Memorandum

From: Denis Lawrence and Tim Coelli **Date:** 18 May 2020

To: AER Opex Team

Subject: Review of reports submitted by CitiPower, Powercor and United Energy on opex input price and output weights

The Australian Energy Regulator (AER) has asked Economics Insights to review three reports submitted by CitiPower, Powercor and United Energy (hereafter 'CPU') as attachments to their regulatory proposals for the period 2021–2026. The first report is one by Frontier Economics (FE) addressing the weights used in forming the opex input price index used in the AER's rate of change component of its base/step/trend method for assessing distribution network service providers' (DNSPs') opex requirement forecasts. The other two reports are ones by NERA Economic Consulting (NERA) and FE addressing the weights applied to output component forecasts in the rate of change. We review each of the reports in turn after briefly setting out the base/step/trend method by way of context.

1. The AER's base/step/trend method

As noted in Economic Insights (2014), the base–step–trend method for assessing NSPs' future opex requirements proposals can be summarised as follows:

$$Opex_t = \prod_{i=1}^{t} (1 + rate\ of\ change_i) \times (A_f^* - efficiency adjustment) \pm step\ changes_t \qquad (1)$$

where:

- *rate of change*$_i$ is the annual percentage rate of change of opex in year i
- A^*_f is the estimated actual opex in the final year of the preceding regulatory control period
- *efficiency adjustment* is an adjustment for the difference between efficient and estimated actual opex in the final year, and
- *step changes*$_t$ is the determined step change in opex in year t.

Under this forecasting approach the product of the annual rates of change accounts for changes in real opex input prices (changes in opex input prices relative to changes in the consumer price index), output growth and opex partial productivity in the forecast regulatory control period. The rate of change can be summarised as:

$$Rate\ of\ change_t = output\ growth_t + real\ price\ growth_t - productivity\ growth_t \qquad (2)$$

To put this another way, the rate of change rolls forward efficient opex (in real terms) according to changes in: DNSP output – an increase in output will typically require additional opex; real opex price growth – an increase in opex prices relative to the CPI will require additional opex in real terms, all else equal; and, changes in opex partial productivity – an increase in opex partial productivity will reduce the amount of opex the DNSP requires to produce a given level of output.

To maintain logical consistency, the same specification of output needs to be used in the calculation of efficiency adjustments and the output growth and productivity growth components of the rate of change in the base–step–trend method. Similarly, the same specification of opex input prices needs to be used in the calculation of efficiency adjustments and the real price growth and productivity growth components of the rate of change in the base–step–trend method.

Implementation of the base–step–trend method requires us to divide nominal opex into its price and quantity components as accurately and consistently as possible. The efficiency adjustment and opex productivity growth components rely on estimates of the quantity of opex while the real opex price growth component relies on a measure of the opex price that is consistent with the quantity measure used in the efficiency adjustment component.

DNSP opex costs comprise labour costs (both direct and contracted) and a wide range of intermediate inputs spanning operational consumables, office activities and professional services. Productivity studies have generally divided opex inputs into labour, materials and services components with separate price indexes for each used to deflate nominal values into quantities (or constant price series).

2. The opex input price index

As we have noted on a number of occasions previously, it has become increasingly difficult to ascertain what the exact split between the labour component and the materials and services component of DNSP opex is with the move to greater (and varying) use of contracting out of field (and other) services by DNSPs. Similarly, DNSPs themselves are generally not able to identify the price and quantity components of their increasingly contracted out activities as they are only interested in the overall cost and it is up to the contractor how many labour and non–labour resources they use, provided they meet the agreed service standards. However, to allow efficiency assessment and estimation of past opex productivity growth it is necessary to estimate the split of opex into its price and quantity components and, at a minimum, the split of opex between its labour and non–labour components.

Up until 2017 Economic Insights' economic benchmarking studies for the AER used an industry–wide opex price index following Pacific Economics Group (2004) which used the Australian Bureau of Statistics (ABS) Electricity, Gas, Water and Waste Services sectoral wage price index (WPI) for labour with a weight of 62 per cent and five ABS producer price indexes (PPIs) with a combined weight of 38 per cent. In 2017 the AER undertook an exercise to collect additional information on labour and non–labour opex inputs from the Australian NSPs and the weights were refined to 59.7 for labour and 40.3 per cent for non–labour opex inputs in total.

CPU have submitted a report by FE (2019a) which argues for the use of what it describes as 'actual' labour/non–labour weights rather than the industry–wide weights currently used by the AER in the application of the rate of change. At the outset we note that the use of the description 'actual' weights by FE (2019a) is unlikely to be accurate and is potentially misleading for the reasons outlined above. Given the prevalence of contracting out among the DNSPs, DNSPs will typically not have accurate data on the labour/non–labour split of the services they contract out. Consequently they will generally not be able to provide 'actual' data on the overall labour/non–labour split of their opex. A more accurate description of DNSP–specific weights is reported weights. This issue will be explored further below.

We also note that Economic Insights (2016) has previously reviewed issues associated with opex input price weights in response to an earlier FE (2015) report. The analysis and discussion presented in Economic Insights (2016) is equally applicable today.

Economic Insights has been asked to review five issues raised in FE (2019a).

2.1 Sensitivity to using industry–wide versus reported opex price index weights

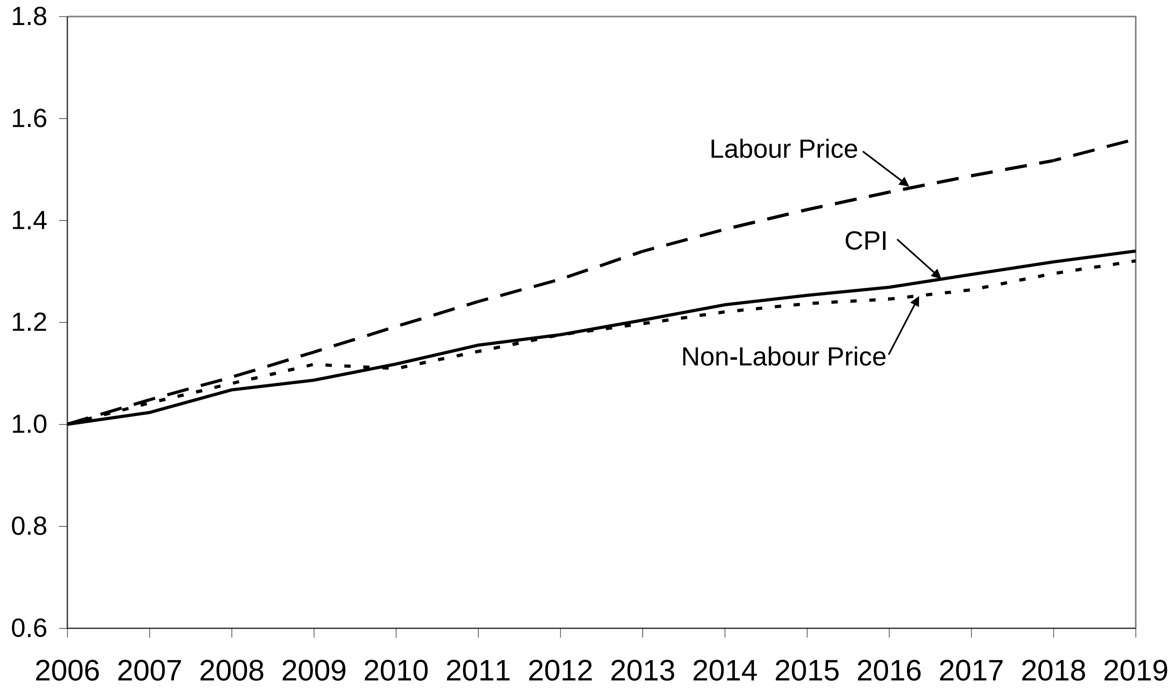
Section 2.3 of FE (2019a) presents analysis which it claims relates to the AER (2016, pp.86–7) summary of the following quote from Economic Insights (2016, pp.7–8):

