because the application of opex PFP is limited to the Australian DNSPs we have opted to address the data variability problem with regard to forming output cost shares by estimating a very basic Leontief cost function on a DNSP–by–DNSP basis. 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. This can be characterised as a 'bottom up' estimation method. Our confidence in the resulting output cost share estimates is further enhanced by the estimation of a translog opex cost function across the whole Australian sample in Economic Insights (2018). While the degree of variability across the Australian DNSP data is still less than ideal, it is improved by the 50 per cent increase in time–series observations compared to Economic Insights (2014) and the translog opex cost function produces very similar output cost shares to those obtained from the bottom up Leontief methodology.

The use of alternative models, estimation methods, more reliance on bottom up approaches and the inclusion of different output specifications is consistent with the recommendations of the Australian Competition Tribunal (2016).

We therefore reject the criticism of NERA (2018, p.iii,15–16) that the estimation of the opex PFP output weights lacks sufficient precision. Rather, the estimation method has made the best use of available information, has built in risk reduction mechanisms and has been corroborated by different methods.

The use of energy throughput as an output

Having based much of its objections to the opex PFP model's output specification on the inclusion of energy throughput in the model, NERA (2018, pp.16–24) then proceeds to devote another section to trying to mount a case for not including energy throughput as an output. NERA (2018, p.16) claims that:

> 'a … fundamental problem with the AER's proposal to index allowed opex to changes in energy throughput is that it does not reflect changes in DNSPs' efficient operating costs'.

We have already addressed many of the issues raised by NERA (2018, pp.16–24) and will not cover them in detail again. For completeness, however, a summary of the related points above is as follows:

- 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
- the key billed outputs should be included as a subset of functional outputs (and energy throughput remains a key billed output)

- energy throughput scores well on the output selection criteria used in Economic Insights (2013):
  - it is explicitly recognised as an important part of standard control services in the implementation of the NER objectives
  - it is the major service consumers actually use
  - it is significant to consumers, and
- estimated cost functions produce a positive output cost share for energy throughput but one that is substantially smaller than for the other outputs as would be expected on an engineering basis.

NERA (2018, pp.16–24) introduces three new arguments in this section as follows:

- tariff reform in Australia and the US is leading to less emphasis being placed on throughput charges
- UK and US regulators are placing less emphasis on energy throughput in setting DNSPs' revenue allowances, and
- the growth of embedded generation may be 'breaking down' the positive relationship between energy throughput and DNSP costs.

The arguments raised by NERA (2018) regarding tariff reform have no bearing on the inclusion of energy throughput as an output. The bulk of DNSP charges are on energy deliveries but it is acknowledged they should receive a relatively small weight on a cost reflective basis. For example, an examination of the AER's Economic Benchmarking Regulatory Information Notice database indicates that in 2012 around 60 per cent of DNSP revenue came from delivery (or throughput) charges. This is far higher than the 12 per cent output cost weight currently given to energy throughput in the one model where it is included. Consequently, moves to reduce the emphasis DNSPs place on throughput charges do not invalidate its inclusion as an output in economic benchmarking models or in calculating output growth in the rate of change.

The approaches of UK and US regulators to setting their DNSPs' revenue allowances are of interest and developments in those countries should be monitored. However, the history of regulation and the consequent regulatory frameworks that have evolved in those countries are different to Australia. In particular, much of the US remains on cost of service regulation while some states have adopted varying degrees of productivity–based regulation. Both these regulatory regimes are quite different to Australia's building blocks regulatory regime.

Similarly, the UK regime's approach and its reliance on 'totex' is quite different to Australia's building blocks regime. We note that early feasibility studies for the development of Ofgem's RIIO–ED1 totex benchmarking models found high correlation between energy deliveries and DNSP costs and considered output specifications broadly similar to those we use (Frontier Economics 2012). However, subsequent implementation of Ofgem's totex benchmarking has largely used more simple methods with much reliance on single variable regressions, sometimes using 'composite' variables. Ofgem (2014, p.187) noted:

> 'For our top–down totex model we considered the following set of drivers: customer numbers, *units distributed*, network length, MEAV, peak and density.' (emphasis added).

