evoenergy

Appendix 3.1: Frontier Economics – AER benchmarking of DNSP opex

Revised regulatory proposal for the Evoenergy electricity distribution determination 2024 to 2029

November 2023

AER benchmarking of DNSP opex

A report prepared for Evoenergy | 30 November 2023

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1.1 Background

1. On 28 September 2023, the Australian Energy Regulator (AER) published a draft decision on Evoenergy's revenue determination for the 2024-29 regulatory control period, commencing 1 July 2024. Attachment 6 of the draft decision deals with the AER's determination of the allowance for efficient operating expenditure (opex) for Evoenergy over the 2024-29 regulatory control period.[1]

2. The Draft Decision concluded that the actual opex incurred by Evoenergy in 2021-22 (the base year proposed by Evoenergy in its initial proposal), $67.4 million ($2023-24), is a materially inefficient basis for forecasting Evoenergy's opex requirement over the 2024-29 regulatory control period. Using benchmarking analysis, the AER determined in the Draft Decision that the "efficiency gap" between its estimate of efficient base year opex and actual base year opex was 15.7%.

3. Recognising that it will take time and involve costs for Evoenergy's management to implement the programs required to realise opex reductions, the AER has proposed a linear glide path transition to what it regards as a more efficient opex level over the 2024-29 regulatory control period. This glide path transition resulted in the AER adopting in the Draft Decision an alternative estimate of base year opex that is 9.4% lower than Evoenergy's actual opex in 2021-22.

4. Evoenergy has asked Frontier Economics to review the Draft Decision and:

   a Derive an updated estimate of efficient base year opex for Evoenergy:

      i Using 2022-23 (rather than 2021-22) as the base year for forecasting Evoenergy's opex requirement for the 2024-29 regulatory control period;

      ii Revised data to be applied in the benchmarking analysis;

      iii Using appropriate Operating Environment Factor (OEF) adjustments for Evoenergy;

      iv Considers and addresses the AER's reasons for not accepting Evoenergy's inclusion of a step change for efficient vegetation management expenditure when rolling forward an estimate of efficient opex to the base year;

      v Considers how the AER should account for statistical uncertainty when deriving an estimate of efficient base year opex; and

   b Review the reliability of the AER's econometric benchmarking models and explains the implications for the AER's Final Decision on the efficiency of Evoenergy's actual base year opex.

[1] AER, *Draft Decision Evoenergy Regulatory proposal 2024 to 2029 (1 July 2024 to 30 June 2029)*, Attachment 6, September 2023 (Draft Decision).

1.2 Key findings

1.2.1 OEF adjustments

5. We have adopted in our analysis the following OEF adjustments applied in the Draft Decision:

   a Sub-transmission (Licence conditions);

   b Termite exposure;

   c Backyard reticulation (updated by the AER in the Draft Decision); and

   d Workers' compensation insurance costs.

Vegetation management OEFs

6. The Draft Decision implemented two vegetation management OEFs, which the AER describes as follows:

   a Bushfire risk obligations — the effects on opex of variations in mandated standards of bushfire mitigation activities (generally related to vegetation management), specifically the bushfire regulations in Victoria; and

   b Division of responsibility — the differences in opex between distribution businesses due to differences in the division of responsibility for vegetation clearance between the networks and other parties, such as local councils, road authorities and landowners.

7. The Draft Decision is the first time these two OEFs have been applied to Evoenergy.

8. We note that the bushfire risk obligation OEF makes strong assumptions, including the following:

   a The introduction of the Victorian bushfire regulations placed all Victorian DNSPs at a cost disadvantage to non-Victorian DNSPs rather than bringing Victoria more in line with other jurisdictions;

   b The full step change in vegetation management opex the AER approved for the 2011-15 regulatory control period represents the full cost disadvantage faced by the Victorian DNSPs following the introduction of the Victorian bushfire regulations; and

   c Any cost disadvantage faced by the Victorian DNSPs once the new regulations were introduced has remained unchanged since.

9. The AER has not provided evidence to support any of these assumptions.

10. During the AER's 2018 review of OEFs, the AER's consultant Sapere-Merz considered the vegetation management OEFs applied in the Draft Decision and advised that further work was required by the AER to undertake a systematic quantification of any vegetation management OEFs.

11. Sapere-Merz did not endorse either of the vegetation management OEFs. Rather, Sapere-Merz advised that:

   a there could be many factors other than efficiency that explain the differences in vegetation management expenditure between DNSPs;

   b it would be preferable to identify the combined effect of these explanatory factors on the differences in vegetation management expenditure between DNSPs, rather than to quantify the effect of one or more factors individually (i.e., differences in bushfire obligations and differences in the division of responsibility) as the AER had done in previous decisions; and

c further data collection by the AER was required before any vegetation management OEFs could be quantified reliably.

12. Sapere-Merz advised that a vegetation management OEF (or set of OEFs) could be applied on a case by case basis by the AER. However, Sapere-Merz was explicit that in order to do so, the AER would require “adequate supporting data and information, including improved evidence and data” from the DNSPs in question.[2]

13. In the five years that have passed since Sapere-Merz made these recommendations, the AER has not collected any such information or undertaken any further work to improve the method for quantifying the vegetation management OEFs. Rather, the AER has simply reverted to using the vegetation management OEFs it had developed prior to the 2018 review conducted by Sapere-Merz. This is not what Sapere-Merz recommended when it advised that the AER could apply vegetation management OEFs on a case by case basis.

14. Several DNSPs have consistently raised concerns about the reliability of the AER’s vegetation management OEFs and have called for the AER to undertake a review and consultation process on this issue. No such process has been initiated by the AER.

15. We note that, similarly, many stakeholders consistently raised concerns, over several years, that the AER’s benchmarking analysis failed to account properly for differences in capitalisation practices between DNSPs. When the AER did eventually conduct a review on that issue, it concluded that differences in capitalisation practices do distort benchmarking outcomes and therefore need to be accounted for within the analysis. Moreover, once the AER developed a method to account for differences in capitalisation practices, the benchmarking outcomes changed materially for some DNSPs. The same could be true in relation to vegetation management.

16. There are strong parallels between the issue of capitalisation differences and vegetation management expenditure:

a Both satisfy the AER’s OEF criteria;

b Both are multifaceted and complex, and therefore require careful investigation; and

c Both have the potential to distort benchmarking outcomes materially if not accounted for properly.

17. In our view, there is a strong case for the AER undertaking a serious review into the appropriate method for quantifying a vegetation management OEF or set of OEFs along the lines recommended by Sapere-Merz. Until such time as the AER has completed such a review, it should not apply the vegetation management OEFs, since the existing vegetation management OEFs are based on very strong assumptions and incomplete information. The application of the existing vegetation management could seriously distort benchmarking outcomes and produce unreliable forecasts of efficient opex.

18. For these reasons, we have not applied the vegetation management OEFs adopted in the Draft Decision.

[2] Sapere-Merz, *Independent review of Operating Environment Factors used to adjust efficient operating expenditure for economic benchmarking*, August 2018, p. 66.

Jurisdictional taxes and levies OEF

19. One of the standard OEFs adjustments developed by Sapere-Merz, and which the AER applies to most DNSPs, is for differences in the jurisdictional taxes and levies incurred by DNSPs. However, the AER has not previously applied this OEF to Evoenergy because it was advised by Sapere-Merz that Evoenergy recovers these costs via "the B factor in annual pricing determinations."[3]

20. We make two points in relation to this:

   a The B factor referred to by Sapere-Merz is simply a term in the annual price adjustment formula that increases or reduces the regulated tariff to account for past under/over-recovery of allowed revenues. It plays no role in the recovery of jurisdictional taxes and levies incurred by Evoenergy; and

   b Even if the B factor were a mechanism for Evoenergy to recoup jurisdictional taxes and levies, it does not follow that the jurisdictional taxes and levies OEF adjustment should not be applied to Evoenergy. The role of an OEF adjustment is to normalise cost differences between DNSPs that arise from differences in operating environment that would otherwise confound like-with-like comparisons between DNSPs when making efficiency assessments. The mechanism by which such costs are recovered is not relevant to whether cost differences related to operating environment should be normalised.

21. Evoenergy has advised us that there are two types of taxes and levies that are included within the historical standard control services opex that it has reported via its Economic Benchmarking RIN responses:

   a payroll taxes; and

   b land taxes.

22. Both of these are examples of taxes and levies identified by Sapere-Merz as relevant to the jurisdictional taxes and levies OEF adjustment.[4]

23. The AER's approach is to calculate the OEF adjustment using the average level of taxes and levies over the period 2010-15. Applying this method to the data provided by Evoenergy resulted in the following jurisdictional taxes and levies OEF adjustments for Evoenergy:

   a Long sample – 5.42%; and

   b Short sample – 5.15%.

Network overheads OEF

24. The AER's method for accounting for differences in capitalisation practices between DNSPs, when conducting benchmarking analysis, involves treating all corporate overheads as opex.

25. Evoenergy proposed that the AER should also treat all network overheads as opex because there are many categories of network overheads that could be treated as opex or capex. The AER did not accept this proposal for the following reasons:

[3] Draft Decision, p. 26.

[4] Sapere-Merz, *Independent review of Operating Environment Factors used to adjust efficient operating expenditure for economic benchmarking*, August 2018, Table 12, p. 69. Payroll taxes are identified in the third column of Table 2, as are the land taxes.

a network overheads are lumpier than corporate overheads, which are recurrent, stable and opex-like in nature;

b corporate overheads are delineated from other opex categories in a more stable and consistent way than are network overheads; and

c the regulatory framework has safeguards that protect against strategic cost reallocations between corporate and network overheads.

26. In our view, there is strong case for accounting for differences in DNSPs' capitalisation practices in relation to network overheads.

a There is significant variation in the share of network overheads that individual DNSPs have capitalised historically. Any opex benchmarking analysis that ignores this fact will tend to penalise DNSPs like Evoenergy that have tended to capitalise fewer of these costs.

b The lumpiness of network overheads is not a relevant consideration when deciding whether to account for differences in capitalisation practices between DNSPs. Certain operating costs are lumpy by nature (e.g., setup costs when transitioning to Software-as-a-Service). The lumpiness of those costs does not mean they should be misclassified as capex. If the AER considers that network overheads are more capex-like than opex-like, due to their lumpiness, then the AER could consider treating all reported network overheads as capex (i.e., excluding all such costs from the opex being benchmarked). That would put all DNSPs on a level playing field for the purposes of benchmarking historical opex. However, if the AER considers it important to test the efficiency of these costs, then the simplest approach would be to treat all network overheads as opex, thereby subjecting them to benchmarking.

c The fact that network overheads are not defined consistently between DNSPs (the AER's second reason above) helps explain the significant variation between DNSPs and strengthens (rather than weakens) the case for normalising the differences between DNSPs' capitalisation practices for network overheads.

d Finally, notwithstanding that the AER's framework has safeguards to protect against DNSPs seeking to game the AER's benchmarking analysis by allocating network overheads between opex and capex, the fact remains that DNSPs have adopted very different capitalisation practices in relation to network overheads historically.

27. In this report, we estimate a Network Overheads OEF adjustment for Evoenergy by calculating the percentage by which actual opex reported by Evoenergy historically would have exceeded the level of opex that Evoenergy would have reported had it capitalised the comparator average share of total network overheads (i.e., 31% over the years 2006 to 2022).

28. The resulting Network Overheads for Evoenergy are:

a Long sample – 13.7%; and

b Short sample – 15.3%.

1.2.2 Vegetation management step change in the roll forward of opex

29. In its original proposal to the AER, Evoenergy submitted that the AER should recognise the step change in efficient opex approved by the AER for the 2019-24 regulatory control period in the process for rolling forward efficient opex to the base year by adding the approved step change amount to the rolled-forward estimate of efficient base year opex.

30. The Draft Decision rejected that proposal because the AER considered that the positive time trend term used in the opex roll-forward calculation allows for a general increase over time in the regulatory obligations faced by DNSPs.

31. The AER also noted that other DNSPs have similarly faced step changes in opex in the past, which would have affected the estimated efficiency of those DNSPs negatively.

32. The AER concluded that its preference is to reflect the step change in Evoenergy's vegetation management costs through the vegetation management OEF. Specifically, the AER offset its estimate of the cost disadvantage faced by the reference DNSPs by the approved step change in Evoenergy's efficient vegetation management costs, for the years the step changes were allowed.

33. In our view, the Draft Decision does not account properly for the prudent and efficient step change in Evoenergy's opex in the base year. The estimated time trend is capable of reflecting only the *average* impact on opex of the regulatory obligations faced by DNSPs (across New Zealand, Ontario and Australia) expanding over time. An opex allowance that provided only for this average impact would not be a *realistic* forecast of the *efficient* and *prudent* opex that the *DNSP in question* would need to incur in order to achieve the opex objectives (including compliance with all relevant regulatory obligations) specified in the National Electricity Rules (NER).

34. The main shortcoming of the AER's approach of recognising the step change in Evoenergy's efficient costs via an OEF adjustment is that it fails to account adequately for the change in Evoenergy's regulatory obligations (and the associated impact on opex) when rolling forward the estimate of efficient opex to the base year.

35. In our view, it is appropriate for the AER to account for the step change in costs associated with a regulatory obligation (such as the additional vegetation management responsibilities imposed on Evoenergy) via an OEF adjustment as the AER proposed in the Draft Decision when deriving an estimate of the *period average level of efficient opex*. However, in order to derive a reliable estimate of a prudent and efficient level of *base year opex*, the AER must also recognise any additional increase in costs that would be faced by the DNSP (between the middle of the sample period and the base year) in order to comply with those new obligations.

36. Alternatively, and equivalently, the AER could apply no OEF adjustment to the benchmark comparison point but would then need to add to its estimate of efficient base year opex the full step change in efficient opex needed to comply with the obligations — consistent with Evoenergy's proposal.

1.2.3 Accounting for statistical uncertainty around the estimate of efficient base year opex

37. The AER's methodology for determining an estimate of efficient base year opex relies on its econometric benchmarking models. The parameters in these models are estimated from data and are subject to statistical uncertainty. As a consequence, the AER's base year opex target is also subject to statistical uncertainty.

38. However, the AER does not account for this statistical uncertainty when assessing the efficiency of a DNSP's actual base year opex because the AER effectively treats its point estimate of efficient base year opex as certain. The AER does not allow for any range of uncertainty around its point estimate of efficient base year opex. Rather, if its point estimate of efficient base year opex is lower than the DNSP's actual base year opex, then the AER concludes that the latter is materially inefficient.

39. In our view, this is a serious shortcoming in the AER's approach. The statistical uncertainty involved in estimating a DNSP's efficiency and the elasticities and other parameters specified in the econometric benchmarking models can be very material. This uncertainty means that the AER does not *know* the *true* level of efficient base year opex for a particular DNSP with certainty. Instead, the true level of efficient base year opex lies within a range of uncertainty that is defined by (amongst other factors) the statistical error involved in estimating:

   a the true level of average efficiency of a DNSP over the historical benchmarking period;

   b the true relationship between a DNSP's opex and outputs; and

   c the true values of other parameters specified in the AER's econometric models.

40. In our view, the AER should quantify formally the statistical uncertainty around its point estimate of efficient base year opex, by constructing confidence intervals around that estimate, and then use those confidence intervals to make a probabilistic assessment about the evidence for material inefficiency.

41. The Stata output files that accompany the Annual Benchmarking Reports provide information on the statistical uncertainty associated with:

   a AER's estimates of the period average efficiency; and

   b other relevant parameter estimates used to roll forward the period average estimate of efficient opex to the base year.

42. Using this information, and a well-accepted statistical technique known as the 'delta method', we have constructed confidence intervals around the estimates of efficient base year opex derived using each of the AER's econometric benchmarking models.

43. The AER's approach is to compare a DNSP's *actual* base year opex to an *estimate* of efficient base year opex, where that estimate is derived using statistical analysis. If the former is greater than the latter, then the AER concludes that the DNSP's actual base year opex is materially inefficient.

44. However, if the DNSP's actual base year opex lies within the confidence interval, then the AER cannot reject the possibility that there is no difference between a DNSP's revealed level of actual base year opex and the efficient level of base year opex—because the latter can only be estimated with statistical uncertainty, and the former lies within the range of statistical uncertainty.

45. In these circumstances, one could not conclude that a DNSP's revealed base year opex is efficient. But one could conclude that there is no evidence of material inefficiency. This approach to using confidence intervals is entirely consistent with standard hypothesis testing.

1.2.4 Shortcomings associated with the econometric benchmarking models

46. The AER uses four econometric opex cost function models to estimate the average efficiency of DNSPs' historical opex. The four models reflect two different specifications of the cost function (Cobb-Douglas and Translog) and two different estimation methods (Least Squares Econometrics (LSE) and Stochastic Frontier Analysis (SFA)).

47. We have identified several serious problems with these benchmarking models—the details of which are presented in Appendix A. In summary, we found that:

   a Statistical test results presented by Quantonomics indicate that the Cobb-Douglas model is seriously misspecified and that the Translog model, which allows for more flexibility in the specification of the output elasticities, fits the data significantly better than the Cobb-

Douglas model. In view of this, it is difficult to find a statistical justification for including estimates derived from the Cobb-Douglas models in the assessment of the efficiency of the DNSPs.

b The Translog models (particularly those estimated using the short sample) have exhibited monotonicity violations for a number of DNSPs and in a number of years. As the AER itself acknowledges, these monotonicity violations are becoming more prevalent over time.[5]

c These monotonicity violations are likely to be a symptom of a more fundamental model misspecification problem. Quantonomics' approach of restricting the flexibility of the Translog functional form to reduce the number of monotonicity violations simply treats the symptom rather than the root cause of the problem.

d Our analysis indicates that the Translog models are also misspecified. For example, plots of the residuals of the Translog models for the Australian DNSPs make it abundantly clear that the residuals of the models for the Australian DNSPs are not random with respect to time, and that there is a time-related factor that is not accounted for properly in the AER's models.

e There is convincing evidence that the DNSP industry as a whole in Australia has become more efficient over time—an observation that the AER itself has made.[6] However, all of the AER's benchmarking models assume that efficiency remains constant over time. This assumption of constant efficiencies over time is hard-wired into the specification of the models. Consequently, the AER's models are incapable, due to their specification, of accounting for the fact that some DNSPs have improved their level of efficiency considerably over time. Since the models cannot account for these changes in efficiency over time directly, they will tend to overfit the data to other time-varying variables in the model.

  i Given the highly flexible functional form of the Translog models, this response to the lack of time variation in the efficiencies in the model is likely to be more pronounced for the Translog models. This could be a key reason why the Translog models are prone to monotonicity violations—particularly when estimated using the short sample, which overlaps almost perfectly with the period over which the AER has been conducting benchmarking analysis.

  ii Given the significant changes in DNSP efficiencies since 2014, the assumption of constant efficiencies is likely to cause a serious misspecification problem for the Cobb-Douglas models as well as the Translog.[7] However, the consequences of this misspecification problem are harder to detect (e.g., as monotonicity violations) for the Cobb-Douglas models due to their more restrictive functional form. Nonetheless, both classes of models suffer from the same underlying issue.

f In short, there is compelling evidence that the Cobb-Douglas and Translog models are misspecified and therefore should not be relied upon by the AER. Misspecification of the benchmarking models will result in biased estimates of efficiency for individual DNSPs (and other model parameters). This means that the resulting estimates of efficient base

[5] AER, *Annual Benchmarking Report, Electricity distribution network service providers*, November 2022, p. 58.

[6] For example: AER, *Draft Annual Benchmarking Report, Electricity distribution network service providers*, October 2023, p. v.

[7] As shown in Appendix A, the residual plots for the Cobb-Douglas models also exhibit a clear negative trend over time for the Australian DNSPs.

year opex derived using those models will be unreliable, and unsafe for the purposes of setting opex allowances.

48. Given the seriousness of the statistical problems we have identified, what is required is a fundamental review of the AER's econometric benchmarking models to ensure that they are capable of fitting the salient features of data well. Such a review should be done carefully and in proper consultation with stakeholders. Therefore, it should not be rushed.

49. Until this work can be completed properly, the AER should exercise extreme caution when interpreting the results derived from its existing models. The AER should not use those models mechanistically, as it has done in recent determinations, when assessing whether a DNSP's actual base year opex is materially inefficient.

1.2.5 Estimate of efficient base year opex

50. Evoenergy has instructed us to assume, for the purposes of modelling Evoenergy's efficient base year opex, that the relevant base year will be 2022-23.

51. In addition, Evoenergy has asked us to make use of the following revised data to perform the benchmarking analysis and modelling of efficient base year opex:

   a Audited actual data for 2022-23 provided to us by Evoenergy;

   b Revised circuit length data that corrects errors in historical network length data previously submitted to the AER by Evoenergy; and

   c Data used by the AER in the 2023 Draft Annual Benchmarking Report.

52. For the purposes of modelling an efficient level of base year opex for Evoenergy, we have also:

   a applied the OEF adjustments summarised in section 1.2.1;

   b applied the AER approved step-change in Evoenergy's opex when rolling forward the estimate of efficient opex to the base year as discussed in section 1.2.2; and

   c constructed confidence intervals around the estimate of efficient base year opex, as described in section 1.2.3.

53. Aside from the changes described above, we follow the AER's method for estimating an overall efficient level of base year opex, which involves:

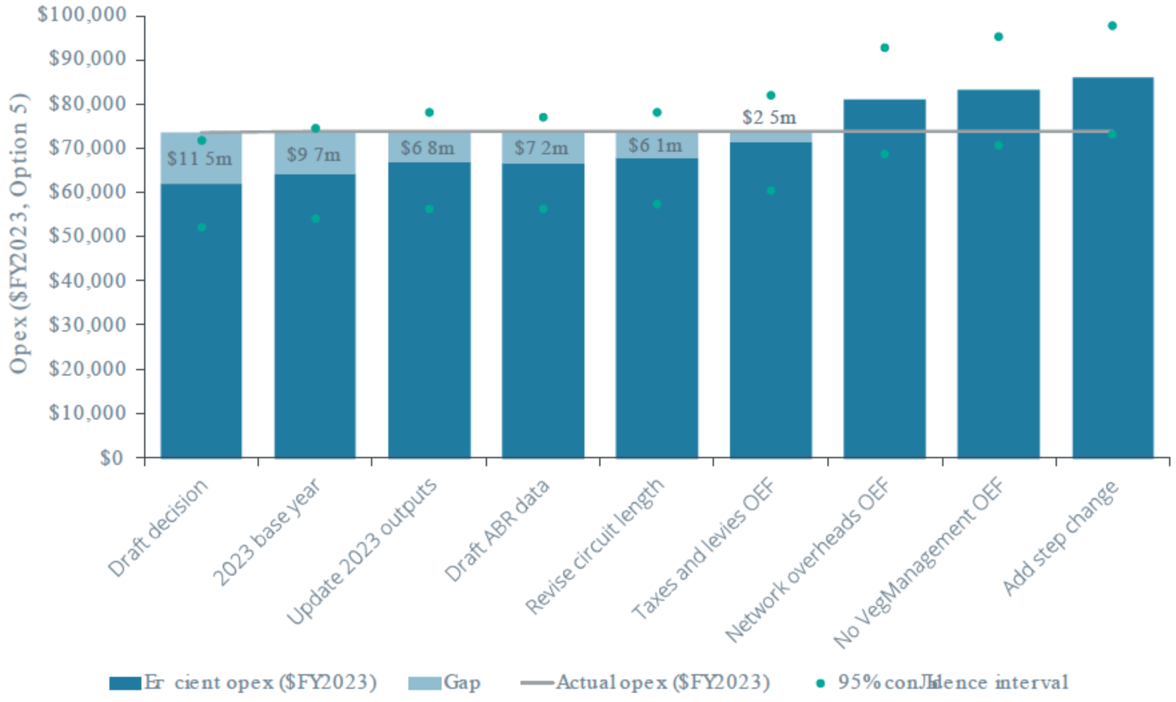
   a Estimating an efficient level of opex over the relevant historical benchmarking period, using each statistical model that is not rejected due to monotonicity violations (i.e., the 'valid models');

   b Rolling forward each of those estimates to the base year (using the AER's roll-forward procedure); and

   c Averaging the estimates across all of the valid models.