> 'It is technically possible that a DNSP could in fact be using (or reporting) a much higher share of an opex input whose price has increased less rapidly than, say, the WPI. *If these* [DNSP–specific] *weights were used* in the efficiency assessment then the DNSP's estimated opex quantity would increase relative to the current [industry–wide weights] assessment and the DNSP *could then be found* to be inefficient. This is because the same dollar value of opex is then being deflated by a price index which has increased less rapidly and hence the quantity of opex has increased more rapidly than is the case in the current efficiency assessment. This would make the DNSP a less efficient opex performer – and *perhaps* an inefficient performer relative to other DNSPs – than is currently the case. We admit this scenario is unlikely to occur in practice but it is possible technically. What it does highlight is the need to use a consistent price index in the efficiency assessment and the opex real price growth component of the rate of change when applying the base–step–trend method.' (emphasis added)

This discussion noted that the use of different opex price weights could affect the outcome of a DNSP's efficiency assessment and that this could hypothetically lead to an efficient performer using industry–wide weights being found to be inefficient if the change was made to DNSP–specific weights. The importance of this in practice depends on the extent of divergence in growth rates between the labour and non–labour price indexes.

In figure 1 we plot the labour price index (WPI), the non–labour price index (as a Fisher index of the five component PPIs) and the CPI. We see that the labour price index has increased faster than the non–labour price index over the entire 2006 to 2019 period. The CPI has closely followed the non–labour price index over this period. For the entire period the labour price index increased at an average annual growth rate of 3.4 per cent compared to a rate of only 2.1 per cent for the non–labour price index – a difference of 1.3 per cent per annum. Over the period from 2006 to 2012 the labour price index average annual growth rate exceeded that of non–labour opex inputs by 1.5 per cent while in the period since 2012 the labour price index growth rate exceeded that of non–labour opex inputs by 1.1 per cent. With this extent of difference between the growth rates in these prices, it is clear that DNSPs have a strong incentive to obtain an opex price forecast in the rate of change formula that is as heavily weighted towards labour as possible as the difference in growth rates is quite material. Similarly, an opex price index that is more heavily weighted towards labour will make a DNSP appear more efficient, all else equal, as it implies a smaller opex quantity over time for a given dollar value of opex.

Figure 1 **Labour and non–labour prices indexes and the CPI, 2006–2019**



Source: Economic Insights' calculations based on ABS price indexes

FE (2019a) makes two criticisms of the proposition quoted above that the opex price index weights used could have a material impact on efficiency scores and consistent treatment is required.

The first criticism is that the AER is not consistent in its own application of the rate of change in that it uses a forecast of the CPI in place of a forecast of the non–labour price index. Just as the composition of the opex price index used in the real price component of the rate of change formula should be the same as that used in the efficiency assessment component of the base–step–trend method, then ideally the forecast of the opex price index should contain the same components as the index used for historic analysis. However, while forecasts of the sectoral WPI are currently produced by a number of forecasters, forecasts of the disaggregated PPIs are not currently available and would be unlikely to be sufficiently robust. Consequently, the AER has used the CPI to escalate non–labour opex costs instead of disaggregated PPIs in recent determinations. An earlier sensitivity analysis of the effect of using the CPI compared to the five disaggregated PPIs indicated no material difference in DNSP efficiency assessment results (Economic Insights 2014, p.14). This is confirmed in figure 1 where aggregating the five PPIs using the Fisher index method produces a non–labour price index which tracks the CPI closely. This indicates the CPI is likely to be a good proxy for the non–labour price component for forecasting purposes. Forecasts of the CPI are readily available from a number of forecasters. The FE (2019a, p.14) criticism is thus not reasonable and does not hold water.

FE (2019a, p.15) next attempts to show that using reported firm–specific opex price weights compared to the industry–wide weights has no material impact on whether DNSPs are found to be efficient or not. We note that FE (2019a) does not provide any source for the 'actual (firm–specific)' opex weights it uses in the analysis. It is not clear whether these reported weights are from the AER's 2017 spreadsheet (and, if so, whether they are the adjusted or unadjusted reported weights), DNSPs' annual Regulatory Information Notices (RINs) reporting in–house and 'outsourced' opex labour or some other source. FE (2019a) also does not indicate what operating environment factor adjustments it has used in rolling its efficiency scores forward from the average to the 2017 base year. We thus cannot verify whether the accuracy of the calculations. For present purposes we will take the reported FE (2019a) results at face value.

It is not at all clear what FE (2019a, Appendix A) is trying to demonstrate with the efficiency analysis comparison it reports. While FE (2019a, p.15) claims that the comparison shows there is 'no evidence that the benchmarking results are, in practice, as sensitive to the input weights used as the AER has speculated', the results show the opposite. Across the four opex cost function models and two time periods reported, there are eight instances of DNSPs' efficiency scores changing from being classed as efficient to inefficient in the move from using industry–wide weights to using reported firm–specific weights. And, for the rolled forward to base year opex comparisons where results are only presented as averages across the four models for each of the two time periods, two DNSPs change from having opex lower than the efficient level to having opex higher than the efficient level (ie that change from being classed as efficient to inefficient). The percentage point movements in opex in these two cases are 4.3 and 3.6 per cent. And, higher percentage point movements of up to 5.2 per cent are seen for other DNSPs that remain being classed as either efficient or inefficient.

The materially higher growth rate in the labour price index compared to the non–labour price index seen in figure 1 makes it likely that the choice of opex price weights will have a material impact on DNSPs' efficiency scores as well as on their rates of change. While we previously thought a material impact on DNSP efficiency assessments from the choice of opex price weights was a technical possibility, the FE (2019a) analysis shows that it can be observed in practice as well. That is, the FE (2019a) analysis shows that the choice of opex price weights can have a material impact on DNSPs' efficiency scores as well as on their rates of change.

2.2 Consistency of using reported opex price weights and common productivity growth

Under 'pure' productivity–based regulation prices are adjusted by the difference between the CPI and industry average productivity growth. Industry average productivity growth is used rather than the NSP's own productivity growth to remove the incentive for the NSP to manipulate its productivity growth to obtain a less onerous price or revenue cap. Similarly, most applications of productivity–based regulation use industry average weights in constructing opex price indexes to overcome information gaps and asymmetries (PEG 2004).

While there are a number of key differences between pure productivity–based regulation and the use of productivity information in building blocks regulation applications, many of the key principles carry over. In the opex rate of change, for example, it is common practice to include an industry–wide opex productivity growth rate forecast rather than an NSP–specific productivity growth forecast. While the opex productivity growth rate included in the rate of change is intended to capture the scope for movement of the efficient frontier only (rather than also including movement towards the frontier), use of an industry–wide measure reduces the scope for an individual NSP to behave strategically or to exploit its information advantage relative to the regulator.