Ofgem goes on to describe difficulties encountered with estimation given the limited number of observations it had available (given its decision to use domestic data only) and multicollinearity issues. It subsequently decided to use only MEAV and customer numbers in its preferred single composite variable regression.

It should also be noted that Ofgem recently commissioned the Energy Policy Research Group (EPRG 2018) to provide an analysis of productivity growth in electricity and gas networks. EPRG looked at electricity distribution models involving five different specifications of outputs and inputs. Energy delivered was used as an output in all five models.

Finally, NERA (2018, p.23) speculates that the relationship between energy throughput and network costs 'could reverse' with the expected growth of embedded generation. It goes on to quote some examples of expenditure SA Power Networks forecasts it will need to make to accommodate local peaks from 'highly localised export flows' associated with growing distributed generation. NERA (2018, p.24) again makes the incorrect statement that the opex PFP model 'imposes a positive weight [on energy throughput] by assumption by using squared coefficients'. We have noted above this statement involves an incorrect understanding of how constrained non–linear regression methods work. We also note that Economic Insights (2018, p.5) illustrates that, for the industry as a whole, there have been small increases in both energy throughput and ratcheted maximum demand in recent years.

We are not opposed to re–examining the opex PFP output specification at some point in the future to make sure it adequately accommodates changes in industry characteristics associated with growing embedded generation. However, this should be part of a wider periodic review of economic benchmarking rather than part of a price determination process. The outcome of such a review would be likely to involve including additional outputs rather than removing current outputs.

In conclusion to this section, the predominant focus of NERA (2018, pp.13–24) on attempting to mount a case for not including energy throughput as a component of the rate of change output variable needs to be put in context. Only one of the four economic benchmarking models AER (2018) averaged output growth rates over includes energy throughput as an output. And this model only allocates 12 per cent weight to energy throughput. The weight given to energy throughput in the AER (2018) output growth rate is thus only 3 per cent (12 per cent of 25 per cent). If the SFATLG model included in Economic Insights (2018) was included in the averaging process, the weight given to energy throughput would drop further to 2.4 per cent (12 per cent of 20 per cent). Thus, apart from its arguments being based on flawed reasoning as demonstrated above, the NERA (2018, p.16) statement that the AER proposes 'to index allowed opex to changes in energy throughput' is an overstatement.

Translog model

Plausibility of estimated relationships

NERA (2018, p.24) makes the following claim:

> ‘the AER has derived weights in a way that does not capture the relationship between opex and the output drivers in the translog model specification. When interpreted correctly, the implied relationships between outputs and opex are not plausible from an economic or engineering perspective, so the use of this model is therefore unlikely to satisfy the operating expenditure criteria.’

NERA (2018, pp.24–27) attempts to justify this statement by arguing that some of the Economic Insights (2018) LSETLG model’s second order coefficients and associated elasticities are implausible and that the model produces overall elasticities for customer numbers of the wrong sign. However, NERA (2018) does not interpret the coefficients in the correct framework and makes a fundamental error in its calculation of elasticities.

Firstly, NERA (2018, p.24) makes a technical error by describing selected second order coefficients in the model as indicating ‘almost constant returns to scale’. This is incorrect as constant returns to scale relates to the situation where an increase in all outputs by a given percentage leads to the same percentage increase in costs, being opex in this case. However, the situation NERA (2018, p.24) attempts to analyse is actually a situation of constant partial elasticity – the distinction being that only the output in question changes and all other outputs are held constant. This in turn points to the problematic nature of attempting to do this type of exercise. Trying to cherry pick second order coefficients and interpret them is difficult because of all the other things that need to be held constant in the thought process. It is for this reason that this exercise is virtually never undertaken in reporting the results of cost function studies using flexible functional forms such as the translog.

Rather, the best way to assess the plausibility of the results from a translog cost function model is to calculate the overall partial elasticities for each output and each observation and check whether these are positive and the model thus satisfies the required technical property of monotonicity. This property states that no output can be increased without an associated increase in cost or, to put it another way, that no ‘free lunches’ are available which would be the case if an output could be increased and this led to a reduction in costs.