54. The resulting estimates are presented in Figure 9 below. Each bar in the figure below adds one additional change to the scenario represented in the previous bar, such that each bar represents the cumulative effect of the preceding scenarios.

Figure 1: Estimates of efficient base year opex ($FY2023) under each scenario modelled



Source: Frontier Economics analysis of Evoenergy, Quantonomics data.

55. We make two observations in relation to the results presented in Figure 1:

a Firstly, in every scenario modelled (excluding the Draft Decision outcome applying an FY2022 base year), Evoenergy's actual opex in the relevant base year lies comfortably within the 95% confidence interval around the estimate of efficient opex. This suggests that there is no reliable statistical evidence that Evoenergy's actual FY2023 opex is materially inefficient under any scenario modelled.

b Secondly, once the first six changes have been adopted (i.e., adoption of 2022-23 as the base year, use of 2023 audited outputs data for Evoenergy, use of 2023 Draft Annual Benchmarking Report data, use of Evoenergy's revised circuit length data, application of the jurisdictional taxes and levies OEF and inclusion of the Network Overheads OEF), the resulting estimate of efficient opex is higher than Evoenergy's actual base year opex.

56. Based on either or both of these observations, we conclude that there is no evidence that Evoenergy's base year opex is materially inefficient.

1.3 Structure of this report

57. The remainder of this report is structured as follows:

a Section 2 discusses the OEF adjustments relevant to Evoenergy;

b Section 3 discusses the issue of how approved step changes in Evoenergy's vegetation management costs should be taken into account when estimating an efficient level of base year opex; and

c Section 4 explains how we take into account the statistical uncertainty associated with the estimates of efficient base year opex.

58. Appendix A discusses the statistical shortcomings associated with the AER's econometric benchmarking models, and the implications the AER's assessment of the efficiency of Evoenergy's revealed base year opex for the 2024-29 regulatory control period.

2 OEFs relevant to Evoenergy

2.1 Summary of OEF adjustments applied in the Draft Decision

59. Table 1 summarises the OEF adjustments applied in the Draft Decision to Evoenergy for each of the two historical benchmarking periods.

Table 1: OEF adjustments applied to Evoenergy in the Draft Decision (%)

OEF	2006-21 period	2012-21 period
Sub-transmission (Licence conditions)	-0.40	-0.17
Termite exposure	0.02	0.03
Backyard reticulation	3.53	3.44
Workers' compensation insurance costs	0.75	0.75
Vegetation management (bushfire)	-2.94	-4.2
Vegetation management (division of responsibility)	0.0	0.0
Total	**1.0**	**-0.1**

Source: Draft Decision, Table 6.6, p. 26.

60. We make the following observations about the OEF adjustments applied in the Draft Decision:

   a The first two OEF adjustments—relating to ownership of sub-transmission assets and to termite exposure—are computed using the data and methodology recommended by the AER's adviser Sapere-Merz in 2018.[8]

   b The backyard reticulation OEF adjustment adopted the approach recommended by Sapere-Merz but made use of updated backyard reticulation cost data proposed by Evoenergy. We agree with the AER that Evoenergy's proposed calculation for this OEF adjustment "includes reasonable updates to the previous costings used for the Sapere-Merz process."[9] Hence, we agree with the backyard reticulation OEF adjustment adopted by the AER in the Draft Decision.

   c The AER accepted a new OEF adjustment proposed by Evoenergy to account for the fact that the cost of workers' compensation insurance in the ACT is the most expensive in any Australian jurisdiction and is materially higher than in the jurisdictions from which the reference DNSPs are drawn. Based on the evidence submitted by Evoenergy, we consider that the application of this new OEF adjustment to Evoenergy is reasonable.

[8] That advice to the AER was set out in: Sapere-Merz, *Independent review of Operating Environment Factors used to adjust efficient operating expenditure for economic benchmarking*, August 2018.

[9] Draft Decision, p. 32.

d The AER has applied two new vegetation management OEF adjustments: one related to differences in bushfire risk obligations, and the other related to the division of responsibility for vegetation management between the DNSP and third parties (e.g., local councils or landowners). Evoenergy submitted in its regulatory proposal that the AER should not apply these two OEF adjustments for a number of reasons. We have those reasons and, as explained in section 2.2, we agree with Evoenergy that these two new vegetation management OEFs should not be applied to non-Victorian DSNPs without further data collection, analysis and broad consultation.

e The AER has not applied an OEF adjustment to Evoenergy for differences between DNSPs in jurisdictional taxes and levies—one of the OEF categories recommended by Sapere-Merz.[10] The AER excluded an OEF adjustment for taxes and levies due to concerns that the recovery of these costs through mechanisms other than standard control tariffs could breach the 'non-duplication' criterion used by the AER to identify relevant OEFs. We disagree with the AER's conclusions on this issue and explain our reasons for doing so in section 2.3.

61. In addition to these matters, in section 2.4 we propose a new OEF adjustment that accounts for differences between DNSPs in terms of capitalisation of network overheads (the 'Network overheads OEF').

2.2 Vegetation management OEFs

62. The Draft Decision applies two new vegetation management OEF adjustments to Evoenergy, which the AER describes as follows:[11]

a Bushfire risk obligations — the effects on opex of variations in mandated standards of bushfire mitigation activities (generally related to vegetation management), specifically the bushfire regulations in Victoria; and

b Division of responsibility — the differences in opex between distribution businesses due to differences in the division of responsibility for vegetation clearance between the networks and other parties, such as local councils, road authorities and landowners.

63. We refer to these as 'new' OEF adjustments because the AER has not previously applied these in previous determinations for Evoenergy. However, as we explain below, the AER has applied those OEF adjustments to a select number of other DNSPs.

64. Evoenergy submitted that the AER should not apply either of these OEF when setting Evoenergy's opex allowance for the 2024-29 regulatory control period because:

a The bushfire risk obligation OEF adjustment assumes (without evidence) that:[12]

i Victorian DNSPs have faced a historical cost disadvantage compared to non-Victorian DNSPs, due to more stringent obligations to manage bushfire risk; and

[10] Sapere-Merz, *Independent review of Operating Environment Factors used to adjust efficient operating expenditure for economic benchmarking*, August 2018, section 3.4.

[11] Draft Decision, p. 29.

[12] Evoenergy, *Regulatory proposal for the ACT electricity distribution network 2024–29, Appendix 2.1: Operating expenditure – base year efficiency*, January 2023, p. 24.

ii Any such cost disadvantage has remained unchanged over time, even though vegetation management obligations in non-Victorian jurisdictions have expanded over time.

b The Victorian DNSPs have also contested the materiality of the division of responsibility OEF adjustment applied by the AER; and[13]

c Neither of these OEF adjustments have been subject to broad consultation of the kind undertaken by the AER in 2017/18 when it commissioned Sapere-Merz to develop a standard set of (material) OEFs.

2.2.1 History of the vegetation management OEFs

65. The AER first developed and applied the bushfire risk obligation OEF adjustment to Ergon Energy in 2015. In its final determination for Ergon Energy's 2015-20 regulatory control period, the AER stated the following:

> *In the preliminary decision we applied a –2.6 per cent OEF adjustment for differences in bushfire risk between service providers (bushfire OEF adjustment). We did this because of our assessment of the differences in the impact of bushfires in Queensland, South Australia and Victoria and the costs associated with changes to vegetation management and other bushfire related regulations in Victoria. While service providers can take action to manage their bushfire risk, the natural environment and regulations with which they must comply are generally beyond their control. The CD SFA model does not account for bushfire risk. In our view, the difference in opex associated with bushfire risk and vegetation management regulations between Ergon Energy and the comparison firms is material. A bushfire OEF adjustment satisfies all of our OEF adjustment criteria.*[14]

66. The AER reapplied this OEF adjustment in its final determination for Ergon Energy for the 2020-25 regulatory control period, and also applied the OEF adjustment for the first time to Jemena in its final determination for the 2021-26 regulatory control period.[15]

67. However, between the first application of this OEF adjustment to Ergon Energy in 2015 and the reapplication the adjustment to Ergon Energy in 2020, the AER conducted a comprehensive review of OEFs, which attracted significant industry participation through an open consultation process.

68. The AER's adviser through that review, Sapere-Merz, considered the case for OEF adjustments related to vegetation management and concluded that a vegetation management OEF (or set of OEFs) would likely meet the OEF criteria for a significant portion of DNSPs.[16] However, Sapere-Merz advised that there could be many factors other than efficiency that explain the differences in vegetation management expenditure between DNSPs. Sapere-Merz also recommended that it

[13] AER, *Annual Benchmarking Report, Electricity distribution network service providers*, November 2022, p. 9.

[14] AER, *Ergon Energy determination 2015−16 to 2019−20, Attachment 7 – Operating expenditure*, October 2015, p. 65.

[15] AER, *Jemena Distribution Determination 2021 to 2026, Attachment 6 – Operating expenditure*, April 2021 pp. 29-30.

[16] Sapere-Merz, *Independent review of Operating Environment Factors used to adjust efficient operating expenditure for economic benchmarking*, August 2018, p. 65.

would be preferable to identify the combined effect of these explanatory factors on the differences in vegetation management expenditure between DNSPs, rather than seeking to quantify the effect of one or more factors individually (i.e., differences in bushfire obligations and differences in the division of responsibility) as the AER had done in previous decisions:

> *our preferred overall approach to assessing OEF candidates is to seek to quantify the effects of one or more qualifying variables on efficient OPEX, rather than to seek to quantify the individual causes of higher OPEX (i.e. the individual variables set out above). Treating one or more causal variables as independent OEFs is problematic in that it can result in various combinations of double counting or omission (discussed further below with regard to related OEF candidates).*
>
> *This reflects the fact that vegetation management OPEX is often multi-purpose. Ensuring adequate clearances protects lines from both bushfires and extreme storms. Attributing vegetation management activities (and related cost) to one environmental risk or another is challenging.*[17]

69. This advice is consistent with Evoenergy's submission to the AER that the bushfire risk obligation OEF:

> *does not reflect the costs associated with managing bushfire risks but, rather, the impact of bushfire-related regulations imposed on Victorian networks in 2011.*[18]

70. However, due to data limitations, Sapere-Merz was unable to quantify any vegetation management OEF adjustment. The AER acknowledged this in the Draft Decision.[19]

71. The key point is that Sapere-Merz explicitly considered the bushfire risk obligation OEF adjustment the AER had applied to Ergon Energy in 2015 and the division of responsibility OEF adjustment. However, Sapere-Merz did not endorse the AER's methodology for quantifying either of these OEF adjustments.

72. Sapere-Merz was clear that further work was required by the AER to undertake a systematic quantification of any vegetation management OEFs.

73. The Draft Decision states that whilst Sapere-Merz was unable to quantify the vegetation management OEFs, it advised that this should not prevent the AER from estimating this OEF adjustment "on a case by case basis until such time as a systematic quantification is implemented."[20] In fact, what Sapere-Merz actually advised the AER was the following:

[17] Sapere-Merz, *Independent review of Operating Environment Factors used to adjust efficient operating expenditure for economic benchmarking*, August 2018, p. 59.

[18] Draft Decision, p. 30.

[19] Draft Decision, Table 6.6, p. 26.

[20] Draft Decision, p. 29.

> *It does not follow from the preliminary conclusion that a vegetation candidate OEF (or set) could not be quantified in the context of a future regulatory determination by the AER, in response to proposals submitted by DNSPs on a case by case basis.* ***With adequate supporting data and information, including improved evidence and data on exposure to the exogenous variables identified, and the efficiency of related OPEX (including any significant inter-annual factors), this OEF candidate (or set) should be capable of being quantified by individual DNSPs and the AER.***[21]

74. That is, Sapere-Merz recommended that the "case by case" quantification and application of the bushfire risk obligation OEF should be supported by "improved evidence and data." Sapere-Merz clearly envisaged that if the AER wanted to apply vegetation management OEF adjustments (including a bushfire risk obligation OEF) in future determinations, it would collect new data from the relevant DNSPs that would allow improved quantification of any such OEFs.

75. Specifically, Sapere-Merz recommended that the AER collect the following information:[22]

    a For DNSPs in jurisdictions not directly subject to the Victorian Bushfire regulations, an estimate of any incremental vegetation management activities (beyond vegetation trimming) for the purpose of minimising bushfire risks (such as advertising and educational campaigns). Consideration should be given to the extent to which the Victorian regulations are informing the definition of good industry practice across the jurisdictions.

    b For Victorian DNSPs, the proportion of the vegetation-exposed network that is affected by the Victorian Bushfire regulations, in particular the proportion defined in the regulations as high risk. This would include evidence on the additional costs (above standard vegetation trimming) of creating and maintaining auditable records on compliance with bushfire regulations.

76. In the five years that have passed since Sapere-Merz made these recommendations, the AER has not collected any of this information or done any further work to otherwise improve the methodology for quantifying bushfire risk obligation OEF.

77. The 2022 Annual Benchmarking Report explained that following Sapere-Merz's 2018 recommendations, the AER recognised that there was a need to improve the quantification of its vegetation management OEFs.[23] Therefore, in 2020 the AER undertook analysis into the quantity and quality of data related to vegetation management. The AER explained that its main focus was assessment of network characteristic data in the RINs relating to spans, including the total number of vegetation management spans, with a view to calculating an OEF. However, the AER was unable to develop any clear conclusions from that analysis due to concerns regarding the comparability and consistency of some of the data. For example, the AER suspected that:

[21] Sapere-Merz, *Independent review of Operating Environment Factors used to adjust efficient operating expenditure for economic benchmarking*, August 2018, p. 66. [Emphasis added]

[22] Sapere-Merz, *Independent review of Operating Environment Factors used to adjust efficient operating expenditure for economic benchmarking*, August 2018, p. 65.

[23] AER, *Annual Benchmarking Report, Electricity distribution network service providers*, November 2022, p. 50.

a there may be some inconsistency in DNSPs' definitions of active vegetation management span; and

b differences in contractual arrangements and vegetation management cycles.

78. Having been unable to implement the approach suggested by Sapere-Merz, or to use the further work it conducted in 2020, the AER reverted to using the vegetation management OEF methodology it had developed in 2015. The AER reapplied its 2015 methodology to determine a bushfire risk obligation OEF for Ergon Energy in 2020 and for Jemena in 2021.

79. The AER has also started to apply the division of responsibility OEF adjustment in decisions for non-Victorian DNSPs, and has published a vegetation management OEF model, which it has applied in its draft determinations for the NSW and ACT DNSPs for the 2024-29 regulatory control period.

80. In short, the bushfire risk obligation OEF adjustment and the division of responsibility OEF adjustment appear to have become standard features of the AER's benchmarking analysis, notwithstanding that Sapere-Merz:

a did not endorse the ongoing use of those OEF adjustments over the long-term;

b recommended that if those OEF adjustments were to be employed (in the near term), the AER should collect further information from the relevant DSNPs; and

c recommended that the preferable approach would be a more systematic quantification of the effect of (a range of environmental factors) on DNSPs' efficient vegetation management.

81. The 2023 Draft Annual Benchmarking Report notes that several DNSPs—including Evoenergy, CitiPower, Powercor and United Energy, Essential Energy and AusNet—have raised concerns about the vegetation management OEFs.[24]

82. In our view, a major weakness of the bushfire risk obligation OEF adjustment is that makes strong assumptions without supporting evidence. For example, it assumes that:

a Prior to the Victorian Bushfire regulations coming into force, all jurisdictions faced similar obligations to manage bushfire risk and, therefore, that the introduction of the Victorian Bushfire regulations placed all Victorian DNSPs at a disadvantage to non-Victorian DNSPs. In doing so, the AER appears to have discounted the possibility that the Victorian Bushfire regulations simply brought the Victorian DNSPs more into line with the standards adopted by non-Victorian DNSPs;

b The step change in vegetation management opex the AER approved for the 2011-15 regulatory control period represents the full cost disadvantage faced by the Victorian DNSPs following the introduction of the Victorian Bushfire regulations. It could be that if these new regulations did introduce a cost disadvantage for the Victorian DNSPs, that disadvantage is only a fraction of the step change approved by the AER; or

c The AER assumes that any cost disadvantage faced by the Victorian DNSPs once the new regulations were introduced has remained unchanged ever since. The AER seems to have excluded (without evidence) the possibility that the obligations to manage bushfire risk

[24] AER, *Draft Annual Benchmarking Report, Electricity distribution network service providers*, October 2023, p. 56.

(or good industry practice) in other jurisdictions have increased over time. This is an area that Sapere-Merz recommended the AER gather further evidence.

83. Given these shortcomings, the fact that a number of DNSPs have consistently raised concerns about the AER's vegetation management OEF adjustments, and that Sapere-Merz recommended further information gathering by the AER, we agree with Evoenergy's proposal that the vegetation management OEFs should not be applied more widely without further work by the AER and consultation with stakeholders.

2.3 Jurisdictional taxes and levies OEF

84. One of the standard OEFs adjustments developed by Sapere-Merz, and which the AER applies to most DNSPs, is for differences in the jurisdictional taxes and levies incurred by DNSPs. The Draft Decision explains that Sapere-Merz did not apply this OEF adjustment in Evoenergy's case because Sapere-Merz considered that:

> *where DNSPs recover taxes and levy costs through recovery mechanisms other than standard control tariffs, inclusion of some taxes and levies in an OEF adjustment could breach the non-duplication criterion. In Evoenergy's case, it was understood that it recovered these costs via the B factor in annual pricing determinations, and hence this OEF was not calculated for Evoenergy.*[25]

85. The Draft Decision sought further information from Evoenergy on whether it would be appropriate to apply the jurisdictional taxes and levies OEF to Evoenergy.

86. We make two observations on this issue.

87. Firstly, the B factor referred to by Sapere-Merz is simply a term in the annual price adjustment formula that increases or reduces the regulated tariff to account for past under/over-recovery of allowed revenues. Specifically, the AER defines the B factor for a given year $t-1$ as follows:

[25] Draft Decision, p. 26.

the sum of annual adjustment factors for year t. It includes adjustments to balance the unders/overs account, relating to previous under/over-recoveries of revenue. This is as per the approved t-1 pricing proposal.

For the avoidance of doubt, the B factor for t-1 should be equal to that used to calculate t-1 revenue in the previous pricing proposal and should not be updated for movements in the unders/overs accounts in the year t pricing proposal.[26]

88. We are advised by Evoenergy that the B factor is not a mechanism to recover or pass through to consumers the cost of jurisdictional taxes and levies. Rather, it is simply a mechanism to true-up any under/over-recovery of allowed revenues from on year to the next. The role of the B factor appears to have been misunderstood by Sapere-Merz.

89. Secondly, even if the B factor were a mechanism for Evoenergy to recoup jurisdictional taxes and levies (which we understand it is not), it does not follow that the jurisdictional taxes and levies OEF adjustment should not be applied to Evoenergy. The role of an OEF adjustment is to normalise cost differences between DNSPs that arise from differences in operating environment that would otherwise confound like-with-like comparisons between DNSPs when making efficiency assessments. The mechanism by which such costs are recovered has no bearing on whether cost differences related to operating environment should be normalised.

90. The key consideration is whether there are any jurisdictional taxes and levies included within the standard control services opex that the AER applies benchmarking analysis to. Evoenergy has advised us that there are two types of taxes and levies that are included within the historical standard control services opex that it has reported via its Economic Benchmarking RIN responses:

    a payroll taxes; and

    b land taxes.

91. Both of these are examples of taxes and levies identified by Sapere-Merz as relevant to the jurisdictional taxes and levies OEF adjustment.[27] Figure 2 below plots Evoenergy's payroll taxes and land taxes over the period 2006-23.[28]

[26] AER, *Annual Pricing Process Review Final position paper – Side constraint mechanism*, November 2022, p. 12.

[27] Sapere-Merz, *Independent review of Operating Environment Factors used to adjust efficient operating expenditure for economic benchmarking*, August 2018, Table 12, p. 69. Payroll taxes are identified in the third column of Table 2, as are the land taxes.

[28] Only the payroll tax allocated to opex is used – we exclude the portion of payroll tax that is capitalised. Evoenergy has advised us that land taxes for the years FY2010 to FY2014 (inclusive) are estimates based on the best available information as there was a change in Evoenergy's financial system in 2014.

[redacted]

[redacted]

Source: Evoenergy data

92. The AER's approach is to calculate the OEF adjustment using the average level of taxes and levies over the period 2010-15. Hence, the relevant average of [redacted] reflects payroll tax costs and land taxes over the averaging period 2010-15. Using this figure for Evoenergy, maintaining the existing approach for other DNSPs, results in the following jurisdictional taxes and levies OEF adjustments for Evoenergy:

   a Long sample – 5.42%; and

   b Short sample – 5.15%.