It should be noted that if an NSP–specific productivity growth rate were used, it could reduce the incentive for the NSP to report a higher proportion of the opex component with the fastest price growth. This is because the advantage gained by reporting a higher proportion of this component and hence receiving a larger increase in opex allowance from it would be partly offset by the associated higher productivity growth from reporting a higher proportion of the component with the fastest price growth. In the case of building blocks regulation, using an industry–wide opex productivity growth rate in the rate of change removes the incentive to manipulate productivity growth but, ironically, increases the incentive to report a higher proportion of the component with the fastest growing price because an advantage can be gained through the rate of change input price component with no offsetting effect from the opex productivity component. This incentive to over–report the proportion of the component with the highest price growth is removed if industry–wide information is used to set the opex price weights. Rather, the NSP then has a clear incentive to seek out the cost–minimising combination of opex components.

We thus conclude that if the opex productivity component of the rate of change is based on industry–wide information then the opex price weights should also be based on industry–wide information to maintain consistency. Use of NSP–specific reported weights in this case would create an incentive to increase the proportion of the component with fastest price growth and reduce the incentive to use opex components in cost minimising proportions.

2.3 Reliability of the AER's opex input weight estimates

In 2017 the AER undertook an exercise to collect information from DNSPs on the split of opex between in–house labour, contracted expenditure (further split into labour and non–labour components) and other non–labour and non–contracted expenditure across six opex categories. Three of the categories covered DNSP field services (vegetation management, maintenance and emergency response) and three covered non–field services (non–network expenditure, network overheads and corporate overheads). The total labour content of opex would then be the sum of in–house labour, the labour component of field services and the labour component of non–field services.

Not all of the 13 DNSPs were able to allocate field services and non–field services between their labour and non–labour components. Seven of the DNSPs reported field services to be either all labour or all non–labour while four did the same for non–field services. FE (2019a, p.20) notes:

> '…there is significant variation in the allocation of costs between labour and non-labour costs for these two groups. For example, ActewAGL classifies all field services expenditures as non-labour costs; Endeavour classifies all these expenditures as labour costs; and AusNet classifies 76% to labour costs and 24%

> to non-labour costs. Essential Energy seems to have split costs equally both for field and non-field services expenditures.'

As noted in section 2 above, it is not surprising that not all DNSPs have exact knowledge of the labour content of their contracted services. Rather, the DNSP is interested in the services being provided at the lowest cost while ensuring required standard are met. How the contractor allocates its resources between labour and non–labour components is the contractor's responsibility. This is a significant part of the reason the economic benchmarking RINs have concentrated on collecting opex data for network services and not on component parts of network services opex or its labour content.

The AER next moved to fill gaps in the field services and non–field services disaggregations between labour and non–labour by allocating the overall average proportions of labour and non–labour for these two types of services found for the DNSPs that reported feasible splits to those DNSPs that allocated all of a service to either labour or non–labour. The adjusted field services labour and non–field services labour amounts were then combined with reported in–house labour to form an estimate of the labour content of opex for each DNSP. While not perfect, we are of the view that this is the best strategy for making the most reasonable estimates across the 13 DNSPs based on the information available.

FE (2019a, section 3.1) criticises the quality of the data supplied by the DNSPs, including Powercor, to the AER in the 2017 exercise. They also criticise the AER for not insisting that DNSPs fill the gaps in the data they reported. However, as noted above, it is likely that not all of the DNSPs were in possession of the requested information and for them to obtain that information it would require their contractors handing over extensive and often commercially sensitive information. It needs to be borne in mind that economic benchmarking is a high level or 'tops down' method rather than a process that involves a detailed forensic examination of all cost items. As such, the strategy adopted by the AER to develop industry–wide estimates from the available information is reasonable. An intrusive information collection exercise of the type suggested by FE (2019a, p.25) would involve a disproportionate burden being placed on both DNSPs and their contractors.

FE (2019a, section 3.3) raises what it claims to be a number of methodological problems with the AER's 2017 analysis of labour weights. It firstly claims that the period examined, 2014 to 2016, was a time of transformation within DNSPs and so may not be representative of business as usual. Some DNSPs, particularly those in NSW and the ACT, were moving to reduce excess staffing levels during this period. All else equal, this could be expected to lead to an overestimate of the business as usual industry–wide labour weight and so could be expected to advantage the DNSPs somewhat.

FE's second criticism is the AER's use of the overall average for those DNSPs that reported non–zero proportions for both labour and non–labour to adjust the data of those DNSPs that reported all of a contract category as either all labour or all non–labour. FE suggest that the contracted services could be all either labour or non–labour for those DNSPs. We agree with the AER that this is not feasible as all contracted services will involve the combining of labour with a range of intermediate inputs. The assumption the AER has made makes the best use of the information available from those DNSPs that have reported feasible splits to fill the gaps in reporting by other DNSPs.

FE also criticises those DNSPs that appear to have allocated labour and non–labour splits to contracted categories in rounded proportions. However, this simply reflects that DNSPs are not usually in possession of detailed data on contractors' disaggregated resource use and so the estimates provided are based on their best assumptions. FE also argues the adjustment process is biased towards the larger DNSPs and against those DNSP that only reported data for one year. However, the largest DNSP on most measures, AGD, is one of those that has their data adjusted and only one DNSP reported data for only one year. Consequently, these are unlikely to be significant issues.

FE's third and fourth criticisms are merely restatements of aspects of its second criticism discussed above. The third criticism claims the industry–wide weights are biased towards those DNSPs that reported non–zero splits while the fourth again claims that the industry–wide weights are skewed towards larger DNSPs by the averaging process adopted which uses a weighted rather than unweighted average. However, a weighted average will be most reflective of the overall industry–wide situation where there is considerable diversity in DNSP sizes. To reiterate, in our view the AER made the best use of the information it had available in allocating overall average labour/non–labour splits for field services and non–field services to those DNSPs that reported zero for either labour or non–labour in one or both of these contract categories.

The AER also requests DNSPs to provide data in their annual RINs on in–house labour and labour 'outsourced' to related parties and unrelated parties. We have compared the proportions of these reported labour categories relative to total opex for the year 2016 – the last year for which the AER collected data in its 2017 targeted data collection exercise – for a selection of DNSPs. The difference between the annual RIN in–house plus outsourced labour proportions and the AER's corresponding 2017 labour content data for the same year is up to 23 percentage points in some instances. This suggests the annual RIN data have been provided on different bases. For some DNSPs where there is closer correspondence between the annual RIN and 2017 data collection labour proportions, the 2017 data involves all of field and/or non–field contracted services being allocated wholly to either labour or non–labour. This suggests that in these cases the annual RIN data suffers from the same shortcomings as the data supplied for the 2017 exercise. This all highlights the difficulty in obtaining reliable and consistent information in this area. It is surprising that FE (2019a) advocates the use of reported or what it calls 'actual' data at the same time it is critical of the information the DNSPs supplied to the AER in the 2017 data collection exercise.

Finally, FE (2019a, section 3.4) identifies three potential formula errors in the AER's 2017 spreadsheet used to form the adjusted industry–wide opex price weights. All three errors relate to the way data is transferred from the AGD sheet to the DNSP summary analysis sheet. We have examined the formulae identified and concur with FE that they are indeed errors. Correcting these three errors has the effect of changing the adjusted labour weight from 59.7 per cent to 59.2 per cent. We will use the corrected labour weight in future DNSP economic benchmarking.

2.4 Comments on productive and cost efficiency

FE (2019a, section 2.4) raises three issues regarding the distinction between productive efficiency (producing as much output as is technically possible from a given quantity of inputs) versus cost efficiency (ensuring a given quantity of outputs is produced at minimum cost.

FE's (2019a, p.16) first argument is as follows:

> 'the AER's first step when forecasting opex allowances is to determine whether an NSP's revealed base year opex is efficient. When doing so, the AER focusses [sic] exclusively on productive efficiency, rather than cost efficiency.'