NERA (2018, p.27) purports to calculate these overall partial output/cost elasticities and claims the customer numbers elasticity is negative. However, the NERA (2018) calculations contain a fundamental error. The Economic Insights (2018) cost functions, along with all our previous cost function models, use mean–corrected output data. This was clearly documented in Economic Insights (2014, pp.34–35) and is clearly documented in the Stata input and output files accompanying all our economic benchmarking reports. This is common practice in cost function studies and allows one to interpret the translog first order coefficients as elasticities at the sample means. NERA (2018) has not mean–corrected the output data in its calculations and so has totally mismatched the data and coefficients. The NERA (2018) ‘elasticities’ calculations are thus a classic case of ‘garbage in, garbage out’.

It is also surprising that NERA (2018) saw the need to calculate these elasticities as they are not only correctly calculated but also listed in their entirety in all our Stata output files. Inspection of the file accompanying Economic Insights (2018) confirms that the partial output elasticities are indeed all positive for all the Australian DNSP observations and for most of the overseas observations.

We thus reject the NERA (2018) claim that the LSETLG model estimates are not plausible.

UK CMA criticism of translog

NERA (2018, pp.27–28) states:

> ‘The UK’s regulatory appeals body, the Competition and Markets Authority (CMA), has found similarly implausible modelled relationships between costs and drivers in a translog model estimated by the water sector regulator, Ofwat.
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> ‘Ofwat set price controls using a series of translog models to model water and wastewater companies’ total expenditure (totex) … One company, Bristol Water, appealed Ofwat’s determination to the CMA. … In short, the CMA came to the same conclusion with respect to the Ofwat models that we have come to with respect to the AER translog model: the translog model as defined does not appear to capture plausible relationships between opex and the drivers of distribution network costs.’

However, NERA (2018) fails to present the context in which the CMA made its decision. CMA (2015, p.72) states the following:

> ‘Ofwat used models with a particularly complex model specification, which it described as translog. The models involve relatively complex explanatory variables ... *In the context of the relatively small sample size, the translog structure seemed overly ambitious*.’ (emphasis added).

In a footnote on the same page the CMA notes that the Ofwat model had 27 explanatory variables and a sample size of only 90 observations. This contrasts to the LSETLG model in Economic Insights (2014) which, excluding DNSP–specific dummy variables, has only 14 explanatory variables and 544 observations. The LSETLG model in Economic Insights (2018) has the same number of explanatory variables and uses a more recent data set with 402 observations. Our translog models, therefore have many times more degrees of freedom than the Ofwat model the CMA criticises as being overly ambitious given its small sample size.

CMA (2015, p.A4(1)–35) was even more explicit that is was not making a general criticism of the translog methodology (as implied by NERA 2018):

> ‘For the purposes of our assessment, we did not focus on the general question of whether a translog functional form was a useful model for econometric analysis of costs or efficiency. Instead, our focus was on the specific translog implementation used in Ofwat’s models, within the specific context of our determination for Bristol Water.’

CMA (2015, p.A4(1)–14) provides more details on the specific objection Bristol Water raised:

> ‘Bristol Water identified several cases where the estimated results from Ofwat’s models seem counter–intuitive. These are cases where the relationship between costs and an explanatory variable go in the opposite way to what it would have expected. Bristol Water provided several examples of what it considered to be the unexpected cost relations from Ofwat’s models:
>
> (a) Each additional property would lead to predicted costs being £50 per year lower.

(b) Each additional megalitre of water supplied to customers would result in predicted costs being £83 lower.

(c) Each additional customer being metered would result in predicted costs being lower by £62 per year.'

In other words, the results objected to by Bristol Water related to its estimated partial output/cost elasticities being of the wrong sign. We have explained above that the NERA (2018) attempt to calculate these elasticities for our LSETLG model (and which also produce an elasticity of the wrong sign for one output) involve a fundamental error in failing to mean–correct the output data. We also noted that the correctly calculated elasticities calculated and reported in the files accompanying Economic Insights (2018) and earlier reports are all of the correct sign for all Australian DNSP observations.

The criticisms of Ofwat's translog model made by the CMA (2015) and quoted by NERA (2018, pp.27–28) in support of its flawed criticism of the Economic Insights (2018) LSETLG model are demonstrably not applicable to our models.