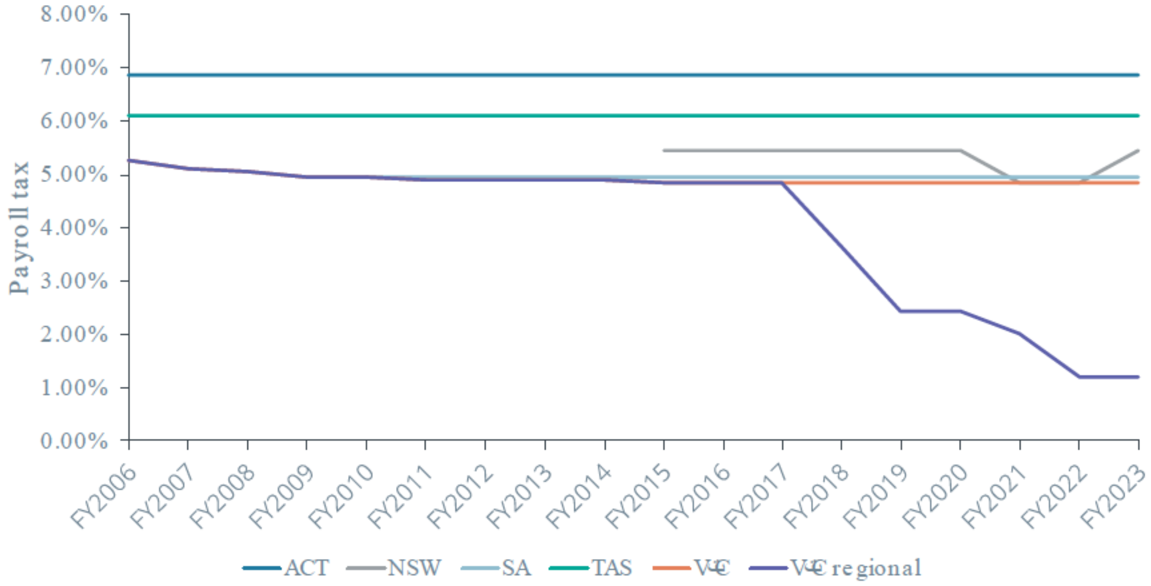
93. A key contributor to the positive OEF is the high level of payroll tax payable by Evoenergy. This appears to be driven by the relatively high payroll tax rates applicable to Evoenergy compared to other states, particularly Victoria, as shown in Figure 3 below.

94. These differences can be seen more readily when comparing the payroll tax rate in ACT to a blended rate of the reference DNSPs, weighting by customer numbers as in the Sapere-Merz OEF model.[29,30] Figure 4 illustrates that the ACT payroll tax rate is around 2 percentage points higher throughout the sample period, with a larger gap in recent years. In other words, Evoenergy faces a significant cost disadvantage compared to the reference DNSPs by virtue of the high payroll tax rates imposed by the ACT Government.

[29] The regional Victoria rate is applied to Powercor.

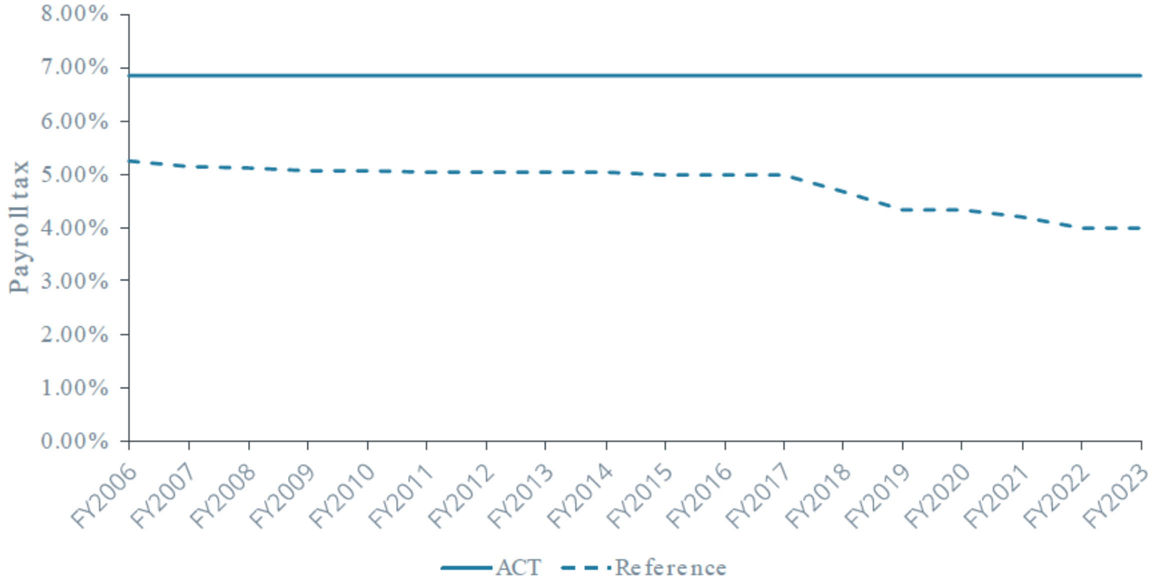
[30] Applying the customer numbers as used to derive the OEF adjustments for the 2006-2022 sample.

Figure 3: Comparison of payroll tax rates



Source: State revenue offices

Figure 4: Comparison between ACT and the reference firm weighted average



Source: State revenue offices, EB RIN data

2.4 Network overheads OEF

2.4.1 The AER's approach to account for differences in capitalisation practices

95. The AER's method for accounting for differences in capitalisation practices between DNSPs, when conducting benchmarking analysis, involves treating all corporate overheads as opex.[31]

96. Evoenergy proposed that the AER should also treat all network overheads as opex because there are many categories of network overheads that could be treated as opex or capex, such as procurement, fleet management, labour costs for engineers, control room costs. Furthermore, Evoenergy noted that there was significant variation in how DNSPs have historically expensed or capitalised network overheads and noted that the benchmarking results could be quite sensitive these differences in capitalisation practices.[32]

97. The AER did not accept this proposal for the following reasons:

   a network overheads are lumpier than corporate overheads, which are recurrent, stable and opex-like in nature;

   b corporate overheads are delineated from other opex categories in a more stable and consistent way than are network overheads; and

   c the regulatory framework has safeguards that protect against strategic cost reallocations between corporate and network overheads.

98. In our view, there is strong case for accounting for differences in DNSPs' capitalisation practices in relation to network overheads. We agree with Evoenergy that there is considerable variation in the capitalisation of network overheads across DNSPs. This is evident from the data presented in in Figure 5.

99. The figure shows that there is indeed considerable variation in the share of network overheads that individual DNSPs have, on average, capitalised over the period 2006 to 2022. The average (across all DNSPs) share of network overheads that are capitalised is 31%. By contrast:

   a SA Power Networks has, on average, capitalised only 11% of its network overheads;

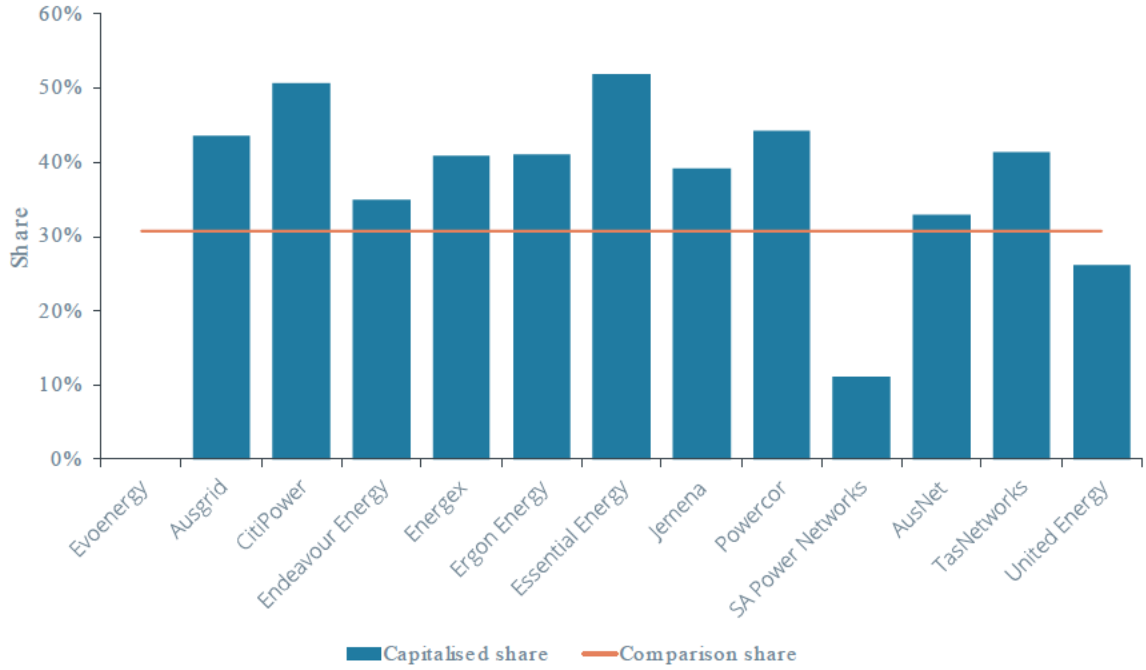
   b United Energy has, on average, capitalised only 26% of its network overheads; and

   c Evoenergy has historically capitalised none of its network overheads.

[31] AER, *How the AER will assess the impact of capitalisation differences on our benchmarking, Final Guidance note*, May 2023.

[32] Evoenergy, *Submission on the draft guidance note on the impact of capitalisation on the AER's benchmarking*, February 2023.

Figure 5: Capitalised share of network overheads, 2006-22 sample



Source: Frontier Economics of Quantonomics data

100. Any opex benchmarking analysis that ignores this fact will tend to penalise SA Power Networks and Evoenergy significantly, and United Energy to a lesser degree. Had any of these DNSPs simply adopted a different policy historically that involved capitalising a large share of network overheads, all three DNSPs would likely perform better in the AER's benchmarking analysis.

101. However, SA Power Networks and United Energy are both regarded as reference DNSPs with by the AER. Therefore, it is only Evoenergy that is really disadvantaged seriously if the AER does not account for the differences in DNSPs' capitalisation practices in relation to network overheads.

102. In our view, none of the AER's reasons for not normalising the differences in the network overheads capitalisation practices between DNSPs, when conducting benchmarking analysis, are convincing:

a The lumpiness of network overheads is not a relevant consideration when deciding whether to account for differences in capitalisation practices between DNSPs. The AER's concern seems to be that networks overheads tend to be more capex-like due to their lumpiness. However, not all opex is recurrent in nature. For example, there are typically large upfront setup operating expenditures associated with transitioning to Software-as-a-Service (SaaS). The fact that such costs are lumpy does not mean they should be treated as capex. The key point is that there is significant variation in the way DNSPs have chosen historically to allocate network overheads between opex and capex. That fact is evident from the data presented in Figure 5. What matters is that these differences should not be allowed to distort the benchmarking analysis.

If the AER considers that network overheads are more capex-like than opex-like, due to their lumpiness, then the AER could consider treating all reported network overheads as capex (i.e., excluding all such costs from the opex being benchmarked). That would put all DNSPs on a level playing field for the purposes of benchmarking historical opex. However, if the AER considers it important to test the efficiency of these costs, then the simplest approach would be to treat all network overheads as opex, thereby subjecting them to benchmarking.

b The AER's second reason is that corporate overheads are more clearly defined and delineated compared to network overheads. The fact that network overheads are not defined consistently between DNSPs explains the significant variation between DNSPs evident in Figure 5, and strengthens (rather than weakens) the case for normalising the differences between DNSPs' capitalisation practices for network overheads.

The AER notes that the differences in DNSPs' operating models (e.g., outsourcing versus insourcing of network support activities) will affect whether costs are treated as direct costs or network overheads. The AER suggests that allocation of capitalised network overheads to opex for benchmarking purposes could undermine like-with-like comparisons between DNSPs. To the contrary, the treatment of all network overheads as opex would enhance like-with-like comparisons between DNSPs. Excluding these costs from the benchmarking analysis would be akin to excluding the costs of contracted labour from opex, and only including the costs of internal labour when benchmarking opex—on the grounds that some DNSPs choose to outsource labour whilst others choose to insource. That would be an arbitrary distinction that would result in less reliable conclusions from the benchmarking analysis because it failed to consider costs relevant to the benchmarking analysis merely on the grounds that DNSPs make different outsourcing decisions about certain inputs.

c The AER's final reason is that its framework protects against DNSPs seeking to game by allocating network overheads between opex and capex simply to improve their benchmarking outcomes. However, DNSPs can (and do) adopt different capitalisation practices in relation to network overheads for reasons unrelated to gaming. The measures that the AER has put in place to minimise the risk of gaming do not prevent such differences in capitalisation practices. In our view, it is important to account for those differences in order to draw meaningful conclusions from the benchmarking analysis.

103. We recognise that the AER has undertaken a comprehensive review and consultation process on its approach to accounting for differences in capitalisation practices and has settled on the 'Option 5' approach set out in its final guidance note. However, the benchmarking outcomes are so badly distorted in Evoenergy's case by a failure to account for differences in how DNSPs capitalise network overheads that we think the AER should consider the application of an ex-post OEF adjustment for Evoenergy that allows a fairer, more like-with-like assessment with other DNSPs. The next section proposes a method for doing this.

2.4.2 Method and data for quantifying the Network Overheads OEF

104. To account for differences in capitalisation practices relating to network overheads, we adopt an approach similar to that previously applied by the AER in accounting for capitalisation differences across DNSPs.

105. For each DNSP, for each year 2009 to 2022, we find the capitalised network overheads and expensed network overheads using Category Analysis RIN data. We also take the Option 5 opex measure used by Quantonomics in its supporting analysis for the 2023 Draft Annual Benchmarking Report. We backcast the network overheads between 2006 and 2008 by maintaining the 2009 shares of capitalised and expensed network overheads relative to Option 5 opex.

106. We then find the share of network overheads that are capitalised for each DNSP for each of the years 2006 to 2022, inclusive.

107. To derive the OEF for the long sample, for each DNSP we average the shares over the period 2006 to 2022. Taking the customer weighted average over the five reference DNSPs identified by the

AER yields a comparator average share of 31% of network overheads that are capitalised, as shown in Table 2 below. [33]

Table 2: Capitalised share of network overheads

DNSP	Average share	Average no. customers	Reference DNSP?	Difference to weighted avg
Evoenergy	0%	181,711	No	-31%
Ausgrid	44%	1,661,143	No	13%
CitiPower	51%	325,215	Yes	20%
Endeavour Energy	35%	949,579	No	4%
Energex	41%	1,386,586	No	10%
Ergon Energy	41%	711,598	No	10%
Essential Energy	52%	864,949	No	21%
Jemena	39%	330,509	No	8%
Powercor	44%	774,384	Yes	14%
SA Power Networks	11%	853,894	Yes	-20%
AusNet	33%	696,439	No	2%
TasNetworks	41%	279,092	Yes	11%
United Energy	26%	660,799	Yes	-5%
Weighted average of reference DNSPs	**31%**			

Source: Cat RIN data, EB RIN data, Quantonomics data

108. We then obtain for Evoenergy, for each year, the opex that would result if it had capitalised the comparator average of 31% of network overheads. We then find the percentage by which the actual reported Option 5 opex exceeds the Option 5 opex that would result if Evoenergy had adopted the comparator average capitalised share of network overheads. Averaging these percentages over the years 2006 to 2022 provides the Network Overhead OEF for the long (i.e., 2006 to 2022) sample. We repeat the process described above to estimate the Network Overheads OEF for the short sample for Evoenergy.[34] The resulting Network Overheads for Evoenergy are:

[33] These five reference DNSPs are: CitiPower, Powercor, SA Power Networks, TasNetworks, and United Energy.

[34] The short sample OEF is derived by comparing reported Option 5 opex to the Option 5 opex that would result if Evoenergy had adopted the short sample reference firm customer weighted average of 36% of network overheads that are capitalised (obtained using data from 2012 to 2022).

a Long sample – 13.7%; and

b Short sample – 15.3%.

2.5 Conclusions

109. Based on the analysis above, Table 1 summarises the OEF adjustments that we propose should be applied to Evoenergy.

Table 3: Proposed OEF adjustments for Evoenergy

OEF	2006-22 period	2012-22 period
Sub-transmission (Licence conditions)	-0.49%	-0.39%
Termite exposure	0.02%	0.02%
Backyard reticulation	3.45%	3.27%
Workers' compensation	0.75%	0.75%
Network overheads	13.74%	15.29%
Jurisdictional taxes and levies	7.28%	6.91%
Total	**24.74%**	**25.83%**

Source: Frontier Economics analysis

Notes: Some of the OEF adjustments in this table differ from those applied in the Draft Decision because (a) we have expanded the OEF calculations to include data for 2022, and (b) we have updated the estimates of efficiency for Evoenergy using revised circuit length data, as explained in section 5

3 Vegetation management step change in the roll-forward of opex

3.1 Evoenergy proposal and AER Draft Decision

110. Evoenergy faced a step change in efficient vegetation management costs during the 2019-24 regulatory control period due to 2017 amendments to the *Utilities (Technical Regulation) Act 2014 (ACT)*, which expanded Evoenergy's vegetation management obligations to urban areas.

111. In recognition of this expansion in Evoenergy's regulatory obligations to manage vegetation in more areas, the AER approved a step change in Evoenergy's efficient vegetation management costs of $2.4 million ($2018-19) per annum over the 2019-24 regulatory control period, noting that this represented the approved amounts represented a forecast of the addition prudent and efficient opex required by Evoenergy to comply with its new regulatory obligations.

112. Evoenergy submitted to the AER that the step change in these prudent and efficient costs is not accounted for anywhere in the opex roll-forward approach used to estimate an efficient level of opex for Evoenergy in the base year, or any of the OEF adjustments adopted applied by the AER. Evoenergy therefore proposed that the approved step change in vegetation management costs should be added to the AER's estimate of efficient base year opex (derived using its roll-forward method).

113. The Draft Decision rejected that proposal because the AER considered that the positive time trend term used in the opex roll-forward calculation allows for a general increase over time in the regulatory obligations faced by DNSPs:

> *We have therefore not made adjustments in our benchmarking roll-forward analysis for our alternative estimate. This is because we consider step changes are already implicitly accounted for in the benchmarking roll-forward model procedure. We consider step changes in prudent and efficient opex are implicitly captured in the time trend coefficient from the econometric models, which is used in the roll-forward process. The time trend coefficient is positive, meaning that a percentage increase in time (years) leads to a percentage increase in opex. This indicates negative gross productivity growth over the relevant benchmarking period. This is at odds with economic expectations for positive productivity growth over time due to technological progress and other factors. We consider that measured positive time trend coefficient therefore in part reflects the increase in regulatory obligations over time, the costs for which we allow via forecasts for step changes.*[35]

114. The AER also noted that other DNSPs have similarly faced step changes in opex in the past, which would have affected the estimated efficiency of those DNSPs negatively:

[35] Draft Decision, p. 34.

> *In addition, we do not consider a step change can be viewed in isolation. Other DNSPs have also incurred increases in costs for step changes (including for other regulatory obligations), thus negatively impacting their opex efficiency scores.*[36]

115. The AER concluded that its preference is to reflect the step change in Evoenergy's vegetation management costs through the vegetation management OEF. In particular, the AER offset its estimate of the cost disadvantage faced by the reference DNSPs by the approved step change in Evoenergy's efficient vegetation management costs, for the years the step changes were allowed.

3.2 Assessment of the AER's reasoning

116. In our view, the Draft Decision does not account properly for the prudent and efficient step change in Evoenergy's opex in the base year.

117. We note that the estimated time trend parameter is, by construction in the AER's benchmarking models, common to all DNSPs (including the New Zealand and Ontarian DNSPs) in its sample. We note that the observations that relate to Evoenergy in the benchmarking sample represents just 1.5% of all observations in the sample. Furthermore, the observations that relate to the step change in Evoenergy's vegetation management costs relate to just 0.3% of all observations in the sample. Therefore, the step change in Evoenergy's prudent and efficient vegetation management costs approved by the AER has a negligible effect on the estimated time trend.

118. At best, the estimated time trend is capable of reflecting only the *average* impact on opex of the regulatory obligations faced by DNSPs (across New Zealand, Ontario and Australia) expanding over time. However, an opex allowance that provided only for this average impact, rather than the prudent and efficient costs faced by the DNSP in question, would not be consistent with the requirements of the National Electricity Rules (NER).

119. The AER argues that the positive time trend accounts implicitly for step changes in opex due to expanding regulatory obligations, and therefore it is unnecessary to apply any further adjustment in the opex roll-forward calculation.

120. Consider the following situation. Suppose that:

    a the estimated time trend was large and negative; and

    b the AER had approved a large step change in efficient opex for a particular DNSP that effectively doubled the DNSP's efficient base year opex.

121. The negative time trend would suggest the efficient frontier is shifting inwards (for instance, because regulatory obligations across the industry are *declining*) such that the efficient level of opex is falling over time. Under the AER's approach:

    a There could be no allowance for the DNSP's step change in opex via the time trend, since the estimated time trend is negative; and

[36] Draft Decision, p. 34.

b no adjustment would be made in the base year to recognise the change in efficient opex faced by this particular DNSP—notwithstanding that the AER itself had approved a step change that increased the DNSP's efficient base year opex by twofold.

122. It would clearly be unreasonable to conclude that no account should be taken of the fact that this particular DNSP's efficient base year opex had doubled, simply because the results of the benchmarking analysis suggests that the industry as a whole was becoming more productive over time. Yet, that would precisely be the outcome of applying the AER's proposed approach. That outcome would be unreasonable because understating the efficient level of base year opex would understate the DNSP's efficient opex requirement over the forthcoming regulatory period.

123. Rule 6.5.6(c) requires that the AER must accept a forecast of required opex of a DNSP if it is satisfied that the total forecast of opex for the regulatory control period reasonably reflects three operating expenditure criteria:

a the *efficient* costs of achieving the opex objectives (as defined in rule 6.5.6(a)); and

b the costs that a *prudent* operator would require to achieve the opex objectives; and

c a *realistic* expectation of the demand forecast and cost inputs required to achieve the opex objectives.

124. That is, the total forecast of required opex over the regulatory control period must be a *realistic* forecast of the *efficient* and *prudent* opex that the DNSP would need to incur in order to achieve the opex objectives (including compliance with all relevant regulatory obligations) specified in the NER.

125. The AER forecasts a DNSP's opex requirement over a regulatory control period using the base-step-trend approach, with the AER's determination of base year opex being the starting point for forecasting the opex requirement over the period. If the base year level of opex adopted by the AER excludes prudent and efficient step changes in costs faced by the DNSP (and simply reflects the average change in regulatory obligations faced by all DNSPs in its benchmarking sample), then the forecast of opex over the regulatory control period will not be a realistic forecast of prudent and efficient opex. That is, if there is a step change in prudent and efficient opex in the base year that is particular to a DNSP, and which the AER has already approved, it would be unreasonable for that step change in opex to be excluded from the AER's estimate of efficient base year opex.