This argument is incorrect. The benchmarking methods the AER uses all measure cost efficiency, not productive efficiency. The AER's primary economic benchmarking method used to assess base year efficiency is the estimation of opex cost functions from which efficiency scores are derived. Cost functions measure the *cost* of the operating inputs used relative to the included outputs and allowing for included operating environment factors. As will be discussed in section 3 of this memo, the coefficients estimated for the output quantities provide a means of determining the cost–based weights for the outputs. The opex prices used in assessing cost efficiency in the opex cost function models vary across the three included jurisdictions.

Opex cost function models also allow for substitution between operating and capital inputs – another aspect of cost efficiency. Economic Insights (2014, p.32) notes that the capital stock is highly correlated with the output quantities and so its effect is included in our opex cost function models.

And, the AER also draws on our Multilateral Total Factor Productivity (MTFP) and Opex Multilateral Partial Factor Productivity (opex MPFP) models when assessing a DNSP's base year efficiency. Outputs and inputs in the models are both aggregated into measures of total output, total input and opex input, respectively, using information on cost weights. These models thus also present information on cost efficiency, not productive efficiency.

FE's second argument is that the AER has not established that using industry–wide opex weights rather than reported opex weights ensures cost efficient outcomes. FE argue that the AER assumes that industry–wide opex weights are an efficient benchmark. As discussed above, the AER's 2017 adjusted industry–wide weights provide the best estimate of the undistorted split of opex between labour and non–labour inputs currently available. This is because reported opex is often based on assumptions by DNSPs that some key contracted services are either all labour or all non–labour given that they typically have little, if any, information on how their contractors use resources to achieve agreed outcomes. And, the use of the best estimate of the undistorted weights then creates an incentive for DNSPs to adopt their own cost minimising opex composition as the incentive to distort either opex use in practice or reported opex use towards the components with the fastest growing prices is removed. Thus, the use of industry–wide opex price weights is the most likely to support cost efficient outcomes.

FE's third argument is that the AER has not established that the industry–wide weights derived from the 2017 data collection exercise are the best estimates available and the most likely to be prudent and realistic, as well as efficient, as required by the National Electricity Rules. As discussed above, the DNSP responses to the 2017 data collection exercise highlighted that not all DNSPs have reliable information on the split of their contracted services between their labour and non–labour components with many allocating all to either labour or non–labour when this is clearly infeasible. Short of undertaking a highly resource–intensive and intrusive forensic examination of contractors' activities, should the authority to undertake such an examination exist and which would involve disproportionate cost for a tops down assessment of proposed opex, applying the average results from those DNSPs that did provide credible splits to those that did not makes the best use of available data. This is consistent with good practice where taking an average figure from that data that is feasible but varying and applying that to the sample as a whole, some of which reports clearly infeasible data, minimises risk. As such, the AER's 2017 adjusted weights estimates represent the most prudent and realistic estimates available as well as those most likely to promote efficiency.

2.5 Accuracy of reported labour content data

FE (2019a, pp.11–12) criticise the following statement made in Economic Insights (2016, p.8):

> 'While we recognise that there may indeed be costs in reallocating the actual composition of opex, there is much more scope to alter the reporting of the composition of opex so that reported opex is skewed towards the components with higher growing prices.'

FE (2019a, p.11) allege this is a 'a fanciful claim' for three reasons:

- the National Electricity Law forbids submission of false and misleading information
- if this reported information cannot be relied on, no reported information can be relied on, and
- RINs are required to be audited.

With regard to FE's first reason, we have noted above that, while total network services opex is reported with a relatively high degree of accuracy, in many cases far less confidence can be had in reported disaggregated opex components. In some cases this is due to differing legacy State–based reporting still affecting current reported disaggregations. In the case at hand, however, it is because in many cases DNSPs know the overall dollar value of their contracted services accurately but have little, if any, information on how their contractors use resources to achieve the agreed outcomes. This was amply demonstrated subsequent to the above quote being made when the AER collected additional information on labour weights in 2017. Many DNSPs made assumptions that all contracted services were either all labour or all non–labour, presumably because they did not have this information themselves and had to make high level assumptions instead. By way of an example supporting our 2016 quote above, to the extent that DNSPs reported contract categories as being all labour in the 2017 AER exercise, unintentionally or intentionally, they were skewing reported opex composition towards the component with the fastest growing price. This was because of the assumptions they made to estimate information they did not have in their direct possession. We are not making any judgement about whether this practice was 'false' or 'misleading' but simply note that it illustrates the phenomenon we described in the quote above.

FE's second reason simply does not hold water. We have given the example of total network services opex being something that we can have a high degree of confidence in and rely on because it is known to DNSPs and readily verifiable from multiple directions. However, the composition of opex cannot be relied on as readily because in many cases the DNSPs are not in possession of a fine level of disaggregated information when key elements are contracted services and all they have information on and are interested in is the total dollar value of the contract.

FE's third reason is similarly not convincing. In the absence of information on disaggregated components, there is a range of disaggregation approaches and assumptions that auditors may find acceptable. In these cases, while useful, the requirement for auditing does not guarantee either accuracy or consistency when neither the DNSP nor the auditor is in possession of the relevant actual information.

2.6 Conclusion on labour and non–labour opex price index weights

It is instructive to review the following from Economic Insights (2016, p.7) in response to an earlier FE report:

> 'FE (2015b, p.14) argues that the AER's requirement for EBRIN templates and bases of preparation to be audited and for DNSP CEOs to attest to the accuracy of the data supplied means the AER should be able to have confidence in the disaggregated opex reported by each DNSP – and presumably to use opex weights reported by each DNSP in forming the real opex price index. The problems with this proposition have been highlighted above where the Victorian and South Australian DNSPs have reported extreme variations in their labour, contract and other opex shares. While some of these variations may be due to different operational practices, the extreme size of the ranges indicates reporting differences are also playing a large part. And, as noted above, disaggregated opex reporting by DNSPs is on the basis of legacy state–based reporting which varies widely. There is also a range of disaggregation approaches that auditors may find acceptable. Confidence can only be had in the comparability of aggregate network services opex and not its reported components across DNSPs. Consequently, we are of the view that using the best available estimate of labour and non–labour shares of DNSP opex and applying these shares to all DNSPs remains the most robust and consistent approach available.'

This assessment was made four years ago and despite attempts to collect more detailed DNSP–specific data having taken place in the meantime, including the AER's 2017 exercise and ongoing annual RIN 'Labour' sheets, the conclusions from the above assessment remain true today. While the original PEG (2004) industry–wide weights have been refined as a result of the 2017 exercise and will be further refined to correct the minor formula errors identified by FE (2019a), the use of industry–wide weights for labour and non–labour components of the opex price remain the best estimate to be applied to all DNSPs. Consequently, we recommend that the corrected weights of 59.2 per cent for labour and 40.8 per cent for non–labour be applied to all DNSPs in forming the opex price index going forward.

3. Output weights

CPU have submitted reports by NERA (2018) and FE (2019b) which criticise the AER's use of economic benchmarking models in determining the weights used on individual output growth forecasts in the rate of change component of its efficient opex forecasts. These reports generally argue against including opex MPFP information in forming output weights, against the including energy throughput as an output and against including the translog opex cost function results in forming output weights. The reasons for these criticisms differ between the two reports. We proceed to review each of the reports along with arguments Powercor (2020) makes in its regulatory proposal concerning the treatment of distributed energy resources (DER) before making recommendations on output weights going forward.