Before leaving this subject, it is worth noting that the translog methodology is the most widely used flexible functional form used in cost function estimation. In the context of economic benchmarking, a leading reference work by Greene (2008, p.98) notes:

'The Cobb–Douglas and translog models overwhelmingly dominate the applications literature in stochastic frontier and econometric inefficiency estimation.'

Pacific Economics Group Research (PEG) has generally used the translog method in its work for North American regulators and utilities. For example, in work for the Ontario Energy Board PEG (2013, p.V) states:

'The functional form selected for this study was the translog. This very flexible function is the most frequently used in econometric cost research.'

And, respected academics in the field Guilkey, Lovell and Sickles (1983, p.614) have noted:

'Our effort to turn up a flexible functional form more reliable than the TL [translog] form must be considered a failure. In almost every comparison we have conducted the TL system estimator and the EGCD [extended generalised Cobb Douglas] systems estimator outperform all other estimators, typically by a wide margin.'

There is thus a long history of using both the Cobb Douglas and translog functional forms we use in our economic benchmarking reports and those two remain the most commonly used in empirical studies, including those used in regulatory reviews worldwide.

Including second order terms in elasticity calculations

NERA (2018, p.28) claims:

'the impact of changes in outputs on opex is captured by a wider set of coefficients (including on cross-product and quadratic terms), not solely by the coefficients on the individual output terms. However, the AER has proposed to base weights from the translog model on only these "first-order" coefficients

> (0.507, 0.136 and 0.338 for customers, circuit length and ratcheted maximum demand, as shown in Table 3.1), ignoring the squared and cross–product terms. … Hence, the AER's proposed output weights are inconsistent with the cost-output relationships estimated by the translog model.'

This is incorrect. Because we mean–correct the output data, the first order coefficients we estimate can be interpreted as partial elasticities at the sample means. This was clearly stated in Economic Insights (2014, pp.34–35). Using the sample mean elasticities from the first–order translog coefficients produces output cost shares that are broadly comparable to those obtained from the two Cobb Douglas models we estimate and the weighted average output cost shares obtained from the Leontief cost function model. It is thus entirely appropriate to follow this procedure to form a set of output cost shares for use in the rate of change output growth component from the average of the translog cost function model, the two Cob Douglas cost function models and the opex PFP model results.

The procedure we adopt is similar to that used by other analysts undertaking efficiency and productivity studies for use in regulatory reviews. For example, PEG (2013, pp.61–62) describes its process as follows:

> 'the output quantity subindexes are customer numbers (other than street lighting, sentinel lighting, and scattered unmetered customers), total kWh deliveries, and system capacity peak demand. Output quantity growth is a weighted average of the growth in these subindexes, with weights equal to each output's cost elasticity share. These cost elasticities are equal to the coefficients on the first order terms of associated outputs in the cost model presented in Table 12. These cost elasticities were 0.295 for customer numbers, 0.093 for kWh, and 0.366 for system capacity. The associated cost elasticity shares, which must necessarily sum to one, are 0.3913, 0.1233, and 0.4854 for customer numbers, kWh, and system capacity peak demand, respectively.'

The cost model referred to by PEG is a standard translog model estimated using mean–corrected output data.

The confusion of NERA (2018) on this issue again stems from its failure to recognise that the output data is mean–corrected prior to estimation.

Overall assessment of NERA (2018) and its recommendations

We have shown in this memo that NERA (2018) contains numerous incorrect statements, flawed reasoning and fundamental errors in its calculations. As a result, we reject the criticisms made by NERA (2018) of both the Economic Insights (2014, 2018) economic benchmarking models and the AER (2018) approach to forming output weights for use in the rate of change.

The main reasons the NERA (2018) criticisms do not hold water can be summarised as follows:

- Economic Insights (2013) contains a full discussion of our approach to calculating output cost shares for the opex MPFP model and the methodology has been documented in Economic Insights (2014) and all subsequent benchmarking reports. Detailed regression results are presented in the output files accompanying Economic Insights (2014, 2018). It is thus incorrect to describe our approach as ‘opaque’.