3.3 Illustrative example

126. In the Draft Decision, the AER has applied an OEF adjustment that recognises the step change in Evoenergy's prudent and efficient vegetation management opex during the 2019-24 regulatory control period. We think this is a reasonable way to obtain an estimate of the efficient level of *average* opex over the historical benchmarking period.

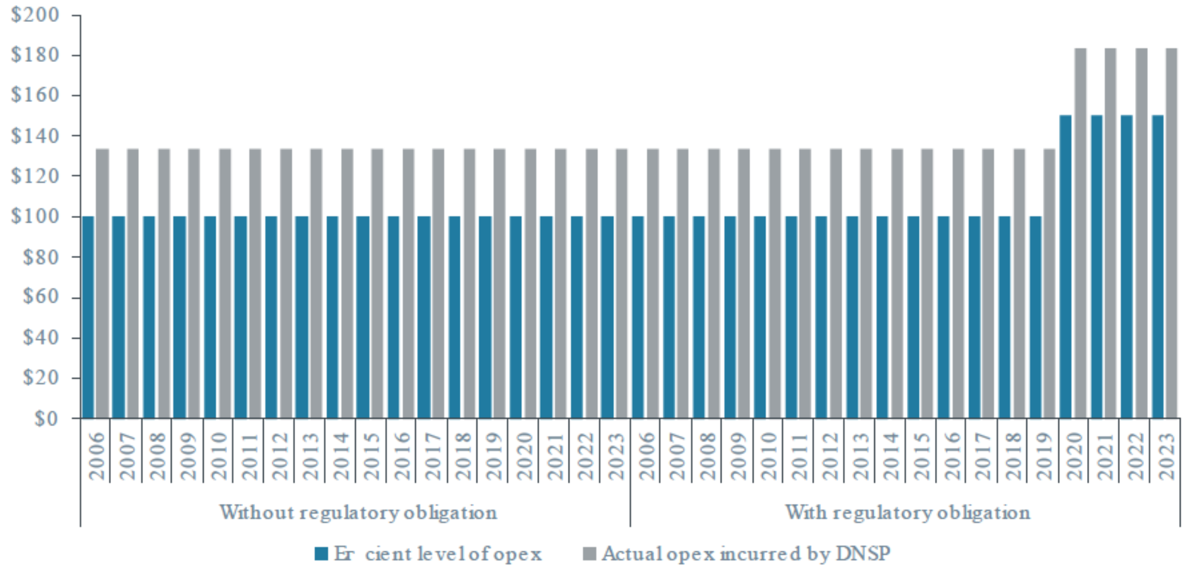
127. In our view, the main shortcoming of the AER's approach is that it fails to account adequately for the change in Evoenergy's regulatory obligations (and the associated impact on opex) when rolling forward the estimate of efficient opex to the base year. Applying the OEF adjustment alone would not result in a realistic estimate of Evoenergy's prudent and efficient opex in the base year.

128. Consider a stylised example of a DNSP operating under two alternative scenarios over the years 2006 to 2023 (as represented in Figure 6 below).

a In the first scenario, the DNSP faces no new regulatory obligation. In this scenario, the efficient level of opex (i.e., the level of opex consistent with operating at the efficient frontier) for the DNSP in each year is $100, and the DNSP actually spends $133 in each year.

b In the second scenario, the DNSP faces a new regulatory obligation from 2020 onwards, which requires it to incur an additional $50 in each year. Under that scenario, the efficient level of opex for each of the years 2006 to 2019 (i.e., before the new obligation comes into force) is $100 and the DNSP spends $133 in each of those years (as before). From 2020 onwards, the efficient level of opex increases to $150 per year and the actual opex spent by the DNSP is $183.

Figure 6: Stylised example of the opex of a DNSP facing a new regulatory obligation



Source: Frontier Economics

129. We consider below three different approaches that could be used to account for the step change in opex associated with the new obligation, when deriving an estimate of efficient base year opex.

a Account for the Account for the full step change in costs in the base year, no OEF adjustment (the Evoenergy approach);

b Apply only an OEF adjustment (AER approach); and

c Apply an OEF adjustment but recognise the additional opex required to comply with the regulatory obligation.

130. We show using the simple illustrative example above that the first and third approaches result in the same overall opex allowance, and provide the DNSP with the appropriate level of opex to cover its efficient costs. We also show that the approach of only accounting for the step change associated with the new obligation via an OEF adjustment results in an opex allowance that is too lower than what the DNSP would actually require to comply with those obligations.

131. The calculations under each approach are presented in Table 4. For simplicity, we present only the calculations pertaining to the long sample. However, the insights from this illustrative example may be generalised to include the short sample as well.

Table 4: Three alternative approaches to accounting for an increase in costs required to comply with new regulatory obligations

	Calculation step	Explanation	A. Evoenergy approach (full step change in base year, no OEF)	B. AER approach (OEF only, no step change in base year)	C. AER approach + opex to comply with change in obligations
(1)	Sample average actual opex	Average actual opex over the years 2006-22	\$142	\$142	\$142
(2)	Sample average efficient opex	Average efficient opex over the years 2006-22	\$100	\$100	\$100
(3)	Efficiency estimate	$\frac{(2)}{(1)}$	70%	70%	70%
(4)	OEF adjustment	$\frac{\textit{Opex step change}}{(2)/75\%} \times \textit{\% of years step change applies}$	NA	7%	7%
(5)	Benchmark comparison point (after OEF)	$\frac{75\%}{1+(4)}$	75%	70%	70%
(6)	Efficiency adjustment to sample average actual opex	$\max\left\{1-\frac{(5)}{(3)},0\right\}$	6%	0%	0%
(7)	Efficient sample average opex	$(1-(6)) \times (1)$	\$133	\$142	\$142
(8)	Base year opex (no growth)	Roll forward (7) to base year at 0% growth rate	\$133	**\$142**	\$142
(9)	Add step change	(8) + *Opex step change* (i.e., \$50)	**\$183**	NA	NA
(10)	Add extra opex to comply with change in regulatory obligation	(8) + *Additional cost of complying with obligation in base year*	NA	NA	**\$183**

Source: Frontier Economics

A. Account for the full step change in costs in the base year, no OEF adjustment (Evoenergy approach)

132. Under this approach, the efficiency estimate is derived by taking the ratio between two numbers:

    a The average actual opex incurred by the DNSP over the period 2006-22 (i.e., $142 in row 2 of Table 4); and

    b The AER's estimate of average opex incurred by a DNSP operating at the efficient frontier (i.e., $100 in row 1).

133. This would result in an efficiency estimate of 70% (row 3).

134. Under Evoenergy's proposed approach, there would be no OEF adjustment to the benchmark comparison point to account for the new obligation (row 4). Hence the relevant benchmark comparison point would be 75% (row 5).

135. Since the DNSP's efficiency estimate of 70% is lower than the benchmark comparison point of 75%, the DNSP's average opex of $142 over the 2006-22 sample period would need to be adjusted down by approximately 6% (row 6), resulting in a sample average efficient level of opex of $133.

136. Assuming (for simplicity) no growth in opex between the middle of the historical benchmarking period and the base year (e.g., for outputs, technical progress or changes in business conditions), the estimate of efficient base year opex would be $133.

137. However, the DNSP would face a step change of $50 in the base year in order to comply with its new regulatory obligations. Therefore, the efficient level of base year opex that would allow the DNSP to comply with those regulatory obligations would be $133 + $50 = $183 (row 9).

B. Apply only an OEF adjustment (AER approach)

138. The second approach would be to seek to address the step change in opex required to comply with the new regulatory obligations by means of an OEF adjustment to the benchmark comparison point. The OEF adjustment would be calculated first calculating the size of the opex step change as a ratio of the average opex of a DNSP operating at 75% efficiency (i.e., $\frac{\$50}{\$133}$) and multiplying that ratio by the proportion of the historical sample period for which the step change in costs apply (i.e., 3 years out of a total of 17 years over the period 2006-22). This results in an OEF adjustment of approximately 7% (row 4).

139. Since the DNSP's estimate of efficiency, 70% (as above), is equal to the adjusted benchmark comparison point of 70% (row 5), no adjustment to the sample average actual opex of $142 would be deemed necessary (row 7).

140. Once again, assuming no growth in efficient opex to the base year, the estimate of efficient base year opex would be $142 (row 8). This would be the starting point from which the DNSP's opex requirement for the next regulatory period would be forecast. However, what the DNSP actually needs to spend in the base year in order to comply with the new regulatory obligations would be $183. Hence, the DNSP would face a shortfall of $41. Since the DNSP needs to spend an additional $50 (over and above its historical expenditure) in order to comply with its regulatory obligations, this this shortfall would be 'baked in' to the forecast of efficient opex over the next regulatory period.

C. Recognition of additional opex required to comply with the regulatory obligation

141. Approach B appropriately recognises that the DNSP faced a cost disadvantage relative to its peers in the final three years of the sample period used to perform the benchmarking analysis and,

therefore, applies a lower benchmark comparison point (via an OEF adjustment) for the purposes of estimating the average efficient level of opex over the historical benchmarking period.

142. The main shortcoming of Approach B is that it fails to recognise, through the roll forward process, that the DNSP's cost of complying with regulatory obligations increased over the period that the period average opex is rolled forward to the base year. The fact that these costs increased is evident from Figure 6.

143. In order to properly estimate the efficient level of base year opex for the DNSP, it would be necessary to add to the base year opex estimate of $142 (derived using Approach B) the additional costs of complying with the regulatory obligations:

$$= Opex\ step\ change - Average\ cost\ of\ complying\ with\ regulatory\ obligation\ over\ \text{2006-22}$$
$$= \$50 - \$9$$
$$= \$41.$$

144. This is precisely the shortfall in the estimate of efficient opex under Approach B. If this amount were added to the figure of $142, that would result in an estimate of efficient base year opex of $183 (i.e., the estimate under Approach A proposed by Evoenergy).

3.4 Conclusion

145. Our key conclusion is that it is appropriate for the AER to account for the step change in costs associated with a regulatory obligation (such as the additional vegetation management responsibilities imposed on Evoenergy) via an OEF adjustment as the AER proposed in the Draft Decision when deriving an estimate of the period average level of efficient opex. However, in order to derive a reliable estimate of a prudent and efficient level of base year opex, the AER must also recognise any additional increase in costs that would be faced by the DNSP (between the middle of the sample period and the base year) in order to comply with those new obligations (i.e., Approach C).

146. Alternatively, and equivalently, the AER could apply no OEF adjustment to the benchmark comparison point but would need to add to its estimate of efficient base year opex the full step change in efficient opex needed to comply with the obligations (i.e., Approach A, consistent with Evoenergy's proposal).

4 Statistical uncertainty around the estimate of efficient base year opex

4.1 Sources of statistical uncertainty

4.1.1 Efficient base year opex is estimated with uncertainty

147. The AER's methodology for determining an estimate of efficient base year opex relies on its econometric benchmarking models. The parameters in these models are estimated from data and are subject to statistical uncertainty.[37] As a consequence, the AER's base year opex target is also subject to statistical uncertainty.

148. However, when testing the efficiency of a DNSP's actual base year opex, the AER does not account for this statistical uncertainty. Notwithstanding the statistical uncertainty around its estimates of each DNSP's efficiency score and other parameters estimated using its econometric benchmarking models, the AER effectively treats its point estimate of efficient base year opex as certain or deterministic. The AER clarifies in the Draft Decision that if the DNSP's actual base year opex is higher than its point estimate of efficient opex, then it concludes that the DNSPs' actual base year opex is materially inefficient:

> *We use results from our econometric opex cost function benchmarking and our benchmarking roll forward model to derive an estimate of efficient base year opex, and compare this to actual base year opex, in order to determine whether there is an efficiency "gap" and of what size. Where modelled efficient rolled-forward base year opex is below actual base year opex, we infer that the latter is materially inefficient.*[38]

149. The AER does not allow for any tolerance limits or range of uncertainty around its point estimate of efficient base year opex. Rather, as the AER explains in the excerpt above, if its point estimate of efficient base year opex is lower than the DNSP's actual base year opex, then the AER concludes that the latter is materially inefficient.

150. In our view, this is a serious shortcoming in the AER's approach. The statistical uncertainty involved in estimating a DNSP's efficiency and the elasticities and other parameters specified in the econometric benchmarking models can be very material. This uncertainty means that the AER does not *know* the *true* level of efficient base year opex for a particular DNSP with certainty. Instead, the true level of efficient base year opex lies within a range of uncertainty that is defined by (amongst other factors) the statistical error involved in estimating:

[37] Statistical uncertainty refers to the 'spread' of estimates of a parameter around its true (unobserved) value. In statistics, statistical uncertainty is measured by the standard error of the estimates of the parameter in question. See Gujarati and Porter, *Basic Econometrics* (5th Edition), 2009, p. 69.

[38] AER, Draft Decision, p. 23.

a the true level of average efficiency of a DNSP over the historical benchmarking period;

b the true relationship between a DNSP's opex and outputs; and

c the true values of other parameters specified in the AER's econometric models.

151. These uncertainties contribute to the overall uncertainty surrounding the AER's estimates of efficient base year opex. Failure to account for these uncertainties when assessing efficient base year opex could result in the AER concluding erroneously that the DNSP's actual base year opex is materially inefficient simply because it lies above the AER's *point estimate* of efficient opex—even if the DNSP's actual base year opex lies comfortably within a range of statistical uncertainty.

152. The AER has previously explained that it accounts for "uncertainties" and other limitations associated with its model by selecting a "conservative" benchmark comparison point of 0.75. For the reasons explained below in section 4.2, we disagree that this is an appropriate or adequate way to account for the statistical uncertainties described above.

153. In our view, an appropriate approach would be to quantify formally the statistical uncertainty around the AER's point estimate of efficient base year opex, by constructing confidence intervals around that estimate, and then using those confidence intervals to make a probabilistic assessment of the evidence for material inefficiency.

154. The remainder of this section presents a standard and well-accepted methodology for doing this.

4.1.2 Statistical uncertainty around estimates of efficiency scores

155. Information on the statistical uncertainty in the AER's estimates of the efficiency scores is provided in the Stata output files that accompany the Annual Benchmarking Reports.[39] The AER's previous adviser on benchmarking issues, Economic Insights, has noted that for the SFA models, information on the uncertainty is provided by confidence intervals around the estimated efficiency scores, and for the LSE models, it is provided by the asymptotic standard errors[40] for the coefficients of the dummy variables for the Australian DNSPs.[41]

156. We have extended these measures of the statistical uncertainty in the estimates of the DNSPs' efficiency scores to obtain confidence intervals around the estimate of efficient base year opex for Evoenergy produced by each of the AER's econometric benchmarking models and opex roll-forward model.

157. The measures of statistical uncertainty provided in the AER's supplementary files only capture part of the statistical uncertainty of the estimated efficiency scores. For both the SFA and the LSE

[39] For example, the supplementary files for the 2022 Annual Benchmarking Report can be found in the Quantonomics folder for Distribution at: https://www.aer.gov.au/networks-pipelines/guidelines-schemes-models-reviews/annual-benchmarking-reports-2022/aer-position. The relevant Stata output files are "anOpexReg1-half.log" and "anOpexReg1-full.log".

[40] Quantonomics' LSE models are not standard linear regression models. For non-standard econometric models, it is sometimes hard to calculate the exact standard errors of some of the estimated parameters for finite sample sizes since the distribution of the uncertainty about the estimated parameter is complex. However, an estimate of the standard error can be obtained by assuming that the sample size becomes infinitely large, in which case the distribution of the uncertainty about the estimated parameter usually converges to the well-known normal distribution for which the standard error is easy to calculate. Standard errors estimated in this way are known as 'asymptotic standard errors.'

[41] Economic Insights, *Comments on 2019 Frontier Economics Benchmarking Reports for EQ*, Memorandum to the AER Opex Team, 11 March 2020, p.17.

models, there are important additional sources of uncertainty of the efficiency score estimates that are not included in the measures provided by the AER.

158. For the SFA models, Quantonomics uses the Stata module "frontier_teci" to produce confidence intervals for the efficiency scores. These confidence intervals are calculated on the assumption that the estimates of the parameters in the truncated normal distribution for the efficiency scores are the true values of these parameters rather than estimates. Treating these values as estimates rather than true values adds to the uncertainty of the estimated efficiency scores.

159. We have been able to replicate results produced by the "frontier_teci" command using the Stata command "nlcom".[42] The "nlcom" command uses the same asymptotic approach as "frontier_teci", but it can be applied to more general algebraic expressions. In particular, "nlcom" can be used to produce asymptotic standard errors and confidence intervals for the estimates of the efficiency scores that take into account the additional source of uncertainty discussed above. Taking this additional source of statistical uncertainty into account can have a large impact on the width of the confidence intervals.

160. For the LSE models, the standard errors for the coefficients of the dummy variable referred to by Economic Insights, which are now produced by the AER's current consultant Quantonomics, do not take into account the fact that the estimated efficiency scores for this model are a function of the difference between the estimated coefficient of a DNSP's dummy variable in the model and the estimated coefficient of the most efficient DNSP.

161. When calculating the uncertainty around the difference between these two coefficients, it is not only the uncertainty in the estimated coefficient for a given DNSP's dummy variable that needs to be taken into account but also the uncertainty in the estimated coefficient of the most efficient DNSP. The Stata command "nlcom" can be used to take this additional uncertainty into account when calculating asymptotic standard errors and confidence intervals for the estimates of the efficiency scores. Taking this additional source of statistical uncertainty into account can have a large effect on the width of the confidence intervals.

4.1.3 Additional sources of statistical uncertainty around estimates of efficient base year opex

162. The AER's procedure for estimating base year efficient opex for each of the econometric benchmarking models involves:

a. estimating an efficient level of average opex over the relevant historical benchmarking period (i.e., the actual level of average opex over the period less the AER's estimate of any material inefficiency); and

b. rolling that efficient level of average opex forward to the base year using an annual rate of change.

163. The annual rate of change described in 162.b depends on the estimated elasticities (i.e., the coefficient on each of the output variables, the share of underground assets and the time-trend

[42] Stata's "nlcom" command computes point estimates, standard errors, test statistics, significance levels, and confidence intervals for (possibly) nonlinear combinations of parameter estimates after any Stata estimation command using the delta method. The delta method is a standard statistical approach for obtaining estimates of the standard errors of non-linear combinations of parameters. See, for example Cramér, H. (1946), *Mathematical methods of statistics,* Princeton University Press.

variable) in the Cobb-Douglas and Translog cost functions. All of these estimated elasticities are also subject to statistical uncertainty.

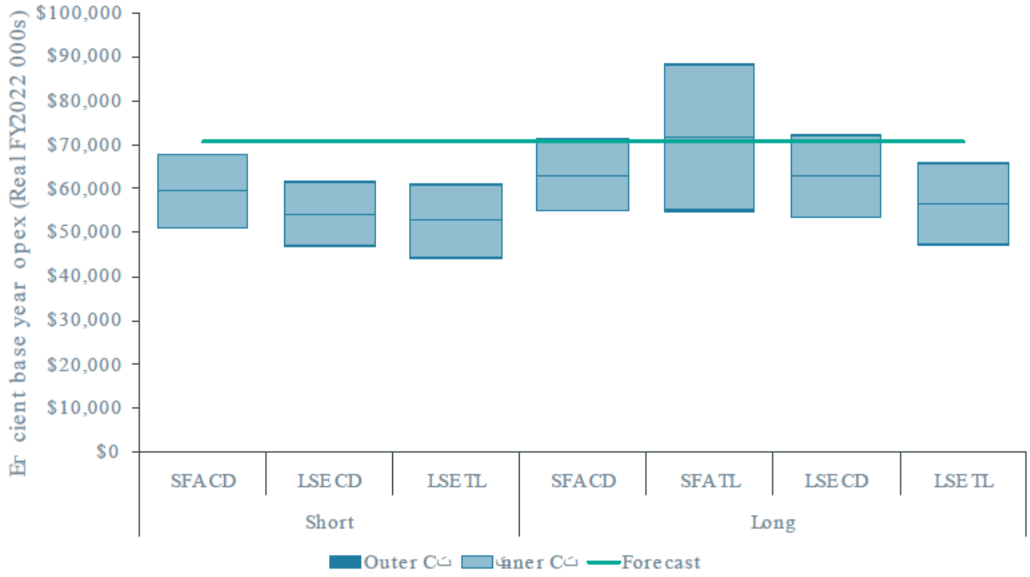
164. When constructing confidence intervals for base year efficient opex, the Stata command "nlcom" can again be used to take into account the uncertainty of the estimates of these parameters.

4.2 Construction of confidence intervals

165. We have converted the sources of statistical uncertainty discussed above into asymptotic standard errors. We then used those asymptotic standard errors to construct confidence intervals around the AER's estimate of efficient base year opex for Evoenergy, as presented in the Draft Decision. We do so by specifying the steps in the AER's opex Excel files as algebraic equations and applying Stata's "nlcom" command. In doing so, we have taken into account constraints such as the fact that the AER restricts the target sample average opex never to be larger than the actual sample average opex.[43]

166. Figure 7 presents the 95% confidence intervals around the AER's estimate of efficient base year opex for Evoenergy (as presented in the Draft Decision) calculated using the approach described above.[44]

Figure 7: Confidence intervals for target base year opex (including capitalised corporate overheads)



Source: Frontier Economics analysis using benchmarking data and models published along with the AER in the Draft Decision.
Note: the central estimate is represented by the blue line at the centre of the confidence interval. The short SFA TL model is not presented as it is excluded due to monotonicity violations.

[43] For the LSE models we note that DNSP dummies, used to derive efficiency scores are random variables but the statistical uncertainty of these estimates is correlated with the error term for the relevant DNSP. To avoid 'double counting', we reconstruct the sample average opex for Evoenergy in the derivation of efficient sample average opex with respect to the regression estimates rather than as a fixed quantity. This consideration does not apply to the SFA models.

[44] Section 5 presents the confidence intervals around our updated estimates of efficient base year opex for Evoenergy.

167. There are two types of confidence intervals computed for each of the eight benchmarking models. The first type of confidence interval accounts for the sources of uncertainty in the estimates of the efficiency scores discussed above, while the second type also takes into account the additional uncertainty that arises due to the uncertainty in the estimated parameters of the Cobb-Douglas and Translog cost functions.

168. We observe that the second type of confidence interval is not always wider than the first type. This may be due to some negative correlation between the efficiency score estimates and the estimate of the growth in opex from the sample average to the base year. For simplicity, the dark blue section of each confidence interval represents the largest extent of both confidence intervals, while the light blue section represents the smallest extent of the two types of confidence intervals.

169. Figure 7 shows that the second source of uncertainty has only a relatively small impact on the width of the confidence intervals. For all of the models, the narrower and wider confidence intervals are almost indistinguishable, indicating that there is minimal difference between the two types of confidence intervals. This reflects the fact that, even though there is considerable uncertainty in the estimate of the elasticity of each output in the cost functions, the uncertainty of the linear combination of outputs is quite small and possibly offsets some of the uncertainty of the efficiency score estimate.