3.1 NERA (2018) report on output weightings

The NERA (2018) report has previously been submitted to the AER by SA Power Networks as part of its regulatory proposal for the 2020–2025 regulatory period (SAPN 2019). The report was reviewed in detail in Economic Insights (2019) and found to contain numerous incorrect statements, flawed reasoning and fundamental errors in its calculations. As a result, Economic Insights (2019) rejected 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. Our rejection of the criticisms made by NERA (2018) remains unchanged and we refer readers to Economic Insights (2019) for our detailed assessment of NERA (2018).

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' as NERA (2018, p.13) does.
- 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' as NERA (2018, p.14) does.
- 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' as NERA (2018, p.15) does.
- 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' due to the small number of observations per regression (NERA 2018, p.15).

- 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. It is not 'an increasingly inappropriate output driver' as claimed by NERA (2018, p.16).
- NERA (2018, pp.26–7) 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, pp.27–8) 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, pp.28–9r) to recognise this means that both its calculation of elasticities and associated interpretations are incorrect.

3.2 FE (2019b) review of Leontief cost functions and associated MTFP output weightings

FE (2019b, section 3) critiques the formation of output cost share weights used in the AER's TFP and MTFP economic benchmarking models. FE criticise the statistical performance of the Leontief cost function models the TFP/MTFP output weights are derived from and, importantly, identify an error in the coding of the Shazam input file used to run these models.

We briefly summarise the FE (2019b) criticisms of the TFP/MTFP output weights before reporting the results of correcting the coding error identified. Correcting this error significantly improves the performance of the Leontief models and allays many of the other concerns raised by FE (2019b).

3.2.1 Background

TFP/MTFP models can be calculated on either a 'billed' output or a 'functional' output basis. The billed output basis only includes the outputs the firm directly charges customers for and the output weights used to form the total output quantity are then the revenue shares of the various billed outputs. This approach is appropriate for competitive industries where revenues can be expected to approximate the costs of providing the various outputs. However, many utilities provide a wider range of services and dimensions of output to customers than those they directly charge for. And, charges are usually implemented on the basis of convenience and historical precedence rather than being cost–reflective. For these industries, outputs in productivity analysis are specified on a functional basis which attempts to quantify the attributes valued by customers. This approach is also necessary where the firm's total revenue allowed by the regulator is designed to cover a wider range of activities than those the firm charges for, as is the case with building blocks regulation.

To form weights for the output quantities included, we can either do a detailed accounting exercise to allocate costs to each output quantity or else estimate the cost shares of each output econometrically. The accounting approach would be prohibitively resource intensive and would suffer from the usual cost allocation problems in any case. This leaves econometric estimation as the only tractable option.

TFP/MTFP indexes use total cost shares for aggregating output components into a measure of total output quantity. The partial productivity indexes measure movements in total output quantity relative to a particular input quantity such as opex and so generally use the same total cost shares applied to total output. This way the TFP index is a weighted average of the various partial productivity indexes with the complexity of the weights depending on the indexing formula being used. To form the output cost shares we thus require data on the prices and quantities of all inputs, both variable and capital.

The output cost shares could thus be estimated from either national or cross–country data. While we have relatively consistent measures of outputs and opex across the three countries in our sample, we do not have complete measures of capital inputs for New Zealand and, in particular, Ontario. This precludes the use of the three–country database used in our opex cost function analysis. We have to rely instead on the Australian NSP data.

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. Instead, we have resorted to using much simpler cost function methods such as the Leontief which can be applied on a DNSP by DNSP basis.

3.2.2 Leontief functions

The Leontief cost function methodology is relatively simplistic. It involves the estimation of 52 separate regressions – 4 input demand equations for each of the 13 DNSPs. The input demand equations cover opex, overhead lines, underground cables, and transformers. Each regression contains five parameters to be estimated – 4 input/output coefficients and a time trend coefficient. When the output shares were updated in Economic Insights (2018), there were only 12 observations per regression (ie 2006–2017). The Leontief model assumes there are fixed input proportions in each output. Stylistically, this can be thought of as fitting a right angle to the data rather than a smooth isoquant curve in two–dimensional space (ie in the case of two inputs and one output). As a result, the Leontief cost function will never produce impressive–looking statistical results. For a 4–output model we, as practitioners, would normally expect to get at least one significant output coefficient per regression equation, occasionally 2 significant and, on very rare occasions, 3 significant coefficients – see, for example, Lawrence (2003) where this methodology was first applied. The statistical performance of a simple fixed proportions model cannot be judged by the same standards we would use for fitting smooth functions such as the Cobb–Douglas or translog.

3.2.3 FE (2019b) criticisms of Leontief–based estimates

FE (2019b, pp.7–15) make the following criticisms of the Economic Insights (2018) Leontief results:

- around half the 52 regressions contain no significant coefficients
- around half the equations have unexpectedly large time trend coefficients
- few significant coefficients on energy throughput and only one in an opex regression
- high levels of multicollinearity between variables
- two regressions not fully converged
- estimates dependent on starting point for time trend, and
- time trend variable differs across regressions.

FE (2019b) argues at some length that energy throughput should not be included in the TFP/MTFP models because it is not a significant 'driver' of opex and this is supported by the lack of a relationship identified in the models between throughput and opex. FE (2019b, p.15) concede that it may be appropriate to include throughput in the efficiency assessment component of the efficient opex forecast but go on to argue that separate models that focus on opex 'drivers' should be used in the rate of change component of the efficient opex forecast. However, we note there is a strong case for consistency across the various components of the efficient opex forecast. Thus, if it is appropriate to include throughput as a functional output in the efficiency assessment (or base year) component of the forecast then it should also be included in the rate of change component as the NSP is tasked with supplying the included functional outputs as efficiently as possible. Changing to engineering–based 'opex driver' variables in the rate of change component instead of continuing to use functional outputs would compromise the integrity of the forecast.

FE (2019b, p.11) have, however, identified a coding error in the formation of the time trend variables included in the regressions. The time trends should have a common base or starting point for each DNSP and, hence, for each of the 52 regressions. In earlier applications of this method the time trend variable was formed outside the Shazam code and was instead read in as part of the data file (eg Lawrence 2003). We adopted the common practice observed in cost function studies of starting the time trend from a common value in the first year of the period and incrementing its value by one each subsequent year. However, in Economic Insights (2014, 2018) the time trend was formed by Shazam code. Instead of resetting the time trend to a common base for the observations applying to each DNSP, the time trend was mistakenly formed over the entire sample. Thus, instead of the time trend running from 1 to 12 for the annual observations for all DNSPs, the time trend runs from 1 to 12 for the first DNSP in the database, from 13 to 24 for the second DNSP and so on. Because the models are non–linear, this could have a significant distorting effect on the results obtained and is likely to explain the wide range of time trend coefficient values noted by FE (2019b).

3.2.4 Correcting the time trend error

Correcting the time trend coding error has a significant beneficial effect on the performance of the models. Regression results are presented in appendix table A. There are now only 3 of the 52 regressions that have no statistically significant coefficients. In terms of output coefficients, 28 of the 52 regressions now have one significant output coefficient, 17 have two significant output coefficients and 2 have 3 significant output coefficients. Furthermore, the energy throughput output is now statistically significant in 10 of the regressions, including 4 of the opex input demand equations. That is, there is now a significant relationship between opex and energy throughput for nearly a third of the DNSPs which contradicts FE's (2019b, p.9–10) argument that energy throughput should not be included as an output. In addition to the output coefficients, there are also 39 regressions that now have statistically significant time trend coefficients.