- We use a functional outputs approach rather than a billed outputs approach in our opex PFP model. The outputs satisfy selection criteria covering the NER objectives, direct relevance to consumers and significance. It is incorrect to say they are ‘chosen based on tariff structure’.
- The Leontief cost model contains a non–negativity constraint on the output coefficients. Because this constraint is incorporated as part of the non–linear estimation process, if a negative relationship existed between an included output and opex, it would produce a zero estimated output coefficient. It is incorrect to say the weights ‘are artificially constrained to be positive’.
- The bottoms up approach to estimating the Leontief model makes the most efficient use of the available Australian DNSP data given its lack of variability across DNSPs and multicollinearity issues. The use of weighted average results across the 52 regressions minimises the risk from limited degrees of freedom from any single regression. In Economic Insights (2018) the results are also corroborated by estimation of a flexible model over the whole Australian sample. It is incorrect to say the weights are ‘estimated imprecisely’.
- Recent reforms to tariff structures in Australia, the US and the UK do not preclude the inclusion of energy throughput as an output. It remains the primary item consumers identify with their electricity supply and receives a small weight in the opex PFP model as would be expected on engineering grounds. It receives only a 3 per cent weight in the AER (2018) averaging process.
- NERA (2018) contains a fundamental error in its calculation of output cost elasticities from the translog cost function model. The failure to recognise that the data are mean–corrected prior to estimation invalidates the NERA estimates. Rather, the correct elasticities for the Australian DNSPs are presented in the files accompanying Economic Insights (2018) and they are all positive as required.
- NERA (2018) quotes the UK CMA’s criticism of a UK application of the translog model out of context. The CMA made it clear its criticism only related to the application in question which was thought to be overly ambitious given the small number of observations available. The Economic Insights translog models have several times more observations available. And the Cobb Douglas and translog models remain the most widely used in efficiency studies.
- Calculating translog model output cost shares based on the first order coefficients produces the shares at the sample mean because the model uses mean–corrected data. The failure of NERA (2018) to recognise this means that both its calculation of elasticities and associated interpretations are incorrect.

NERA (2018, pp.iv–v,31–32) recommends that the AER base its formation of output weights for the output component of the rate of change on only two of the four models used in AER (2018) – the SFACD and LSECD models. We have demonstrated in this memo that the NERA (2018) criticisms of the other two models – the LSETLG and opex PFP models – do not hold water. It is nonetheless instructive to review the impact the NERA (2018) recommendation would have for the CP Group.

Table A: **Effect of NERA (2018) recommendation on CP Group, 2015–2017**

Model	*Output Shares*			
	CustNum	*CircLen*	*RMD*	*GWh*
SFACD	0.708	0.168	0.124	0.000
LSECD	0.676	0.118	0.206	0.000
LSETLG	0.515	0.139	0.347	0.000
SFATLG	0.669	0.173	0.157	0.000
Opex PFP	0.303	0.290	0.283	0.125

	Output Growth Rates 2015-2017			
	CustNum	*CircLen*	*RMD*	*GWh*
	1.64%	0.54%	0.00%	0.13%

	Overall Output Growth Rate 2015-2017	*Opex due to output growth (2017$'000)*
SFACD	1.25%	$7,261
LSECD	1.17%	$6,796
LSETLG	0.92%	$5,331
SFATLG	1.19%	$6,911
Opex PFP	0.67%	$3,887
Average	1.04%	$6,037
AER 2018 Average	1.00%	$5,819
NERA 2018 Average	1.21%	$7,029
NERA-AER Difference		$1,210

In Table A we first present the output weights from the five economic benchmarking models presented in Economic Insights (2018) based on the period 2012 to 2017. Aside from the SFATLG model which is not considered by NERA (2018), the SFACD and LSECD models favoured by NERA (2018) have by far the largest output weights applying to customer numbers. We next present the CP Group output growth rates for the period 2015 to 2017 as an illustration of possible future growth rates. Customer numbers has by far the highest annual growth rate of the four outputs at over 1.6 per cent. This is over three times the growth rate of circuit length at 0.5 per cent. RMD has a zero growth rate and energy throughput is marginally positive at just over 0.1 per cent.

In the lower half of table A we look at the combined effects of differing growth rates and differing weights across the economic benchmarking models. Of the models considered in AER (2018), the SFACD and LSECD model weights produce the highest output growth rates at 1.3 per cent and 1.2 per cent, respectively, due to them allocating the highest weights to the fastest growing output, customer numbers. By contrast, the LSETLG model weights produce an output growth rate of 0.9 per cent while the opex PFP model weights produce an output growth rate of 0.7 per cent. We next take alternative averages of the output growth rates. The AER (2018) four–model average method produces an average growth rate of 1.0 per cent.