170. Figure 7 shows that for three of the seven models, Evoenergy's actual opex lies within the 95% confidence interval surrounding each estimate of efficient base year opex, derived using every econometric model used by the AER in the Draft Decision. This suggests that once the statistical uncertainty over the AER's estimates of:

  a the efficiency scores for Evoenergy; and

  b the elasticities and the other parameters in the Cobb-Douglas and Translog cost functions

are taken into account, one must conclude that there is no evidence that Evoenergy's base year opex is materially inefficient.

4.2.1 Interpretation of confidence intervals

171. When we have previously proposed the use of confidence intervals to assess the efficiency of a DNSP's base year opex, the AER's adviser at the time, Economic Insights, argued that:

  a Regulators do not use confidence intervals to determine a range of efficient costs; and

  b Even if a regulator were to construct confidence estimates around a point estimate of efficient opex, it does not follow that all values within the confidence interval should be interpreted as being efficient.

172. Specifically, Economic Insights stated that:

> *Finally, FE (2019b) appears to argue that where the proposed opex sits within the confidence interval, then there is no evidence of material inefficiency. However, in regulatory applications, the confidence interval has not been used to set range of possible efficient values. Rather, it is a statistical construct used to estimate precision of the point estimate (eg the width of the confidence interval and the precision of the point estimate will generally be negatively related to the sample size). The point estimate provides the best estimate about the unknown true efficient value, while none of the other values within the confidence interval do. Confidence intervals may be useful in informing the degree*

> *of confidence in the point estimate, and thus the weights to apply to the estimate when multiple estimates from different sources/methods are available. They do not mean that all values within the confidence interval can be viewed as being efficient.*[45]

173. We address each of the two points above by Economic Insights in turn.

174. The first point Economic Insights makes is that regulators do not use confidence intervals to determine a range of possible efficient values. This is a misunderstanding of how we proposed that the confidence intervals should be used in the AER's particular context. As Economic Insights notes correctly, a confidence interval is a statistical construct used to assess the precision of a point estimate, and "may be useful in informing the degree of confidence in the point estimate." That is exactly how we propose confidence intervals should be used and interpreted by the AER.

175. The AER derives, with statistical uncertainty, a point *estimate* for the efficient level of DNSP opex in a base year. It would be wrong to simply assume away that statistical uncertainty and proceed as though the point estimate were the true level of efficient opex. Placing confidence intervals around a point estimate simply makes transparent the range of statistical uncertainty around that point estimate. That is precisely what we suggest the AER should do.

176. However, Economic Insights hints at another point—namely that regulators do not typically put confidence intervals around forecasts of efficient opex and, therefore, the novelty of doing so, in this case, should rule it out as a valid approach for the AER to take. If the novelty of a regulatory approach is sufficient to invalidate it, then the AER's entire approach to economic benchmarking should be discarded. No other regulator in the world performs economic benchmarking in the way the AER does. For example, no other regulator:

    a uses the same econometric models employed by the AER; or

    b accounts for OEFs in the way the AER does; or

    c rolls forward an estimate of efficient opex to a base year in the way the AER does;

    d and so on.

177. In our view, it is wrong to suggest that the AER should eschew an approach simply because it is not common regulatory practice. The usefulness of a particular approach should be judged on its own merits.

178. It is also important to recognise that the AER's use of econometric benchmarking models provides the statistical information required to construct confidence intervals in this particular case. Economic Insights itself acknowledges this.[46] Such information is not always available to other regulators. We do not see why the AER should discard such information if it can be useful in making a more informed decision about the efficiency of a DNSP's base year opex.

[45] Economic Insights, *Comments on 2019 Frontier Economics Benchmarking Reports for EQ*, Memorandum to the AER Opex Team, 11 March 2020, p.19.

[46] Economic Insights, *Comments on 2019 Frontier Economics Benchmarking Reports for EQ*, Memorandum to the AER Opex Team, 11 March 2020, p.17.

179. The second major point that Economic Insights makes is that the fact a DNSP's actual base year opex lies within a confidence interval does not mean that level of opex is efficient. This is a misrepresentation of how we say the AER should use confidence intervals.

180. The AER's approach is to compare a DNSP's *actual* base year opex to an *estimate* of efficient base year opex, where that estimate is derived using statistical analysis. If the former is greater than the latter, then the AER concludes that the DNSP's actual base year opex is materially inefficient.

181. We say that if the DNSP's actual base year opex lies within the confidence interval, then the AER cannot reject the possibility that there is no difference between a DNSP's revealed level of actual base year opex and the efficient level of base year opex—because the latter can only be estimated with statistical uncertainty, and the former lies within the range of statistical uncertainty.

182. We cannot conclude from such evidence that a DNSP's revealed base year opex is efficient. However, it would be legitimate to conclude that there is no evidence of material inefficiency.

183. The way we have suggested that confidence intervals be used in this context is entirely consistent with standard hypothesis testing.

4.2.2 Use of a conservative comparison point to deal with "uncertainties"

184. The AER has suggested that it accounts for general limitations associated with its econometric benchmarking models by selecting a conservative benchmark comparison point (75% before any adjustments for OEFs) rather than comparing each DNSP to (what the AER estimates to be) the most efficient DNSP. For example, the 2023 Draft Annual Benchmarking Report states that:

> *we consider our benchmarking comparison point is conservative and provides a margin for general limitations of the models with respect to the specification of outputs and inputs, data imperfections, other uncertainties when forecasting efficient opex and quantification of OEFs.*[47]

185. Neither the AER nor its advisers have been explicit (beyond statements similar to the one above) whether the margin between the efficiency estimate of the most efficient DNSP and the benchmark comparison point of 75% is designed to account for statistical uncertainty. The 75% comparison point was selected by the AER using regulatory judgment and on the advice of its previous adviser Economic Insights, who recommended it as a cutoff point for identifying the reference DNSPs.[48]

186. If the benchmark comparison point did account properly for the statistical uncertainty associated with estimating the efficient level of base year opex, then it would be useful to know exactly how much of the margin between the 75% benchmark comparison point and the estimated efficiency score of the most efficient DNSP (the 'margin for uncertainty') accounts for:

   a The statistical uncertainty involved in estimating the efficient level of base year opex; and

[47] AER, *Draft Annual Benchmarking Report, Electricity distribution network service providers*, October 2023, p. 68.

[48] Economic Insights, *Economic Benchmarking Assessment of Operating Expenditure for NSW and ACT Electricity DNSPs*, November 2014, p. 47.

b All the other general limitations associated with the benchmarking models that are distinct from and unrelated to statistical uncertainty, including (but not necessarily limited to):

i uncertainty around the true form of the opex cost function (sometimes referred to as 'model uncertainty' in the economic literature)—i.e., whether the true functional form is something other than the Cobb-Douglas or Translog specifications;

ii uncertainty about whether the true outputs of the DNSP have been identified and included properly in the models;

iii limitations and imperfections in the data used to perform the benchmarking analysis;

iv the scope for important OEFs that have not been accounted for at all, or not quantified and incorporated properly into the analysis; and

v shortcomings in the process for rolling forward the estimate of efficient opex to the base year.

187. For the purposes of the remaining discussion, we refer to the examples of the uncertainties listed in paragraph 186.b as 'other uncertainties', to distinguish them from statistical uncertainty.

188. If the benchmark comparison point is indeed intended to account for statistical uncertainty, then, as we show below, it is possible to calculate how much of the margin for uncertainty allows for statistical uncertainty. Whatever is left over, therefore, must account for all other uncertainties. We can then consider whether the portion of the margin for uncertainty that does not account for statistical uncertainty would plausibly be sufficient to account for the other uncertainties.

189. To calculate how much of the margin for uncertainty must allow for statistical uncertainty, we first derive the 95% confidence interval for efficient base year opex, assuming a benchmark comparison point of 75%. We then calculate the estimate of efficient base year opex that would allow the AER to be 95% confident that it had not underestimated the true (unobservable) level of efficient base year opex, given the statistical uncertainty associated with its benchmarking models. That estimate of efficient base year opex is simply the upper bound of the 95% confidence interval.

190. If we were to perform this calculation based on the AER's analysis in the Draft Decision, then the resulting estimate of efficient base year opex (i.e., that accounts fully for the statistical uncertainty associated with the benchmarking models applied in the Draft Decision, as measured by the 95% confidence interval around the AER's point estimate of efficient base year opex) would be $58.238 million. In order for the AER's process for deriving a point estimate for efficient base year opex to produce that figure, Evoenergy would have needed an average efficiency estimate of 86.7% (across all valid models).[49]

191. According to the benchmarking analysis relied on by the AER in the Draft Decision, the most efficient DNSP (Powercor) had an average efficiency estimate of 98.6%. That is:

a The total margin for uncertainty allowed for in the Draft Decision was 23.6% (i.e., 98.6% – 75.0% = 23.6%).

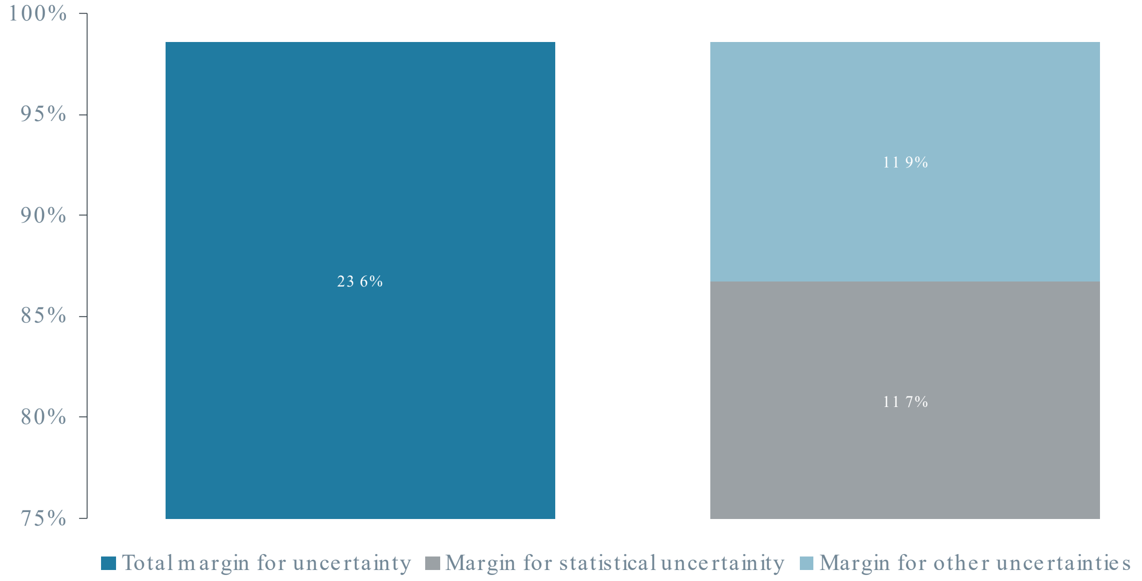
[49] Setting a target of 86.7% (rather than 75%) yields a confidence interval for efficient base year opex with an upper bound of $58.238 million.

b Of the total margin for uncertainty, 11.7% (i.e., 86.7% – 75.0% = 11.7%) would be required in order to allow properly for the statistical uncertainty around the estimate of efficient base year opex.

c That means that only 11.9% (i.e., 98.6% – 86.7% = 11.9%) would be left to account for all of the other uncertainties.

192. This is illustrated in Figure 8 below.

Figure 8: Decomposition of margin for uncertainty into allowance for statistical uncertainty and other uncertainties



Source: Frontier Economics analysis

193. Whilst the AER describes the benchmark comparison point it has selected (and, therefore, the margin for uncertainty) as "conservative", in our view, the existing comparison point of 75% does not allow properly for the significant statistical uncertainty associated with the estimate of efficient base year opex. This is because it is implausible that, once statistical uncertainty has been accounted for properly, the remainder of the margin for uncertainty—just 11.9%—would be adequate to account for all of the other uncertainties, including model uncertainty, uncertainty over the true outputs of the DNSP, data limitations and imperfections, OEFs that have not been accounted for properly, shortcomings in the roll-forward process and other modelling limitations.

194. We conclude from this that the AER's benchmark comparison point of 75% does not account for statistical uncertainty properly; the allowed margin of uncertainty is simply too narrow for that to be so. Therefore, the AER should explicitly allow for statistical uncertainty associated with its estimate of efficient base year opex by quantifying confidence intervals around its point estimate of efficient base year opex. We have developed and applied a simple, standard procedure for doing so. Our method makes use of the information about the degree of statistical uncertainty around key estimated parameters, obtained directly from the AER's benchmarking models. Such an approach would be a more reasonable and transparent way to account for statistical uncertainty than via the benchmark comparison point.

5 Benchmarking outcomes for Evoenergy

195. We set out below benchmarking outcomes for Evoenergy by comparing forecast base year opex to estimates of efficient base year opex, applying successive modifications to the results as presented in the Draft Decision.

5.1 Changes relative to the Draft Decision

196. In its proposal Evoenergy submitted revised maximum demand figures for the years 2015 to 2021, resulting in increased ratcheted maximum demand for those years. The AER has accepted those changes in the Draft Decision, with estimated models reflecting the change as well as the benchmarking models.[50] We accordingly maintain the revised ratcheted maximum demand in all estimates of efficient base year opex.

197. In its proposal, Evoenergy submitted a revised backyard reticulation OEF and a new workers' compensation OEF, which the AER accepted in its Draft Decision.[51] We maintain these OEFs as per the Draft Decision in all scenarios. We also maintain the standard sub-transmission (Licence conditions) and termite exposure OEFs applied to Evoenergy by the AER in the Draft Decision.

198. The AER has applied the capitalisation approach as set out in its final guidance note on its method for accounting for capitalisation differences.[52] Accordingly, we use the Option 5 opex for benchmarking, applying the opex series used by the AER for the purposes of conducting benchmarking analysis in the Draft Decision.[53]

199. The Evoenergy proposal and the AER Draft Decision both used 2021-22 as the base year. However, Evoenergy has instructed us to use 2022-23 as the relevant base year in our modelling, consistent with its Revised Proposal. Accordingly, we consider the impact of shifting to 2022-23 as the base year.

200. In its Draft Decision benchmarking analysis, the AER used forecasts for 2023 using Reset RIN data provided by Evoenergy. As the assessment of 2022-23 base year opex would use audited actuals, we have updated the 2023 data for updated actuals provided by Evoenergy. The updated data are presented in Table 5 below.

[50] Draft decision, p. 16.

[51] Draft decision, pp. 31-33.

[52] AER, *How the AER will assess the impact of capitalisation differences on our benchmarking – Final guidance note*, May 2023.

[53] More specifically, the lower bound opex series which uses the lower opex values for Energex and Ergon Energy which were still preliminary as per footnote 49 of the Draft Decision.

Table 5: 2022-23 data for Evoenergy

	Draft Decision model – data for FY2023	Revised proposal – data for FY2023
Opex ($nominal)	$84,859	$73,733
RMDemand	913	1,029
Customer Numbers	219,493	221,430
Circuit Length	4,887	4,838
Underground Share	52.99%	52.52%

Source: AER, Evoenergy

201. The AER has indicated that it would use the results from the 2023 Draft Annual Benchmarking Report in its final decision, which includes data up to and including 2021-22.[54] We present scenarios using data used for the 2023 Draft Annual Benchmarking Report.

202. We have been informed by Evoenergy that it has corrected a mistake in the calculation of network length and that the corrected data will be resubmitted to the AER. We present scenarios that make this correction to both circuit length and to the share of underground assets. The corrected data are presented below in Table 6.

203. As noted in section 2.3, the AER has not applied an OEF adjustment for differences in jurisdictional taxes and levies to Evoenergy in the Draft Decision. We consider the impact of applying the jurisdictional taxes and levies OEF (accounting for payroll and land taxes) to Evoenergy.

204. As noted in section 2.4.1, the AER did not account for differences in the capitalisation of network overheads in the Draft Decision. We also demonstrate the impact of applying a Network Overheads OEF adjustment to Evoenergy.

205. In its proposal, Evoenergy submitted that the vegetation management OEFs should not be applied. In its Draft Decision, the AER did not apply the division of responsibility OEF. However, the AER did apply the bushfire risk obligations OEF, adjusting for the Evoenergy vegetation management step change in the decision for the 2019-24 regulatory control period.[55] We present scenarios below in which the vegetation management OEF is removed.

206. Evoenergy argued in its proposal that the roll-forward procedure should account for step changes that applied in the base year—in particular step changes related to vegetation management opex approved by the AER for the 2019-24 regulatory control period. The AER did not accept this change in its Draft Decision.[56] The final scenario presented below includes the addition of the step change in allowed vegetation management costs to the estimate of efficient base year opex.

[54] Draft decision, p. 15.

[55] Draft decision, p. 29.

[56] Draft decision, p. 34.

Table 6: Revised circuit length data

	Circuit length		Share UGC	
Year	Original	Revised	Original	Revised
2006	4,085	4,671	42.52%	48.16%
2007	4,128	4,694	43.28%	48.61%
2008	4,173	4,684	44.03%	48.71%
2009	4,219	4,763	44.79%	49.73%
2010	4,268	4,844	45.55%	50.67%
2011	4,317	4,935	46.31%	51.32%
2012	4,369	5,015	47.08%	52.08%
2013	4,422	5,088	47.84%	52.95%
2014	4,477	5,151	48.61%	54.09%
2015	4,535	5,266	49.38%	55.04%
2016	4,593	5,311	50.14%	55.47%
2017	4,619	5,333	50.48%	55.73%
2018	4,664	5,384	51.01%	56.17%
2019	4,699	5,435	51.45%	56.64%
2020	4,774	5,610	51.76%	57.06%
2021	4,813	5,685	52.13%	57.55%
2022	4,828	5,723	52.34%	57.80%
2023	4,838	5,743	52.52%	57.98%

Source: Evoenergy. Note that circuit length in 2021/22 is 5,716 and 2022/23 is 5,736, corrected after finalisation of the benchmarking analysis undertaken in this report.

5.2 Estimates of efficient base year opex

207. Aside from the changes described in section 5.1, we follow the AER's method for estimating an overall efficient level of base year opex, which involves:

a Estimating an efficient level of opex over the relevant historical benchmarking period, using each statistical model that is not rejected due to monotonicity violations (i.e., the 'valid models');

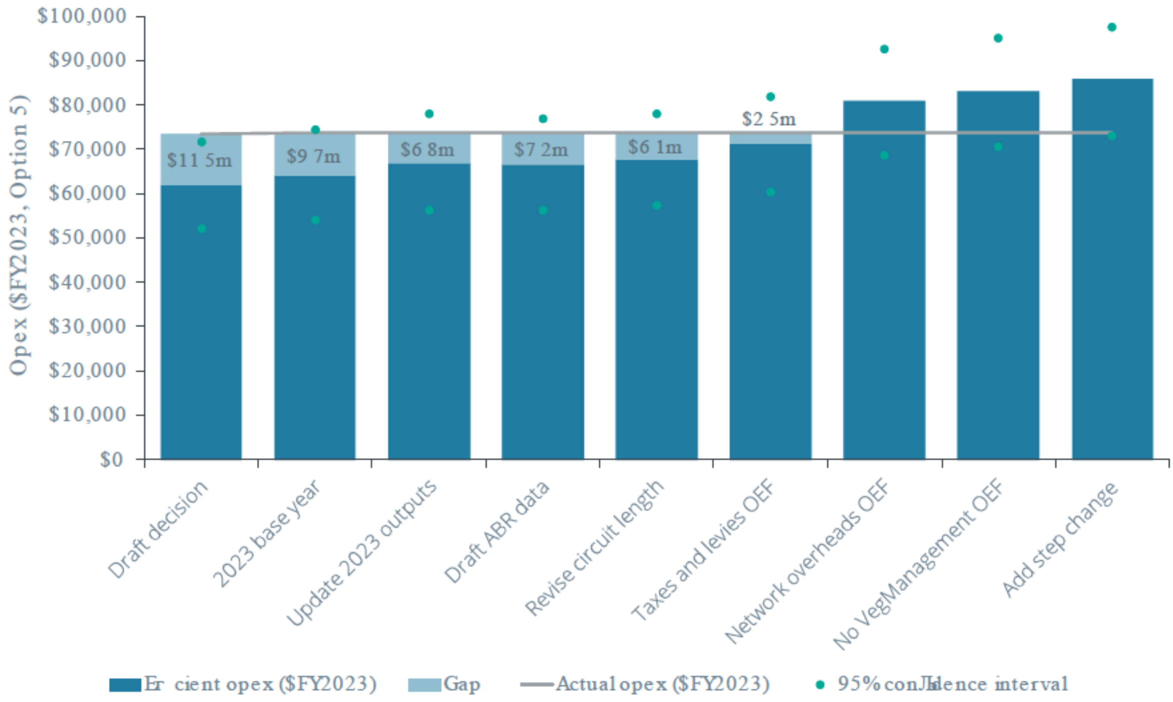
b Rolling forward each of those estimates to the base year (using the AER's roll-forward procedure); and

c Averaging the estimates across all of the valid models.

208. For each scenario, we provide the confidence intervals surrounding our estimate of efficient base year opex in addition to the central estimate, as set out in section 4.2 above. We define the lower bound of the confidence interval for the short sample by averaging the lower bounds of the 95% confidence intervals for the valid models. We adopt a similar approach for the long sample models. We then average the short and long samples. We repeat this by taking upper bounds of the 95% confidence intervals to obtain the upper bound.

209. The resulting estimates are presented in Figure 9 below. Each bar in the figure below adds one additional change to the scenario represented in the previous bar, such that each bar represents the cumulative effect of the preceding scenarios.

Figure 9: Estimates of efficient base year opex ($FY2023) under each scenario modelled



Source: Frontier Economics analysis of Evoenergy, Quantonomics data.

210. For example:

a the second bar shows the effect on the Draft Decision outcome of adopting 2022-23 as the base year, rather than 2021-22;

b the third bar shows the effect on the Draft Decision outcome of adopting 2022-23 as the base year, rather than 2021-22 *and* the effect of incorporating audited actual data for 2023 provided by Evoenergy;

c and so on.

211. For clarity, the estimate of efficient base year opex under each of the scenarios modelled in Figure 9 is presented below in Table 7 below.