The time trend coefficients all now lie well within the range FE (2019b, p.9) nominate as being reasonable, namely –10 per cent to 10 per cent. In fact, the estimated time trend coefficients all lie in a range of –1.11 per cent to 7.28 per cent. If the underground cable input demand equations are excluded, the range narrows further to –1.11 per cent to 4.81 per cent.

Furthermore, using the same coefficient starting values of 0.001, all the input demand equations now converge readily, generally in well under 300 iterations.

The DNSP output cost weights were updated in Economic Insights (2018) based on estimation over the period 2006 to 2017. The plan was to leave these weights unchanged for a period of around 5 years. As we now have an extra year of published data available, we take advantage of this extra year of published data and re–estimate the models over the period 2006 to 2018.

The effect of correcting the time trend error on the output cost weights is shown in table 1. Weight is transferred from customer numbers to circuit length. The uncorrected weight on customer numbers is 31 per cent but this falls to just under 20 per cent with the correction. The uncorrected weight on circuit length is 29 per cent but this increases to around 39 per cent with the correction.

Table 1: **DNSP Leontief cost function output cost weights**

Output	*Uncorrected 2006-2017*	*Corrected 2006-2018*
Energy throughput	12.46%	8.58%
Ratcheted maximum demand	28.26%	33.76%
Customer numbers	30.29%	18.52%
Circuit length	28.99%	39.14%

The combined weight on energy throughput and RMD is around 40 per cent in both cases. However, the distribution of this weight between the two components varies somewhat. The corrected 2006 to 2018 period estimates allocate somewhat less weight to energy throughput and somewhat more to RMD compared to the uncorrected weights.

The reallocation of weight away from energy throughput and customers towards circuit length and RMD in the corrected weights is consistent with views expressed by DNSP representatives on underlying output cost shares in the AER's economic benchmarking workshops in 2013.

We thank FE for identifying this coding error. Although the coding error was a subtle one, correcting it significantly improves the performance of the Leontief models and consequently mitigates the other concerns raised about the model results in FE (2019b). The Leontief models now perform as well as can be expected using a relatively simplistic, fixed proportions specification. Correcting the coding error provides more reliable output weights for the MTFP and opex MPFP models. Consequently, there is no case for not including the MTFP/MPFP weights in the output growth component in applications of the rate of change formula. And, just as FE (2019b, p.15) concedes it may be appropriate to include energy throughput in economic benchmarking models assessing DNSP efficiency, then energy throughput should also be included in the forecast output growth component of the rate of change to maintain consistency and integrity of the resulting opex forecast.

3.3 Powercor's (2020) comments on distributed energy resources and output weights

Powercor (2020, p.130) argues the following:

> 'According to the MPFP model, operating expenditure would decrease with falling energy throughput. This is an inaccurate and misleading representation of actual cost drivers. In fact, the relationship between energy throughput and operating expenditure is likely to be increasingly negative—as the growth in DER reduces energy throughput it also imposes additional distribution costs that are not captured by customer numbers and ratcheted maximum demand.'

We concur that the growth in DER is likely to be having a significant effect on DNSPs and could be increasing their opex as DNSPs strive to maintain network stability and capacity in the face of many new small and unpredictable energy suppliers appearing on their networks. To adequately address this emerging situation we need to consider expanding the outputs included in our economic benchmarking models to include a DER output. That is, a DER output could be creating something of an omitted variable issue as the specification now stands. But the argument Powercor mounts above confuses and conflates throughput and DER outputs. The solution to the problem identified in the above quote, should it be proven, would be to include an additional output covering DER and not to remove an existing output as that would only create its own biases.

Economic Insights (2019, p.11) noted:

> '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.'

A review of the relationship between growing DER and economic benchmarking is on our forward work program.

In the meantime, to the extent that the emergence of DER can be established to be increasing DNSP opex requirements, this would be best handled in the short–term by considering including a relevant step change in the base/step/trend forecasting method. It is not an excuse to exclude either throughput outputs or opex MPFP weights from the output growth component of the rate of change calculation.

3.4 FE (2019b) comments on translog opex cost functions output weights

Unlike the simpler and less flexible Cobb Douglas functional form which produces constant output cost weights across the entire sample, the flexible translog functional form produces output cost weights that vary by observation. Normal practice is to divide the values of the exogenous variables by their sample means prior to econometric estimation of a translog model. The sample average output weights can then be readily derived from the estimated first order coefficients of the translog function. To put this another way, this process sets all the terms in the elasticity calculations involving second order terms equal to zero[1] – not recognising this process is the mistake NERA (2018) made in its incorrect attempt to calculate the translog output weights as noted above.

FE (2019b, section 4) argue that it is inappropriate to evaluate the translog output weights at the three–country sample mean, as has been done in the AER's rate of change applications to date, because the overall sample mean is considerably smaller than the mean for the Australian sample. FE (2019b, p.18) argues that the output levels chosen for evaluating the translog cost function elasticities 'have no economic or statistical justification'. We disagree.

Firstly, FE (2019b) presents information on the size differences between the Australian and full sample in terms of geometric means rather than the more commonly used arithmetic or simple mean. While the functional forms use logarithmic formulae, the geometric means tend to exaggerate apparent differences in this instance. For example, for the Australian sample the average customer numbers per DNSP are 724,000 at the arithmetic mean compared to 232,000 for the full sample – a difference of around 3 times. This is a considerably smaller difference than the 6.5 times difference in geometric means reported by FE (2019b, Table 2). Similar differences between ratios of arithmetic versus geometric means also apply for the other two outputs, circuit length and RMD.

From an economic perspective, the important characteristics are network density differences and economies of scale characteristics. Since we take the shares of the sum of first order coefficients to calculate output weights, economies of scale differences have less impact on the derived output weights, although we will return to this point shortly. In terms of network density differences, rough indicative calculations based on FE (2019b, Table 2) show that customer density (ie customers per line kilometre) is likely to be around 19.8 for Australia compared to 25.4 for the full sample. Similarly, demand density (ie RMD per customer) is likely to be around 3.7 for Australia compared to 4.3 for the full sample. These are not large differences and indicate the characteristics of the full sample mean is not likely to be widely divergent from the characteristics of the Australian sample mean. That is, there is good economic justification for using the full sample mean translog output weights in the rate of change calculations.

And, from a statistical perspective, we note that the confidence intervals on the elasticity estimates at the sample mean should be the narrowest at the full sample mean. Thus, FE

[1] That is, when we divide the sample data for each output variable by its sample mean, the new scaled data series then will each have a mean value equal to one. Given that the log of one is equal to zero, all the second order terms in the elasticity calculations (when evaluated at the sample mean data point) then become equal to zero as well.

(2019b, p.18) is also incorrect in saying there is no statistical justification for the approach used to date.

While normal practice is to normalise translog cost function data sets by their overall exogenous variable sample means, they can also be normalised by the means of a subsample of the data. Hence, dividing the sample by the means of the Australian DNSP exogenous variables would lead to the estimated first order coefficients producing the elasticities for the Australian sample mean. Australian sample output weights can then be derived from these first order coefficients. We have no underlying objection to considering this change. It should be noted that making such a change has no impact whatsoever on measured efficiency scores for any of the opex cost functions and no impact on the output weights derived from the Cobb–Douglas opex cost functions – it only affects the translog–based output weights.