The proposed NERA (2018) two–model average produces an average annual growth rate of over 1.2 per cent – 0.2 per cent higher than the AER (2018) four–model average method. Converting this difference into the difference in resulting rate of change opex allowances for the CP Group leads to the NERA (2018) method giving the CP Group an extra $1.2 million annually or $6 million over the five–year regulatory period (in 2017 prices). If the same exercise is conducted for the 13 included Australian DNSPs as a whole, the NERA (2018) method gives the DNSPs an extra $4.8 million in annual opex allowance or $24 million over the five–year regulatory period (in 2017 prices). Thus, while the arguments presented in NERA (2018) do not hold water on either theoretical or quantitative grounds, the ensuing recommendations do have the effect of maximising the opex allowances – and, thus, consumer prices – that would result if adopted.

References

Australian Competition Tribunal (2016), *Applications Under S71b of the National Electricity Law for a Review of Distribution Determination made by the Australian Energy Regulator in relation to Ausgrid Pursuant to Rule 6.11.1 of the National Electricity Rules*, Sydney, 26 February.

Australian Energy Regulator (AER) (2012), *Better Regulation: Expenditure forecast assessment guidelines for electricity distribution and transmission*, Issues paper, Melbourne, December.

Australian Energy Regulator (AER) (2018), *Ausgrid Distribution Determination 2019−24, Attachment 6 – Operating expenditure, Draft Decision*, Melbourne, November.

Competition and Markets Authority (CMA) (2015), *Bristol Water plc: A reference under section 12(3)(a) of the Water Industry Act 1991*, Report, London, 6 October.

Economic Insights (2009a), *The theory of network regulation in the presence of sunk costs*, Technical Report by Erwin Diewert, Denis Lawrence and John Fallon to the Commerce Commission, Canberra, 8 June.

Economic Insights (2013), *Economic Benchmarking of Electricity Network Service Providers*, Report prepared by Denis Lawrence and John Kain for the Australian Energy Regulator, Eden, 25 June.

Economic Insights (2014), *Economic Benchmarking Assessment of Operating Expenditure for NSW and ACT Electricity DNSPs*, Report prepared by Denis Lawrence, Tim Coelli and John Kain for the Australian Energy Regulator, Eden, 17 November.

Economic Insights (2018), *Economic Benchmarking Results for the Australian Energy Regulator's 2018 DNSP Benchmarking Report*, Report prepared by Denis Lawrence, Tim Coelli and John Kain for the Australian Energy Regulator, Eden, 9 November.

Energy Policy Research Group (EPRG) (2018), *Productivity Growth in Electricity and Gas Networks Since 1990*, Report prepared by Victor Ajayi, Karim Anaya and Michael Pollitt for the Office of Gas and Electricity Markets (OFGEM), Cambridge, 21 December.

Frontier Economics (2012), *The feasibility of total cost benchmarking at RIIO–ED1*, Report Prepared for UKPN and Project Partners, London, August.

Greene, W. (2008). 'The Econometric Approach to Efficiency Analysis', in H.O. Fried, C. A. K. Lovell and S.S. Schmidt (eds), *The Measurement of Productive Efficiency and Productivity Change*, Oxford University Press.

Guilkey, David.K., C.A. Knox Lovell and Robin C. Sickles (1983), 'A Comparison of the Performance of Three Flexible Functional Forms', *International Economic Review* 24(3), 591–616.

NERA Economic Consulting (NERA) (2018), *Review of the AER's Proposed Output Weightings*, Report prepared for CitiPower, Powercor, United Energy and SA Power Networks, Sydney, 18 December.

Office of Gas and Electricity Markets (Ofgem) (2014), *RIIO-ED1: Final determinations for the slow–track electricity distribution companies: Business plan expenditure assessment,* Final decision, 28 November.

Pacific Economics Group Research (PEG) (2013), *Empirical Research in Support of Incentive Rate Setting in Ontario: Report to the Ontario Energy Board*, Report prepared for the Ontario Energy Board, Madison, May.