Table 7: Estimates of efficient base year opex ($FY2023) under each scenario modelled

Scenario	FY2023 opex - $FY23
Forecast – FY2023	$73,733
Efficient opex – FY2023 – draft decision model	$64,060
Update FY2023 outputs	$66,945
Apply 2023 Draft Annual Benchmarking Report data	$66,546
Use revised circuit length data	$67,683
Apply jurisdictional taxes and levies OEF	$71,253
Apply Network overheads OEF	$81,011
Exclude vegetation management OEFs	$83,249
Add vegetation management step change in roll-forward	$85,832

Source: Frontier Economics analysis

212. We make two observations in relation to the results presented in Figure 9:

a Firstly, in every scenario modelled (excluding the Draft Decision outcome applying an FY2022 base year), Evoenergy's actual opex in the relevant base year lies comfortably within the 95% confidence interval around the estimate of efficient opex. This suggests that there is no reliable statistical evidence that Evoenergy's actual FY2023 opex is materially inefficient under any scenario modelled.

b Secondly, once the first six changes have been adopted (i.e., adoption of 2022-23 as the base year, use of 2023 audited outputs data for Evoenergy, use of 2023 Draft Annual Benchmarking Report data, use of Evoenergy's reinstated circuit length data, application of the jurisdictional taxes and levies OEF and inclusion of the Network Overheads OEF), the resulting estimate of efficient opex is higher than Evoenergy's actual base year opex.

213. Based on either or both of these observations, we conclude that there is no evidence that Evoenergy's base year opex is materially inefficient.

A Statistical problems associated with the econometric benchmarking models

214. The AER uses four econometric opex cost function models to estimate the average efficiency of DNSPs' historical opex. The four models reflect two different specifications of the cost function (Cobb-Douglas and Translog) and two different estimation methods (Least Squares Econometrics (LSE) and Stochastic Frontier Analysis (SFA)), resulting in the following four models:

    a Cobb-Douglas Stochastic Frontier Analysis (SFA-CD);

    b Cobb-Douglas Least Squares Econometrics (LSE-CD);

    c Translog Stochastic Frontier Analysis (SFA-TLG); and

    d Translog Least Squares Econometrics (LSE-TLG).

215. These four models are estimated using data over two historical time periods:

    a The long sample (using all the data available from 2006 onwards); and

    b The short sample (using all the data available from 2012 onwards).

216. This Appendix discusses a number of statistical problems associated with the econometric benchmarking models relied upon by the AER in the Draft Decision.

Monotonicity violations

217. For several years now, the AER has expressed concerns that some of the estimated opex cost functions fail to satisfy a mathematical property known as 'monotonicity.' As the AER has explained, monotonicity implies that an increase in output can only be achieved with an increase in inputs, holding other things constant. Monotonicity violations occur if the model predicts that an increase in any particular output leads to a decrease in opex. Such an outcome is inconsistent with economic theory.

218. The Cobb-Douglas models estimated by the AER do not exhibit monotonicity violations. Hence, the AER has typically assumed that these models are statistically sound and, therefore, has not expressed any concerns about its reliance on those models on statistical grounds.

219. However, the Translog models have exhibited monotonicity violations for a number of DNSPs and in a number of years. These violations tend to occur more often in the Translog models estimated using the short sample. The AER has attributed these violations to the more flexible functional form of the Translog models.[57]

220. These monotonicity violations are not becoming less prevalent over time as more data becomes available. To the contrary, the AER acknowledged that:

[57] AER, *Draft Annual Benchmarking Report, Electricity distribution network service providers*, October 2023, p. 66.

> *this issue has generally become more prevalent since 2018.*[58]

221. In the 2023 Draft Annual Benchmarking Report, the AER noted that the number of monotonicity violations had increased since the 2022 Annual Benchmarking Report:

> *For the current report, the number of instances where this property does not hold in the Translog models is prevalent again and has increased since last year. This year, for the 2006 to 2022 period, we observe monotonicity violations in the Translog LSE model for three DNSPs and in the Translog SFA model for a separate group of three DNSPs. In the 2022 Annual Benchmarking Report, we observed no monotonicity violations for all of the Australian DNSPs in both Translog models over the long period.*[59]

222. The 2023 Draft Annual Benchmarking Report notes that for the short sample, and when using the AER's 'Option 5' definition of opex (to control for differences in capitalisation practices):

    a the SFA-TLG model exhibited monotonicity violations for 10 out of 13 DNSPs; and

    b the LSE-TLG model exhibited monotonicity violations for seven out of 13 DNSPs.

223. The AER deals with this problem by excluding from its process for deriving an estimate of efficient base year opex for a particular DNSP any models for which monotonicity is violated for more than half the observations in the sample for that particular DNSP. If, according to this criterion, a model is excluded for more than half the DNSPs, the model is excluded for all DNSPs.[60]

224. In 2022, the AER asked its adviser Quantonomics to investigate ways to overcome the problem of monotonicity violations. Quantonomics explored three models that were a 'hybrid' of the more restrictive Cobb-Douglas and the more flexible Translog functional forms. Quantonomics reasoned that if the cause of the monotonicity violations is the flexible nature of the Translog models, then making the Translog models less flexible (e.g., by excluding some of the second-order terms in the Translog models) might ameliorate the problem.

225. The AER concluded from Quantonomics' work that, whilst the hybrid models showed some promise (in terms of reducing the instances of monotonicity violations), they also suffered from statistical limitations, which meant that those models could not be adopted at the present time.[61]

226. The 2023 Draft Annual Benchmarking Report notes that several DNSPs—including Evoenergy, Ausgrid, Jemena, Ergon Energy and Energex—have raised concerns about the issue of monotonicity violations.

[58] AER, *Annual Benchmarking Report, Electricity distribution network service providers*, November 2022, p. 58.

[59] AER, *Draft Annual Benchmarking Report, Electricity distribution network service providers*, October 2023, pp. 34-35.

[60] Draft Decision, p. 19.

[61] AER, *Annual Benchmarking Report, Electricity distribution network service providers*, November 2022, p. 58.

227. In our view, the monotonicity violations are likely to be a symptom of a more fundamental problem with the AER's econometric models. Quantonomics' approach of restricting the flexibility of the Translog functional form to reduce the number of monotonicity violations is an attempt to treat the symptom rather than the root cause of the problem.

228. As we explain in the remainder of this Appendix, there is mounting evidence that all the AER's econometric benchmarking models are misspecified and, therefore, are incapable of fitting the data well. That is likely to be the root cause of the monotonicity violation problem.

229. This has several important implications:

a The AER's solution of excluding the models that exhibit monotonicity violations is not a proper solution because it simply removes the cases where the symptoms associated with the underlying problem have manifested. That approach does not address the fundamental misspecification problem, which also affects those models that do not exhibit monotonicity violations.

b We also note that when the AER excludes a Translog model for some DNSPs but not for others, the calculation of efficient opex for the different DNSPs is no longer done on a like-with-like basis.

c Because the Quantonomics approach of seeking to make the Translog models less flexible does not address the root cause of the problem, it too is not a proper solution. Therefore, we see little value in the AER pursuing that approach in future.

d What is required is a fundamental review of the AER's econometric benchmarking models to ensure that they are capable of fitting the salient features of data well. We show below that the models do not capture one important feature, namely the time trends in the data. There may be other variables that are omitted. Misspecification of the benchmarking models is likely to result in biased estimates of the DNSPs' efficiencies, making them unreliable for the purposes of setting regulatory allowances.

e Such a review should be done carefully and in proper consultation with stakeholders. Therefore, it should not be rushed. Until this work can be completed properly, the AER should exercise extreme caution when interpreting the results derived from its existing models. The AER should not use those models mechanistically (as it has done in recent determinations) when assessing whether a DNSP's actual base year opex is materially inefficient.

Misspecification of the Cobb-Douglas models

230. Quantonomics undertakes statistical tests of the Cobb-Douglas specifications versus the Translog model specifications. The Cobb-Douglas specification is a special case of the Translog specification with a less flexible functional form. The null hypothesis for this test is that the restrictions imposed on the Translog model to obtain the Cobb-Douglas are consistent with the data. For the LSE models, Quantonomics conducts the Wald test to test this hypothesis, whereas, for the SFA models, Quantonomics conducts both the Wald test and the likelihood ratio test.

231. Quantonomics presents the results of the Wald tests for the Standard approach to opex in Appendices C.1.4 and C.2.4 of the draft report,[62] and notes that the Cobb-Douglas simplification of

[62] Quantonomics, *Economic Benchmarking Results for the Australian Energy Regulator's 2023 DNSP Annual Benchmarking Report*, May 2023.

the Translog model is soundly rejected in all cases. The likelihood ratio test for the SFA models (provided in the model output though not reported in the draft report), also soundly rejects the Cobb-Douglas specifications of the SFA models.

232. Quantonomics presents the results of the Wald tests for the Option 5 approach to opex in Appendices C.3.4 and C.4.4 of the draft report,[63] and notes that the Cobb-Douglas simplification of the Translog model is soundly rejected in all cases. The likelihood ratio tests for the SFA models, (provided in the model output though not reported in the draft report), also soundly rejects the Cobb-Douglas specifications of the SFA models. Evoenergy made a similar submission to the AER in its regulatory proposal.[64]

233. We summarise the results of all these statistical tests in Table 8.

Table 8: Adequacy of the Cobb-Douglas model vs the Translog model – probability values

	Standard approach opex Long sample	Standard approach opex Short sample	Option 5 opex Long sample	Option 5 opex Short sample
LSE CD vs TLG (Wald test)	0.0000	0.0000	0.0000	0.0000
SFA CD v TLG (Wald test)	0.0008	0.0011	0.0004	0.0003
SFA CD v TLG (Likelihood ratio test)	0.0047	0.0001	0.0005	0.0000

Source: Frontier Economics analysis of results in Quantonomics' supporting files for 2023 Draft Annual Benchmarking Report dataset

Note: The probability value (p-value) is the probability that the estimated parameters in the Translog model are consistent with a Cobb-Douglas cost function. The null hypothesis that the data is consistent with the Cobb-Douglas simplification of the Translog specification is rejected if the p-value is smaller than the chosen significance level, which is usually taken to be 0.05. The p-values in this table are far smaller than 0.05.

234. The table shows that the hypothesis that the data is consistent with the Cobb-Douglas simplification of the Translog opex cost function is rejected soundly in all cases since the probability values are far smaller than the usual significance level of 0.05. This indicates that the Cobb-Douglas model is seriously misspecified and that the Translog model, which allows for more flexibility in the specification of the output elasticities, fits the data significantly better than the Cobb-Douglas model. In view of this, it is difficult to find a statistical justification for including estimates derived from the Cobb-Douglas models in the assessment of the efficiency of the DNSPs. However,

[63] Quantonomics, Economic Benchmarking Results for the Australian Energy Regulator's 2023 DNSP Annual Benchmarking Report, May 2023.

[64] Evoenergy, *Regulatory proposal for the ACT electricity distribution network 2024–29, Appendix 2.1: Operating expenditure – base year efficiency*, p. 11.

Quantonomics always includes the results of the Cobb-Douglas models in its assessment of DNSPs' efficiencies despite the models being seriously misspecified from a statistical point of view.

235. In a report published by the AER with the Draft Decision, Quantonomics disagrees that the Translog models should be preferred over the Cobb-Douglas models on the basis of the Wald test because:

> *There are other criteria of model selection to be considered, including goodness-of-fit. Because goodness-of-fit measures penalise loss of degrees of freedom (ie, reward parsimony) the higher order terms can be jointly significant while at the same time, the fit is not improved. This has been shown to be the case in relation to the TLG and CD models*[65]

236. We note that contrary to the AER's assertion, statistical tests do take into account the loss in degrees of freedom when using more flexible models by requiring that the more flexible model fit the data not just better than the simpler model, but significantly better. Table 8 shows that the Translog models fit the data significantly better than the Cobb-Douglas models.

237. We also note that the AER has not presented any goodness-of-fit results to support the statement that the Cobb-Douglas model has a better goodness-of-fit than the Translog when parsimony is taken into account.

238. Table 9 presents the commonly used R-squared and adjusted R-squared measures for the LSE Cobb-Douglas and Translog models estimated by Quantonomics.[66] The R-squared measure does not penalise extra terms in the model, and a more flexible model will always have a higher R-squared value than the simpler version of the model. The adjusted R-squared modifies the R-squared by penalising an increase in the number of explanatory variables included in the model and hence rewards parsimony.

239. Table 9 shows that, as expected, the R-squared value of the Translog model is always larger than the Cobb-Douglas model for the same dataset. However, the adjusted R-squared values for the Translog models are also larger than for the Cobb-Douglas models. This implies that, even after allowing for a decrease in parsimony, the Translog models have the superior goodness-of-fit.

Table 9: Goodness-of-fit measures for the LSE models

[65] Quantonomics, *Benchmarking limitations*, September 2023, p. 5.

[66] The Prais-Winsten regression using the xtpcse command in Stata.

	R-squared	R^2 difference	Adjusted R^2	Adj. R^2 difference
LSE-CD Long	99.168%		99.15%	
LSE-TLG Long	99.204%	0.04%	99.19%	0.03%
LSE-CD Short	99.505%		99.49%	
LSE-TLG Short	99.532%	0.03%	99.51%	0.02%

Source: Frontier Economics analysis

240. For models like the SFA model, the commonly used R-squared measures of goodness-of-fit cannot be calculated, and alternative measures are used to select a preferred model; the most commonly used measures being the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). These goodness-of-fit measures both penalise the loss of degrees of freedom (i.e., reward parsimony), with the BIC penalising the inclusion of additional terms more heavily than the AIC. For both criteria, the specification with the lower value is considered to have the better fit.

241. Table 10 presents the values of these criteria for the SFA Cobb-Douglas and Translog models. The table shows that, for the short sample, both the AIC and the BIC select the Translog model as the preferred model, since the values for these criteria are lower (more negative) for the Translog model than for the Cobb-Douglas model. For the long sample, the Translog SFA is selected by the AIC criterion as the preferred model. However, the BIC criterion selects the Cobb-Douglas model as the preferred model – in this case, the improvement in the model's fit is considered to be outweighed by the decrease in parsimony.

Table 10: Alternative goodness of fit measure – SFA models

	AIC	AIC difference	BIC	BIC difference
SFA-CD Long	-1272.305		-1216.907	
SFA-TLG Long	-1284.286	-11.981	-1198.671	18.236
SFA-CD Short	-914.527		-864.019	
SFA-TLG Short	-969.578	-55.050	-896.111	-32.092

Source: Frontier Economics analysis

242. The above results for the goodness-of-fit of the Translog vs the Cobb-Douglas models indicate that, after allowing for the loss in degrees of freedom in the more flexible models, the Translog model, overall, fits the data better than the Cobb-Douglas model in all cases, except for one case, where the evidence is mixed. It is hard to reconcile these results with the AER's statement that the fit of the Translog models is not improved compared to the Cobb-Douglas model.

243. Quantonomics further observes that:

> *It is difficult to reconcile Evoenergy's apparent argument that the TLG model is to be preferred over the CD model … with its view that the varying rates of monotonicity violations in the TLG models when applied to different periods casts doubt on the reliability of all of the TLG opex cost function models, not just those with monotonicity violations.*[67]

244. This misinterprets Evoenergy's position as being in favour of the current Translog model specification. Evoenergy's main point (which we agree with) is that there is clear evidence that the Cobb-Douglas models are misspecified and are, therefore, unreliable for setting revenue allowances.

245. As we explain below, the Translog models are also misspecified and are therefore also unreliable. We suspect that the misspecification problem affecting the Translog models also applies to the Cobb-Douglas models.

Misspecification of the Translog models

Residual plots

246. A standard technique used to check if an econometric model has been misspecified is to plot the residuals from the model (i.e., the differences between the fitted/predicted opex from the model and actual opex). If the model is well-specified, there should be no discernible pattern in the residual plot (i.e., the plotted residuals would be distributed randomly).

247. The plots show that for the Australian DNSPs there is a clear declining trend in the residuals over time. We found this to be true for all Cobb-Douglas and Translog models.

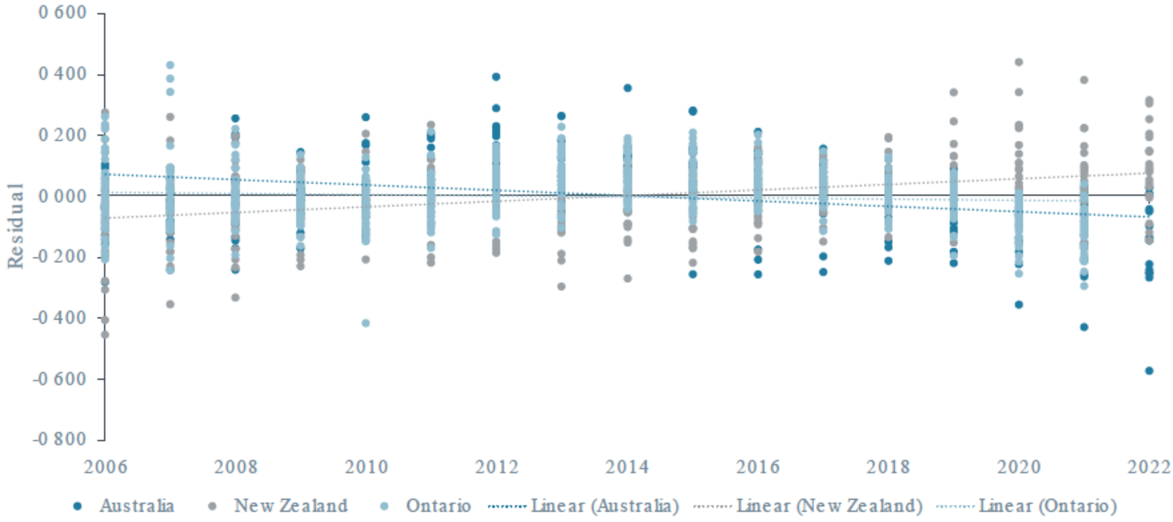
248. We have plotted the residuals from all the models against time. Figure 10 through Figure 13 plot the residuals for the Translog models. The figures also include a simple linear trend for each jurisdiction included in the figure. A downward-sloping trend line implies that residuals are decreasing over time (i.e., efficiencies are increasing), while an upward-sloping trend line shows that efficiencies are decreasing).

249. The figures show a negative trend for Australian DNSPs (i.e., improving efficiency), while New Zealand DNSPs appear to have an increasing trend (declining efficiency). The Ontario DNSPs residuals are relatively flat. The trend for Australian DNSPs is more visible in Figure 11 and Figure 13. The decrease in the residuals for the Australian DNSPs is particularly noticeable from about 2014 onwards, which corresponds to the start of the AER's current approach of using benchmarking to guide the setting of opex allowances.

250. Analogous figures for the Cobb-Douglas models are presented in Figure 14 through Figure 17

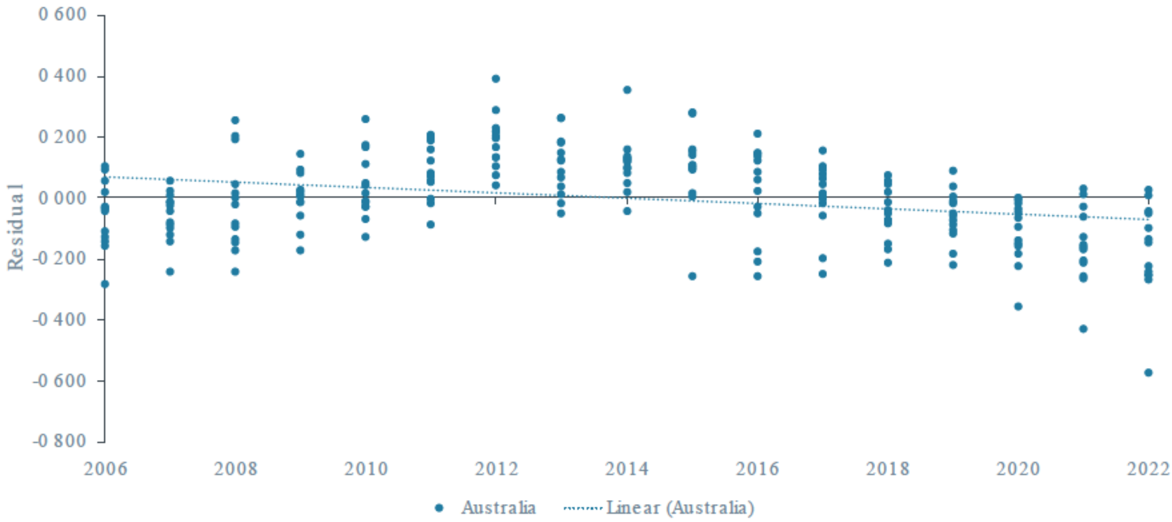
[67] Quantonomics, *Benchmarking limitations*, September 2023, p.5.