Table 2: **Translog opex cost function regression coefficients, 2006 to 2018**

	LSE		*SFA*	
	Data normalised by mean of:		*Data normalised by mean of:*	
Output	*All DNSPs*	*Australian DNSPs*	*All DNSPs*	*Australian DNSPs*
Customer numbers	0.512	0.400	0.673	0.744
Circuit length	0.152	0.223	0.144	0.132
R'd Max Demand	0.303	0.431	0.152	0.191
Scale Elasticity	0.967	1.054	0.969	1.067

In table 2 we report the translog regression coefficients using the 2006 to 2018 sample with full data sample mean normalisation and with Australian sample mean normalisation. Fuller results are presented in the tables in appendix B. In table 2 we also include the relevant returns to scale elasticities at the respective sample means the data are normalised by. A value of one for this elasticity indicates constant returns to scale, a value less than one indicates increasing returns to scale while a value greater than one indicates decreasing returns to scale. For both estimation methods, at the full sample mean there is mild increasing returns to scale of around 0.97 while at the Australian sample mean there is mild decreasing returns to scale of around 1.06. This implies that at the overall sample mean DNSPs could increase their efficiency by becoming larger but at the Australian sample mean DNSPs have already become too large on average and could improve their efficiency by reducing their size.

Table 3: **Translog opex cost function output weights, 2006 to 2018**

	LSE		*SFA*	
	Data normalised by mean of:		*Data normalised by mean of:*	
Output	*All DNSPs*	*Australian DNSPs*	*All DNSPs*	*Australian DNSPs*
Customer numbers	52.95%	37.95%	69.45%	69.73%
Circuit length	15.72%	21.16%	14.86%	12.37%
R'd Max Demand	31.33%	40.89%	15.69%	17.90%

In table 3 we present the output weights derived from the translog opex cost functions with data normalised by the full sample means and by the Australian sample means.[2] The basis of

[2] To calculate these output weights in table 3 we take each of the elasticity estimates in table 2 and divide them

normalisation does not make a material difference to the output weights derived from the SFA estimation method. However, for the LSE method the effect of normalising by the Australian sample means instead of by the full sample means is to transfer weight from the customer numbers output to both the line length and RMD outputs.

With regard to translog opex cost function output weights, FE (2019b, p.18) state:

> 'In our view, these elasticities should be evaluated at output levels that are reflective of the operating characteristics of the Australian DNSPs.'

FE (2019b, p.3) also make the following statement:

> '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.'

We are relatively indifferent as to whether the translog opex cost function output weights are calculated at the overall sample mean or at the Australian sample mean. We have demonstrated that there is economic justification for using either basis and the statistical performance of the models using either basis is little different. There may be some presentational and communication advantages in normalising by the Australian sample mean and so we are prepared to adopt FE's (2019b) recommendations above. Going forward we also propose to normalise by the Australian sample mean in economic benchmarking reporting.

FE (2019b, p.18) goes on to make the following statement:

> '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.'

Powercor (2020, p.130) then use this statement as justification for not including translog opex cost function output weights in their proposed rate of change calculations. However, we have an open mind on whether or not output weights are constant across all utilities in the sample. Consequently, there is no justification for not including the translog opex cost function output weights in the rate of change calculations. The translog function is more flexible than the Cobb Douglas function and so produces additional useful information that should be included in the rate of change calculation, provided its estimation does not produce a large number of monotonicity violations. In this case the translog opex cost function performs well under both estimation methods and so the results should be included.

3.5 Conclusions on output weights to use in the rate of change

In this section we have shown that:

- correction of the time trend coding error identified by FE (2019b) significantly improves the performance of the Leontief cost functions and so there is no case for excluding the MTFP output weights
- throughput is shown to make a significant contribution to costs when the coding correction is made and its weight should be included

by the returns the scale measure and then multiply this scaled weight by 100 to obtain a percentage measure.

- increasing levels of DER could be a reason to consider including a DER output in the economic benchmarking models at some stage in the future and, in the meantime, potentially including a step change if cost can be shown to increase as a result – however, it is not a reason to exclude the throughput output, and
- we have no objection to calculating the translog opex cost function weights at the mean of the Australian sample and translog weights should continue to be included.

Based on this, our recommended output weights for calculating the output growth component of the opex rate of change are shown in table 4 below.

Table 4: **Recommended output cost weights**

Output	*MTFP*	*LSECD*	*LSETLG*	*SFACD*	*SFATLG*	*Overall Weight*
Energy throughput	8.58%	–	–	–	–	1.72%
Ratcheted maximum demand	33.76%	15.48%	40.89%	17.50%	17.90%	25.11%
Customer numbers	18.52%	68.95%	37.95%	67.43%	69.73%	52.52%
Circuit length	39.14%	15.56%	21.16%	15.08%	12.37%	20.66%

The overall recommended weights place just over a half of the total weight on customer numbers, around a quarter on RMD, just over a fifth on circuit length and the remaining 2 per cent on energy throughput.

Appendix A Corrected Leontief regression results

Table A1: **ACT Leontief cost function regression results**

Variable	*OpEx*		*O/H Lines*		*U/G Cables*		*Transformers*	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	0.000	0.00	0.000	0.00	0.000	0.00	0.475	3.04
RMD	2.125	0.05	9.356	12.47	2.226	3.87	0.000	0.00
Customer No	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
Circuit Length	2.728	0.64	1.630	2.87	1.078	6.85	0.722	11.47
Time	0.002	0.14	–0.006	–7.41	0.021	10.88	0.007	3.97
R^2	0.143		0.925		0.975		0.990	

Table A2: **AGD Leontief cost function regression results**

Variable	*OpEx*		*O/H Lines*		*U/G Cables*		*Transformers*	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
RMD	7.928	32.15	0.000	0.00	0.000	0.00	2.028	120.95
Customer No	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
Circuit Length	0.000	0.00	–3.036	–214.71	–2.026	–201.78	0.000	0.00
Time	–0.001	–0.17	–0.003	–2.63	0.007	4.75	0.022	8.49
R^2	0.256		0.439		0.891		0.928	

Table A3: **CIT Leontief cost function regression results**

Variable	*OpEx*		*O/H Lines*		*U/G Cables*		*Transformers*	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	2.193	31.76	0.000	0.00	–0.438	–1.13	–0.721	–3.02
RMD	0.000	0.00	0.000	0.00	0.000	0.00	0.393	0.33
Customer No	0.000	0.00	0.082	1.53	0.000	0.00	0.000	0.00
Circuit Length	0.000	0.00	1.355	5.63	–1.358	–6.98	–0.810	–5.00
Time	0.038	3.39	–0.010	–12.96	0.020	4.07	0.013	2.35
R^2	0.539		0.461		0.982		0.980	

Table A4: **END Leontief cost function regression results**

Variable	OpEx		O/H Lines		U/G Cables		Transformers	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	3.013	2.80	0.000	0.00	0.000	0.00	0.000	0.00
RMD	0.000	0.00	5.275	2.92	0.000	0.00	0.606	0.62
Customer No	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
Circuit Length	–0.719	–0.29	2.842	7.29	0.945	85.79	0.642	5.97
Time	0.018	1.02	–0.010	–11.28	0.073	15.33	0.019	12.93
R^2	0.313		0.090		0.984		0.978	

Table A5: **ENX Leontief cost function regression results**

Variable	OpEx		O/H Lines		U/G Cables		Transformers	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
RMD	6.921	50.42	1.556	1.30	3.243	157.98	1.283	12.40
Customer No	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
Circuit Length	0.000	0.00	2.351	29.86	0.000	0.00	0.520	20.40
Time	0.006	1.06	0.000	–0.03	0.040	18.45	0.018	25.68
R^2	0.674		0.958		0.989		0.995	

Table A6: **ERG Leontief cost function regression results**

Variable	OpEx		O/H Lines		U/G Cables		Transformers	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
RMD	2.786	0.02	6.503	3.44	-1.913	-98.34	0.000	0.00
Customer No	0.000	0.00	0.000	0.00	0.000	0.00	0.130	156.71
Circuit Length	1.225	0.17	1.624	10.82	0.000	0.00	0.000	0.00
Time	0.001	0.01	-0.004	-1.84	0.055	14.44	0.020	10.60
R^2	0.132		0.460		0.980		0.976	

Table A7: **ESS Leontief cost function regression results**

Variable	OpEx		O/H Lines		U/G Cables		Transformers	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	0.000	0.00	3.171	2.26	0.000	0.00	0.000	0.00
RMD	0.000	0.00	0.000	0.00	1.578	1.83	0.000	0.00
Customer No	0.577	23.09	0.000	0.00	0.000	0.00	0.141	92.99
Circuit Length	0.000	0.00	1.423	7.22	0.150	1.32	0.000	0.00
Time	–0.007	–0.56	0.048	15.52	0.072	3.01	0.010	3.35
R^2	0.088		0.962		0.865		0.985	

Table A8: **JEN Leontief cost function regression results**

Variable	*OpEx*		*O/H Lines*		*U/G Cables*		*Transformers*	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
RMD	0.000	0.00	–1.212	–0.85	0.000	0.00	–0.844	–3.22
Customer No	0.383	56.58	0.209	0.68	0.000	0.00	0.000	0.00
Circuit Length	0.000	0.00	2.352	1.66	–1.140	–179.26	0.680	12.60
Time	0.017	3.15	–0.005	–4.13	0.041	20.99	0.021	12.99
R^2	0.738		0.711		0.989		0.976	

Table A9: **PCR Leontief cost function regression results**

Variable	*OpEx*		*O/H Lines*		*U/G Cables*		*Transformers*	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
RMD	2.220	0.21	0.000	0.00	1.841	5.50	–0.518	–3.23
Customer No	0.000	0.00	0.622	6.75	0.040	0.76	0.000	0.00
Circuit Length	–1.153	–1.84	1.561	4.58	0.000	0.00	0.321	39.43
Time	0.015	1.06	–0.011	–5.02	0.050	7.20	0.025	29.65
R^2	0.408		0.682		0.949		0.997	

Table A10: **SAP Leontief cost function regression results**

Variable	*OpEx*		*O/H Lines*		*U/G Cables*		*Transformers*	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	0.000	0.00	1.457	3.56	0.000	0.00	–0.535	–2.05
RMD	–6.193	–37.13	0.000	0.00	1.495	7.64	–0.602	–1.11
Customer No	0.000	0.00	0.207	2.53	0.000	0.00	0.000	0.00
Circuit Length	0.000	0.00	1.298	10.89	0.439	19.18	0.281	5.44
Time	0.043	4.52	–0.003	–1.82	0.017	19.17	0.029	4.49
R^2	0.816		0.713		0.990		0.975	

Table A11: **AND Leontief cost function regression results**

Variable	*OpEx*		*O/H Lines*		*U/G Cables*		*Transformers*	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
RMD	7.378	37.00	1.176	2.58	0.000	0.00	1.526	9.92
Customer No	0.000	0.00	0.000	0.00	0.152	228.37	0.059	1.37
Circuit Length	0.000	0.00	2.151	160.69	0.000	0.00	0.138	0.44
Time	0.035	3.85	–0.001	–1.44	0.044	28.82	0.014	2.49
R^2	0.797		0.877		0.996		0.986	

Table A12: **TND Leontief cost function regression results**

Variable	*OpEx*		*O/H Lines*		*U/G Cables*		*Transformers*	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	3.398	30.55	–2.069	–4.81	0.000	0.00	0.000	0.00
RMD	0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
Customer No	0.000	0.00	0.000	0.00	0.109	1.79	0.115	208.88
Circuit Length	0.000	0.00	1.908	19.12	–0.558	–3.89	0.000	0.00
Time	0.022	2.07	0.002	1.74	0.014	7.06	0.016	10.82
R^2	0.249		0.944		0.976		0.974	

Table A13: **UED Leontief cost function regression results**

Variable	*OpEx*		*O/H Lines*		*U/G Cables*		*Transformers*	
	Coef	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*	*Coef*	*t–stat*
Energy	3.080	3.84	0.000	0.00	0.000	0.00	0.000	0.00
RMD	1.564	0.23	2.353	2.27	0.877	5.68	0.965	7.90
Customer No	0.000	0.00	0.355	16.49	0.077	2.45	0.086	19.99
Circuit Length	0.000	0.00	0.000	0.00	–0.581	–2.89	0.000	0.00
Time	0.015	1.19	0.003	2.13	0.025	15.74	0.018	16.54
R^2	0.332		0.871		0.993		0.986	

Appendix B Translog opex cost function results, Australian sample mean normalisation

Table B1 **LSE translog cost function estimates using Australian sample mean normalisation, 2006–2018 data**

Variable	*Coefficient*	*Standard error*	*t–ratio*
ln(Custnum)=x1	0.400	0.135	2.970
ln(CircLen)=x2	0.223	0.047	4.720
ln(RMDemand)=x3	0.431	0.107	4.020
x1*x1/2	-0.618	0.273	-2.270
x1*x2	0.271	0.091	2.990
x1*x3	0.271	0.210	1.290
x2*x2/2	-0.013	0.038	-0.360
x2*x3	-0.235	0.073	-3.220
x3*x3/2	0.069	0.168	0.410
ln(ShareUGC)	-0.145	0.025	-5.850
Year	0.018	0.002	9.300
Country dummy variables:			
New Zealand	-0.394	0.122	-3.220
Ontario	-0.218	0.121	-1.800
DNSP dummy variables:			
AGD	-0.074	0.165	-0.450
CIT	-0.720	0.138	-5.230
END	-0.366	0.136	-2.680
ENX	-0.404	0.134	-3.020
ERG	-0.339	0.162	-2.090
ESS	-0.555	0.170	-3.270
JEN	-0.227	0.138	-1.650
PCR	-0.895	0.142	-6.290
SAP	-0.707	0.141	-5.000
AND	-0.545	0.142	-3.850
TND	-0.555	0.143	-3.880
UED	-0.486	0.149	-3.260
Constant	-23.141	3.793	-6.100
R–Square			0.993

Table B2 **SFA translog cost function estimates Australian using sample mean normalisation, 2006–2018 data**

Variable	*Coefficient*	*Standard error*	*t–ratio*
ln(Custnum)=x1	0.744	0.145	5.150
ln(CircLen)=x2	0.132	0.057	2.330
ln(RMDemand)=x3	0.191	0.114	1.670
x1*x1/2	0.095	0.284	0.330
x1*x2	-0.228	0.112	-2.030
x1*x3	0.217	0.208	1.040
x2*x2/2	0.113	0.062	1.840
x2*x3	0.100	0.092	1.090
x3*x3/2	-0.335	0.180	-1.850
ln(ShareUGC)	-0.103	0.037	-2.790
Year	0.015	0.001	12.260
Country dummy variables:			
New Zealand	0.134	0.121	1.110
Ontario	0.322	0.079	4.050
Constant	-18.634	2.471	-7.540
Variance parameters:			
Mu	0.333	0.079	4.200
SigmaU squared	0.044	0.014	3.223
SigmaV squared	0.011	0.001	19.979
LLF			602.556

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