Figure 10: Residuals – SFA-TLG long model



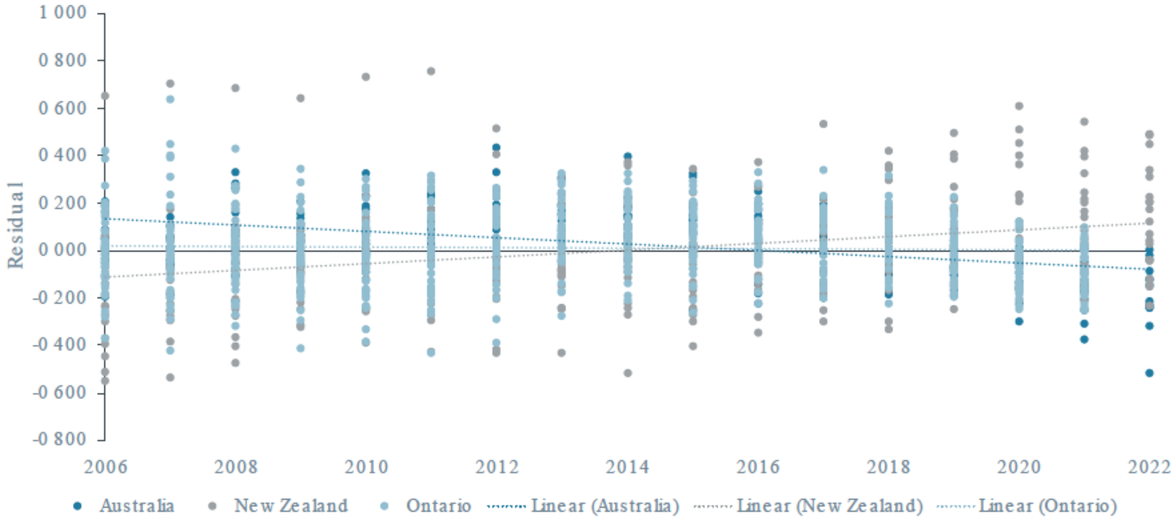
Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 11: Residuals for Australian DNSPs – SFA-TLG long model



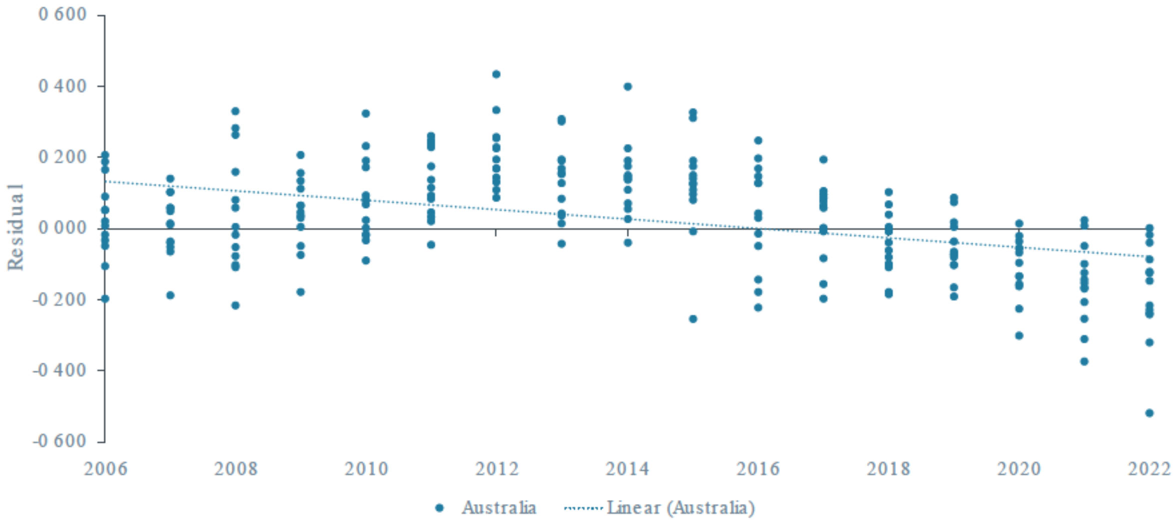
Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 12: Residuals – LSE-TLG long model



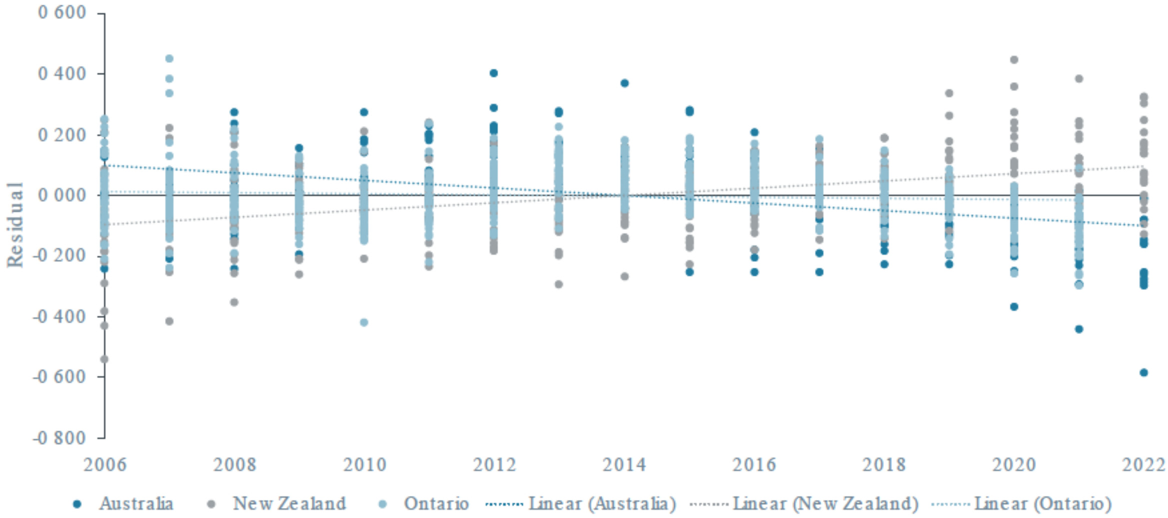
Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 13: Residuals for Australian DNSPs – LSE-TLG long model



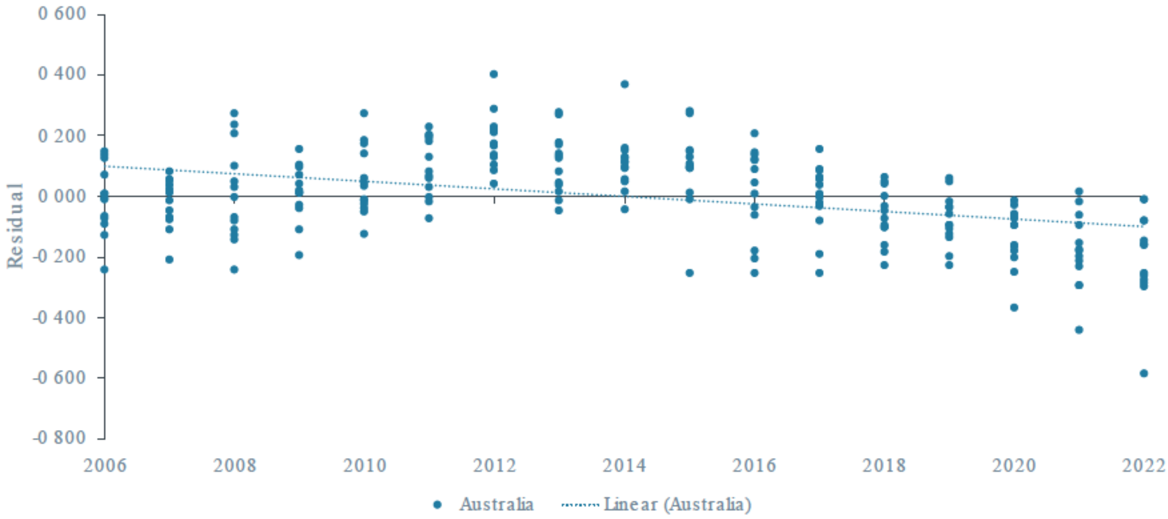
Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 14: Residuals – SFA-CD long model



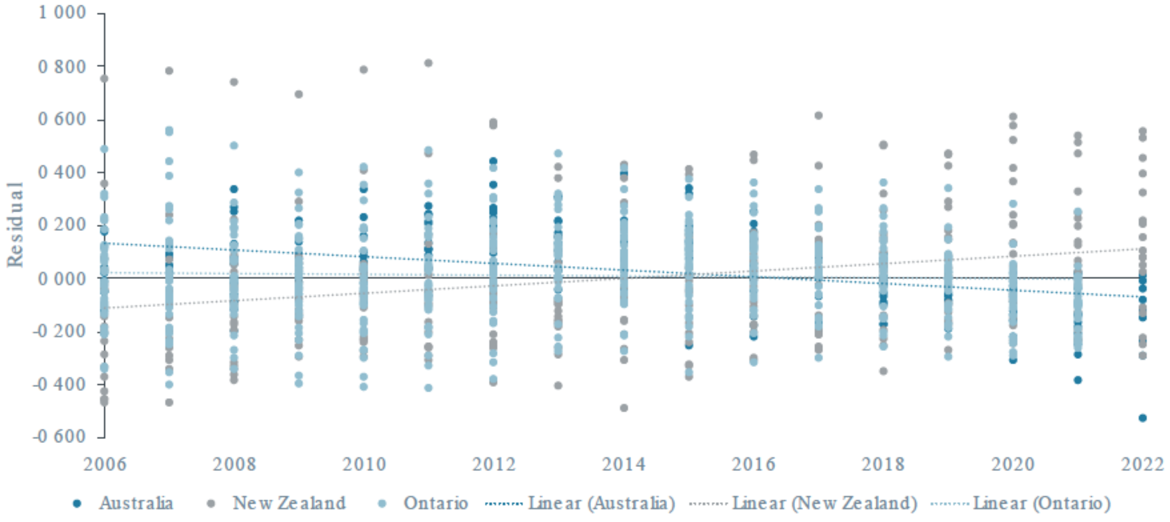
Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 15: Residuals for Australian DNSPs– SFA-CD long model



Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 16: Residuals – LSE-CD long model



Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

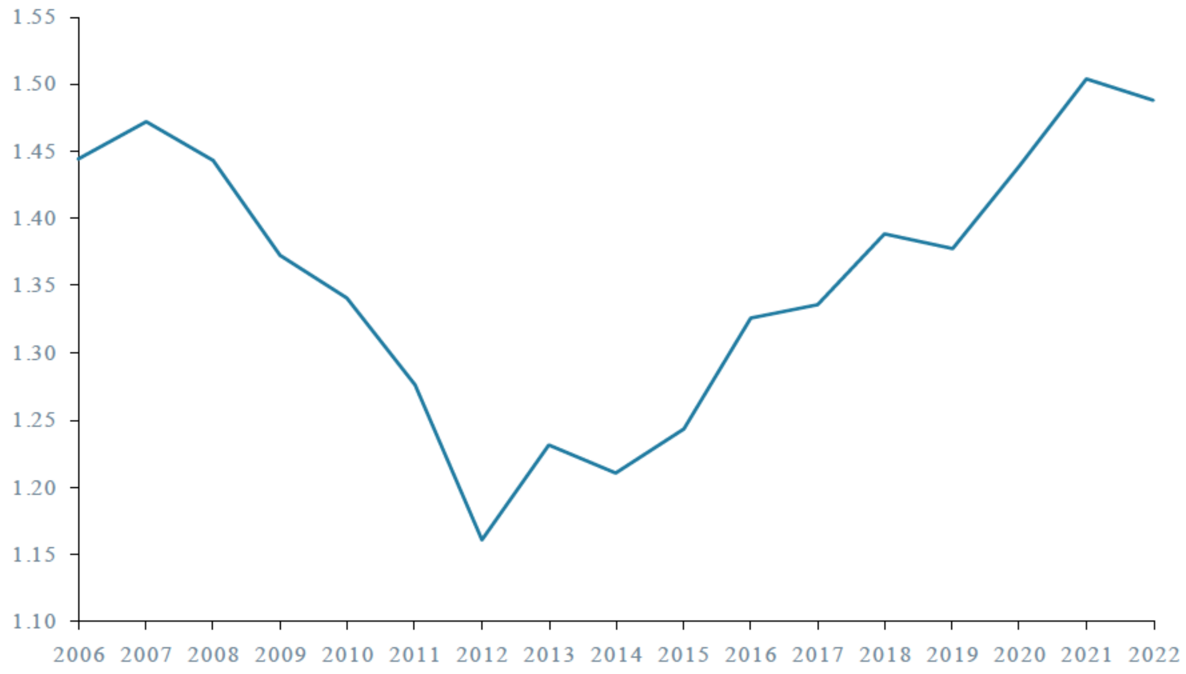
Figure 17: Residuals for Australian DNSPs– LSE-CD long model

Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

251. The above figures make it abundantly clear that the residuals of the models for the Australian DNSPs are not random with respect to time, and that there is a time-related factor that is not accounted for properly in the AER's models when estimating the average efficiency of the Australian DNSPs. The downward trend in the residuals is consistent with the observation that the efficiency of the DNSP industry as a whole in Australia has improved significantly over time—particularly since the AER began using benchmarking analysis in 2014 as part of its revenue determinations, and since the publication of its Annual Benchmarking Reports.

252. This pattern is also observed in plots of the opex multilateral partial factor productivity (MPFP) for the Australian industry, as can be seen in Figure 18, which shows the opex MPFP for the Option 5 definition of opex. In this figure, a positive trend indicates an improvement in efficiency.

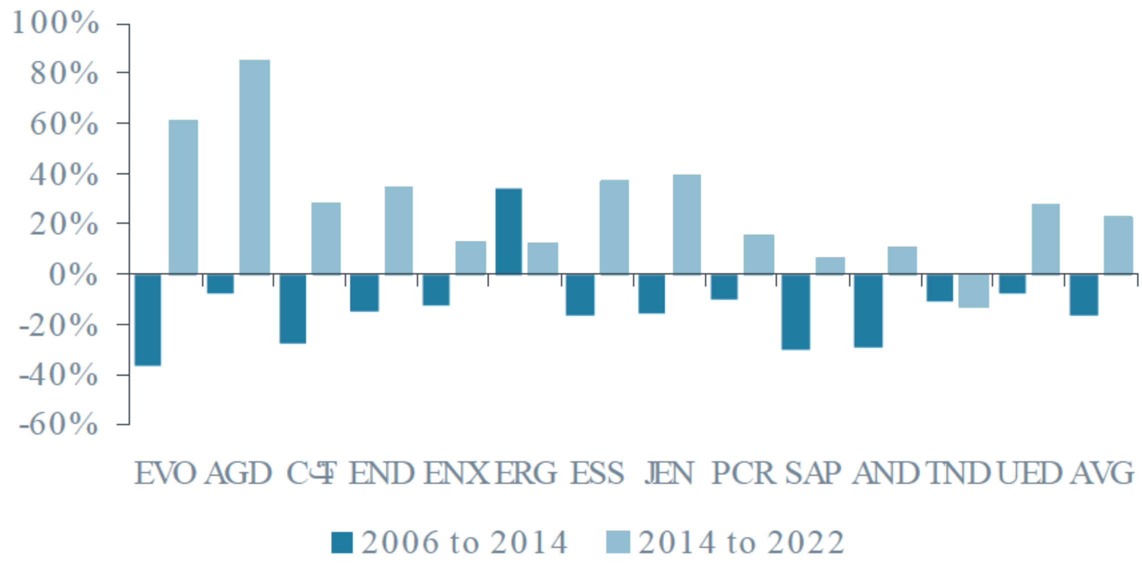
Figure 18: Opex MPFP for Australian DNSPs in aggregate over time



Source: Quantonomics analysis – DNSP23-MTFPtables-charts_Op5_12Oct2023.xlsx

253. The change in the trend in efficiencies of the Australian DNSPs is revealed even more starkly in Figure 19, which plots the change in the opex MPFP index for each DNSP, as well as the change in the weighted average opex MPFP for the industry as a whole, for the period before 2014 (dark blue bars) and after 2014 (light blue bars), i.e., the year when AER began using benchmarking analysis. All but one of the light blue bars are positive (indicating an improvement in efficiency since 2014), while all but one of the dark blue bars are negative (indicating declining efficiency before 2014).

Figure 19: Change in opex MPFP before and after 2014



Source: Quantonomics analysis – DNSP23-MTFPtables-charts_Op5_12Oct2023.xlsx

254. More specifically, Figure 19 shows that between 2006 and 2014 the opex MPFP index fell for the industry (i.e., on average) by approximately 16%. By sharp contrast, since 2014, the opex MPFP increased for the industry by approximately 23%. Evoenergy and Ausgrid have been the standout performers over that period.

255. The AER has recognised that its application of benchmarking analysis has contributed to an improvement in the efficiency of DNSPs. For example, the 2023 Draft Annual Benchmark Report states:

> *Since 2014, the AER has used benchmarking in various ways to inform our assessments of network expenditure proposals. Our economic benchmarking analysis has been one contributor to the reductions in network costs and revenues for DNSPs and minimising retail prices, and retail price increases, faced by consumers.*[68]

256. Commenting on the opex partial factor productivity (PFP) and total factor productivity (TFP) indices for the industry, the AER observes in the 2023 Draft Annual Benchmarking Report that:

> *..since 2012, opex reductions have been the most significant contributor to TFP growth, with opex PFP increasing on average by 2.9% each year.*[69]

257. The 2023 Draft Annual Benchmarking Report also notes that:

> *Those DNSPs which have been the least productive over time have been improving their performance since 2012. In particular, Ausgrid and Evoenergy have increased their overall productivity, largely as a result of improvements in opex efficiency, noting Evoenergy's slight decline since 2016.*
>
> *Several middle-ranked DNSPs have also improved their relative MTFP performance to be closer to the top-ranked DNSPs. In recent years this includes United Energy, Jemena, Endeavour Energy and Essential Energy, again reflecting improved opex efficiency.*[70]

258. It is important to recognise that all the AER's current Cobb-Douglas and Translog models *assume* constant efficiencies over time. This is inconsistent with the AER's recognition that significant efficiency improvements have been achieved by many individual DNSPs and by the industry as a whole. This assumption of constant efficiencies over time is hard-wired into the specification of the

[68] AER, *Draft Annual Benchmarking Report, Electricity distribution network service providers*, October 2023, p. 14.

[69] AER, *Draft Annual Benchmarking Report, Electricity distribution network service providers*, October 2023, p. 20.

[70] AER, *Draft Annual Benchmarking Report, Electricity distribution network service providers*, October 2023, p. v.

models. Consequently, the AER's models are incapable, due to their specification, of accounting for the fact that some DNSPs have improved their level of efficiency considerably over time. Since the models cannot account for these changes in efficiency over time directly, they will tend to overfit the data to other time-varying variables in the model. Given the highly flexible functional form of the Translog models, this response lack of time variation in the efficiencies in the model is likely to be more pronounced for the Translog models. This could be a key reason why the Translog models are prone to monotonicity violations— particularly when estimated using the short sample, which overlaps almost perfectly with the period over which the AER has been conducting benchmarking analysis.

259. Given the significant changes in DNSP efficiencies since 2014, the assumption of constant efficiencies is likely to cause a serious misspecification problem for the Cobb-Douglas models as well as the Translog.[71] However, the consequences of this misspecification problem are less easy to detect (e.g., as monotonicity violations) for the Cobb-Douglas models due to their more restrictive functional form. Nonetheless, both classes of models suffer from the same underlying issue.

Implausibly low efficiency estimates from SFA-TLG models

Detection of issue

260. Another telltale sign of a mis-specification problem is that some of the translog models produce implausibly low estimates of efficiency for some DNSPs. When analysing the preliminary results provided by Quantonomics,[72] we noted that the SFA-TLG models were producing very low estimates of efficiency for Ausgrid, for both the long and short models, and for both the standard opex and Option 5 opex approaches.[73] These scores, ranging from 26.1% to 37.9%, stood out as being low compared to the estimates of efficiency obtained from the other benchmarking models considered by the AER. This is most noticeable in the case of the short sample SFA-TLG.

261. When examining the long sample SFA-TLG model using Option 5 opex, we noted that the estimate of the *mu* parameter (the mean of the distribution of the inefficiency term) was negative at -0.825, while for the other models it was positive, ranging from 0.305 to 0.398.[74, 75]

262. In the SFA models used by Quantonomics, the inefficiency term u_i is distributed as a truncated normal distribution. Underlying this is a normal distribution with mean *mu* and some variance, but only the positive portion of the distribution is used to derive estimates of efficiency. When *mu* is positive, the positive part of the truncated normal distribution has a peak strictly greater than zero, but when *mu* is negative the positive part of the distribution is downward sloping.

263. These two possibilities are illustrated in Figure 20 using the efficiency distributions for the SFA-TL models presented by Quantonomics for Option 5 opex. The shape of the efficiency distribution for the long sample SFA-TLG model is very different to that of the short sample SFA-TLG model and implies that DNSPs with very low efficiency are far more common than would be feasible under

[71] As noted above, the residual plots for the Cobb-Douglas models also exhibit a clear negative trend over time for the Australian DNSPs.

[72] Quantonomics, *Economic Benchmarking Results for the Australian Energy Regulator's 2023 DNSP Annual Benchmarking Report*, 17 August 2023.

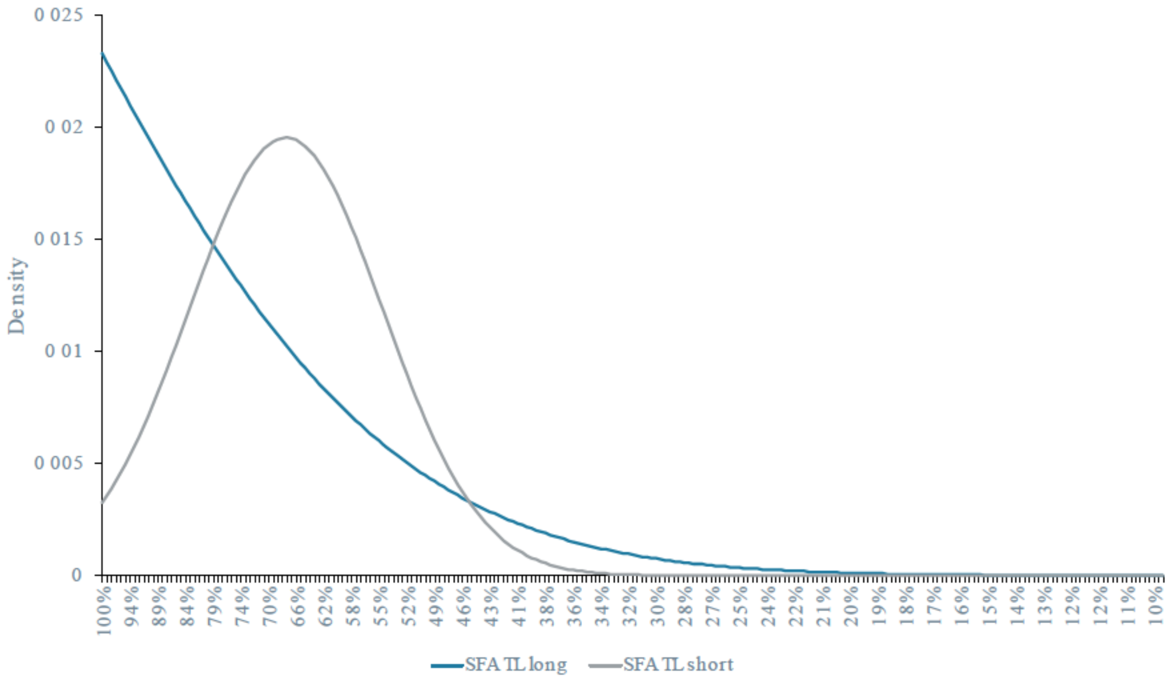
[73] See Tables 3.4, 3.6, 3.7, and 3.9.

[74] See Tables C.3, C.4, C.11, C.12, C.19, C.20, C.27, C.28.

[75] Similar observations apply to results from the standard opex approach.

the distributions resulting from models with positive *mu*. The negative *mu* also implies that 100% efficiency is the most likely outcome, which is not the case for the models that the AER has historically relied upon.

Figure 20: Distribution of efficiency for Option 5 opex models estimated by Quantonomics



Source: Frontier Economics analysis

Note: We have used a non-evenly specified scale on the horizontal axis to better highlight the differences between these two types of efficiency distributions

Mis-estimation of SFA model

264. Another issue of concern with the SFA models is whether the estimation algorithm for the SFA models has identified the best parameter estimates for the model. Unlike the LSE models, the SFA models cannot be estimated using a closed form solution. Instead, the SFA models are estimated iteratively using a technique known as maximum likelihood estimation (MLE). MLE involves searching iteratively for the model that best fits the data, which is achieved when the log-likelihood function associated with the observed data is maximised.

265. The statistical software for estimating the SFA models iteratively changes the values for the key parameters that define the log-likelihood function until the maximum of the log likelihood function is found. To commence the iterative process, it is necessary to specify starting values for *mu* and the other parameters in the model. The outcome of this process may be sensitive to the starting values. For example, the log-likelihood function could have several modes, i.e., several maximum turning points (referred to as local maxima). In these circumstances, it is possible that a *local* maximum for the log-likelihood function is identified rather than a *global* maximum (the global maximum is the largest of the local maxima). In such instances, because the true maximum of the log-likelihood function is not identified, the model will have been mis-estimated. That appears to have occurred in the case of the short sample SFA-TLG model.

266. We first checked whether a global maximum had been found by Quantonomics for the SFA-TLG long model. We obtained a different starting point than Quantonomics by imposing a value for *mu* of 0.35 and estimating the other parameters in the model. We then used these estimates as the starting point for the iterative process used by the Stata package.[76] This approach produced the same parameter estimates for the SFA-TLG long as those obtained by Quantonomics. This suggests that the SFA-TLG long model had not been mis-estimated.

267. We then examined the short SFA-TLG short model, imposed *mu* to be equal to 0 as a starting point, and estimated the other parameters. This is, in fact, a popular simpler version of the truncated normal SFA model known as the half-normal SFA model. This yielded a log likelihood value of 491.7, which is larger than the log-likelihood value of 485.6 for the fitted model presented by Quantonomics. This implies that the half-normal SFA model is, in fact, a better fitting model than the model estimated by Quantonomics.[77,78] Since the truncated normal model is a more flexible model than the half-normal model, it should fit the data at least as well as the half-normal model. The fact that the truncated normal model estimated by Quantonomics fits the data worse than the half-normal model indicates that the results presented by Quantonomics are for a mis-estimated truncated normal model, most likely produced by identifying a local rather than the global maximum of the relevant log-likelihood function.

268. The estimated efficiency scores corresponding to the restricted model with mu=0, i.e., a half-normal model, are presented in Table 11 below.

[76] Stata is a well-known econometric software package that has been used by Quantonomics to estimate the econometric benchmarking models.

[77] Table C.28.

[78] While the revised parameter estimates are a substantially better fit, the Quantonomics parameter estimates should be disregarded by virtue of not maximising the log-likelihood.

Table 11: Efficiency estimates for the short SFA-TLG model using Option 5 opex

DNSP	Quantonomics model	Model with mu=0 (half-normal)
Evoenergy	51.8%	46.5%
Ausgrid	37.9%	4.0%
CitiPower	76.7%	37.7%
Endeavour Energy	58.7%	16.2%
Energex	48.6%	9.2%
Ergon Energy	72.0%	81.2%
Essential Energy	80.9%	94.9%
Jemena	54.8%	33.3%
Powercor	93.4%	62.7%
SA Power Networks	90.2%	62.4%
AusNet	64.4%	40.7%
TasNetworks	94.3%	96.7%
United Energy	66.8%	21.1%

Source: Frontier Economics analysis

269. As Table 11 shows, the SFA-TLG estimates derived by imposing mu=0 (i.e., half-normal) are materially different from those presented by Quantonomics. These estimates are clearly implausible and inconsistent with the estimates produced by the other models used by the AER. For instance, the efficiency estimates for Ausgrid and Energex from this model are below 10%, and the estimate for United Energy, a reference firm, is around 20%.

270. In an attempt to find a better-fitting truncated normal SFA-TLG short model, we imposed a *mu* of -1, re-estimated the other parameters, and used these estimates as the starting point for Stata's iterative process. We selected this starting value for *mu* because it is similar to the estimate of *mu* obtained for the SFA-TLG long model. The final iteration produced a very large negative *mu* and a log likelihood of 500.8, again indicating a substantially better fit than 485.6 for the fitted model presented by Quantonomics, and also a better fit than the half-normal SFA-TLG model.[79]

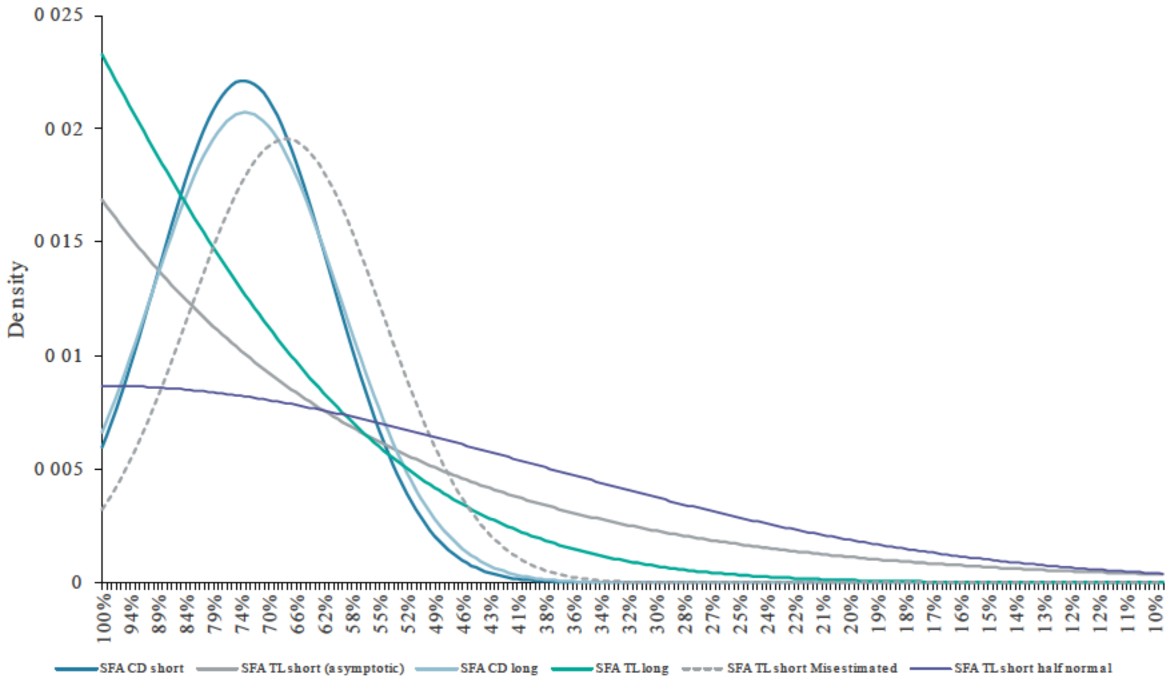
271. We note that the model estimated above did not converge. Instead, we took the result after 1,000 iterations. Upon examining the cause for the lack of convergence, we determined that at large negative *mu* values, the cumulative normal distributions used in the Stata code will give a value of

[79] Table C.28.

0, and so the log of the probability will not be defined.[80] To overcome this shortcoming, we edited the Stata do file to use the lognormal function directly.[81] The Stata code also required an adjustment in another area, as an approximation was used when *mu* was large and negative, which prevented convergence. Again, we edited the code to be able to handle large negative values of *mu*. The corrected Stata code converged and produced an estimate of *mu* of -23,629.3. That is to say, we have now been able to estimate a corrected version of the short sample SFA-TLG model that no longer suffers from lack of convergence.

272. A comparison of the efficiency distributions produced by the different SFA models discussed above is provided in Figure 21.

Figure 21: Distribution of efficiency – Option 5 opex models



Source: Frontier Economics analysis

Note: The derivation of the efficiency distribution referred to as SFA TL short (asymptotic) is discussed in the next subsection

Asymptotic efficiency estimates

273. While we were able to estimate the model and obtain convergence, we do not believe that the parameter estimates are at the global maximum of the likelihood function. Rather, the improvement in fit is so small that Stata identifies the process as having converged. By imposing a much larger negative *mu* than in the solution obtained we are able to improve the large likelihood marginally, though we note that the estimates of interest – the production function and efficiency estimates – do not change.

274. Given the unusual results when estimating the SFA-TLG short model, we examined the nature of the log- likelihood further. We derived a sequence of estimates of the model obtained by restricting

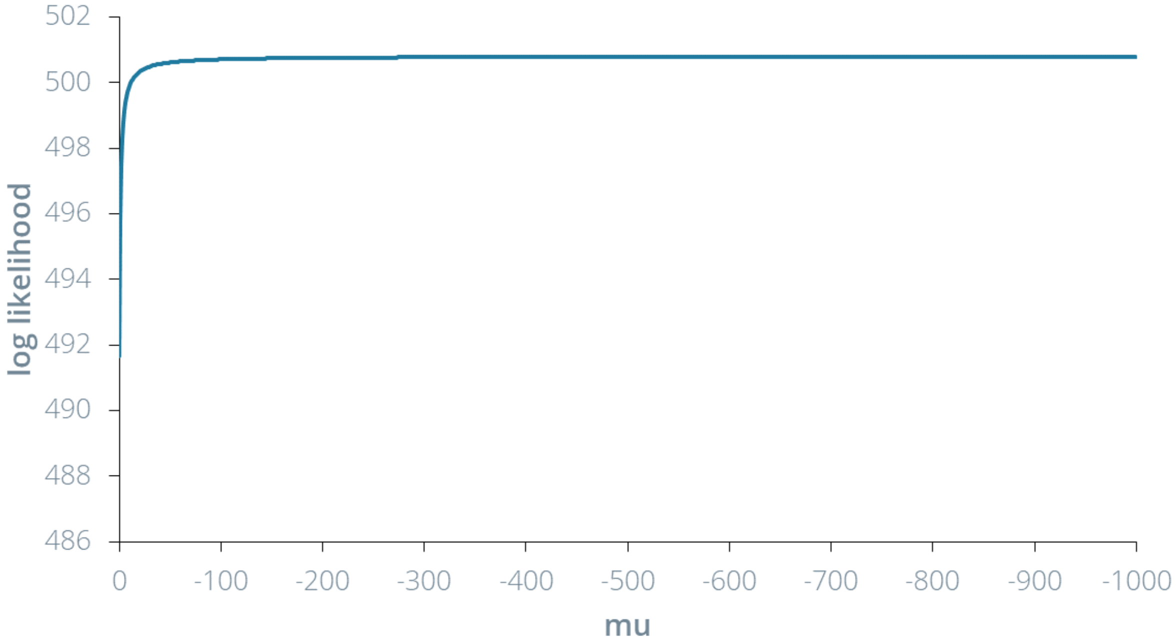
[80] More specifically when mu divided by the square root of the error variance is below -37.5.

[81] This function, lnnormal(), was introduced in Stata 10 in 2007, the SFA code "xtsf_llti.ado" used was written in 2006. See https://www.stata.com/stata10/datamanagement.html.

mu to different values, ranging from 0 to -1,000, and deriving the estimates of the other parameters. The values of the log-likelihood function obtained from the exercise are shown in Figure 22. The figure shows that the log-likelihood function seems to converge asymptotically to a value of about 500.8 as *mu* becomes more negative.

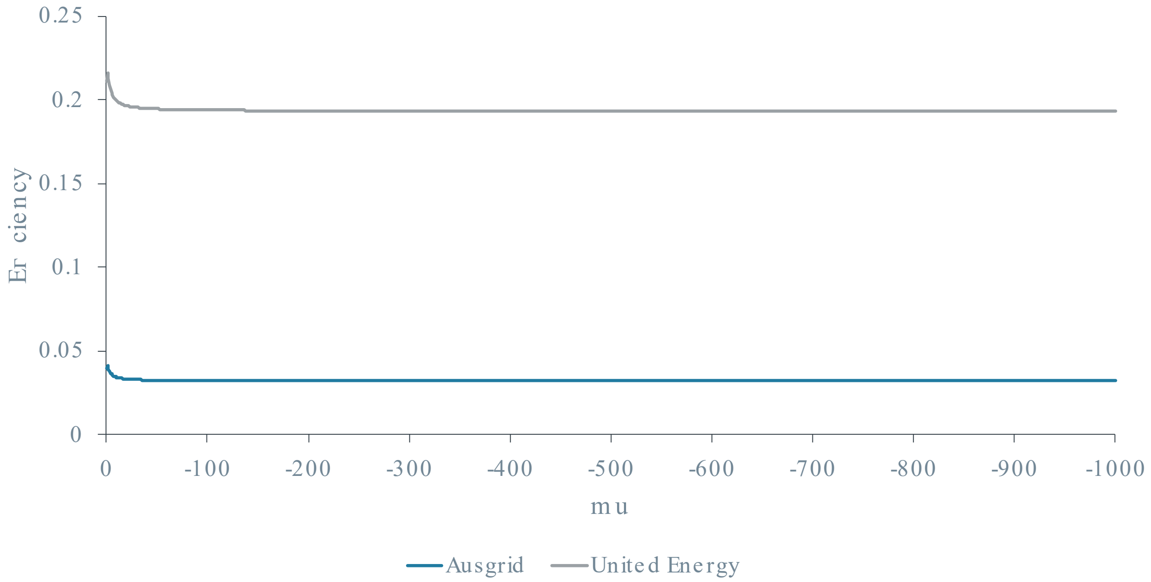
275. The estimates of the efficiency scores and the parameter estimates also seem to converge as *mu* tends to minus infinity, as can be seen in Figure 23 and Figure 24.

Figure 22: Log likelihood for different imposed values of *mu*



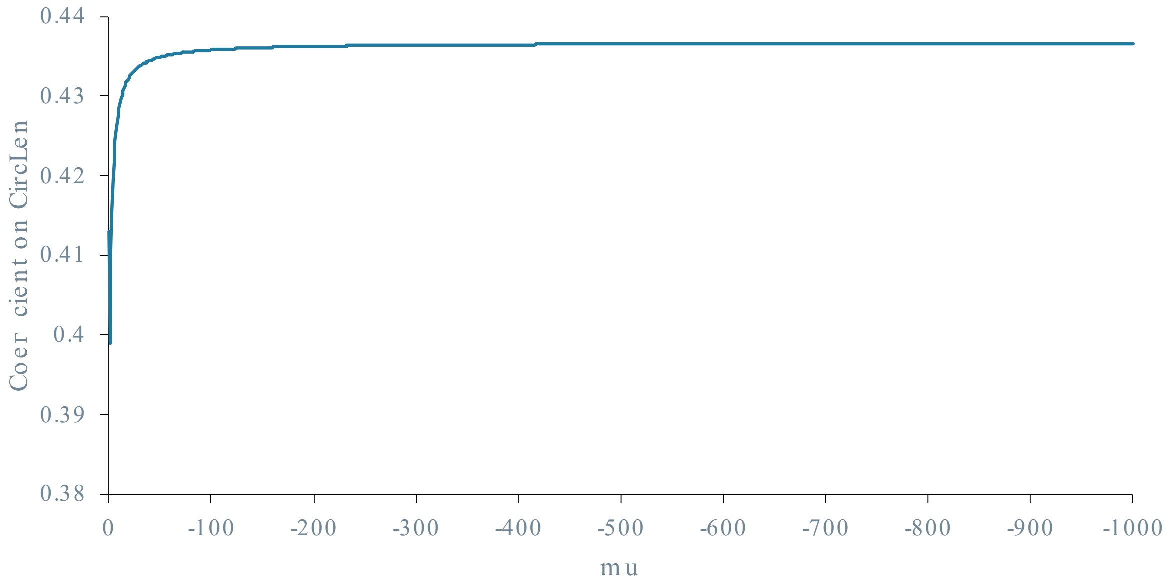
Source: Frontier Economics analysis

Figure 23: Efficiency estimates for different imposed values of *mu*



Source: Frontier Economics analysis

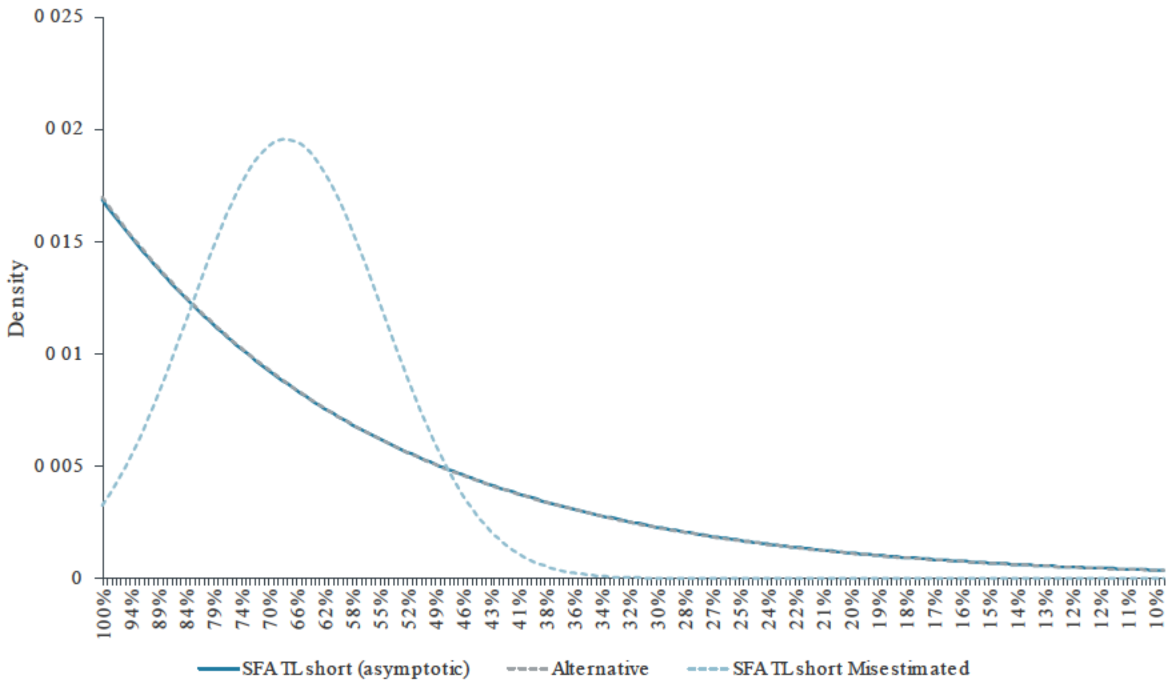
Figure 24: Estimates of coefficient of circuit length for different imposed values of *mu*



Source: Frontier Economics analysis

To illustrate the convergence of the results to asymptotic values as *mu* becomes more negative, in Figure 25 we present the estimates of the truncated normal efficiency distributions for two different large negative values of *mu*, *mu* = -23,629.3 and *mu* = -415.5. We refer to the first case as the asymptotic distribution and the case when *mu* = -415.5 as the alternative distribution. The figure shows that these two distributions are almost indistinguishable. For comparison, we also show the efficiency distribution for the model estimated by Quantonomics, which is vastly different.

Figure 25: Distribution of efficiencies for different estimates of the SFA-TLG short model



Source: Frontier Economics analysis

276. We refer to the efficiency estimates produced by the models with a very large negative *mu* as the asymptotic efficiency estimates for the SFA-TLG short model. The asymptotic efficiency estimates for all 13 DNSPs are presented in Table 12 together with the efficiency estimates presented by Quantonomics. While the efficiency estimates derived from the model estimated by Quantonomics do appear low for some DNSPs compared to the efficiency estimates obtained from the other seven models (most notably for Ausgrid), they did not seem so anomalous as to attract attention. It is only once the mis-estimation is corrected that it becomes obvious that there is a serious problem with the estimation of this which points to a more fundamental misspecification problem.

277. As Table 12 shows, the SFA-TLG estimates derived using the asymptotic approach described above are materially different from those presented by Quantonomics, and are clearly implausible and inconsistent with the estimates produced by the other models used by the AER. For instance, the estimates from the short sample SFA-TLG model for Ausgrid and Energex are below 10%, and the estimate for United Energy, a reference firm, are below 20%.

278. These unrealistically low estimates of efficiency are a warning of a misspecification problem, because one consequence of a misspecified model is biased estimates of model parameters, which leads to biased estimates of efficiency scores. Estimates of the efficiency scores are very sensitive to the estimated shape of the truncated normal distribution of efficiency. Sometimes bias in the estimates is not immediately apparent. However, in this case the anomalously low estimates point to a serious misspecification issue. The AER was not alerted to the specification issue with this model because it had been mis-estimated, i.e., its estimates did not correspond to the highest value of the log-likelihood function.

Table 12: Efficiency estimates for the SFA-TLG short model using Option 5 opex

DNSP	Quantonomics	Asymptotic estimates
Evoenergy	51.8%	46.2%
Ausgrid	37.9%	3.2%
CitiPower	76.7%	36.7%
Endeavour Energy	58.7%	13.6%
Energex	48.6%	7.5%
Ergon Energy	72.0%	82.5%
Essential Energy	80.9%	96.3%
Jemena	54.8%	32.7%
Powercor	93.4%	58.0%
SA Power Networks	90.2%	56.6%
AusNet	64.4%	37.6%
TasNetworks	94.3%	96.6%
United Energy	66.8%	19.3%

Source: Frontier Economics analysis

Implications

279. To avoid any doubt, we do not suggest that the AER should use the asymptotic SFA-TLG short efficiency estimates presented in Table 12, even though Stata was able to obtain a converged estimate. To the contrary, the implausible estimates in the final column Table 12 point to serious *misspecification* of the SFA-TLG models.

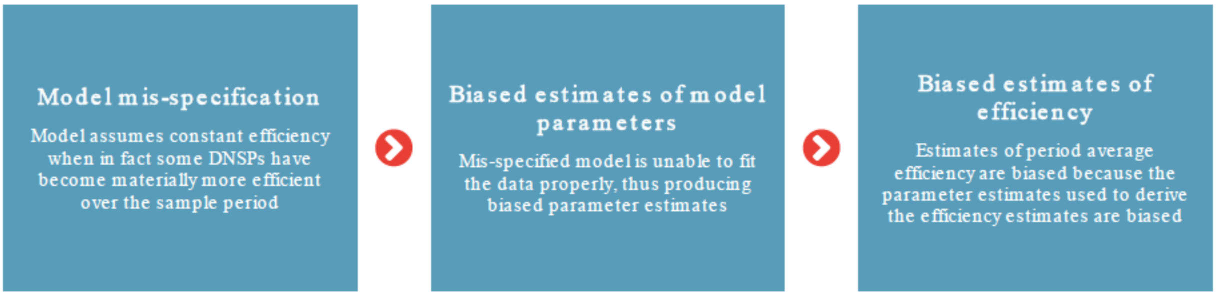
280. The misspecification of those models was obscured by the fact that the model had been estimated incorrectly due to adoption of a local instead of a global maximum solution. Once the mis-estimation is recognised, the implausibility of the better-fitting asymptotic model generating the estimates in the final column of Table 12 is apparent.

281. As summarised in Figure 26, misspecification of the benchmarking models results in biased estimates of efficiency. Therefore, efficiency estimates derived using misspecified models should not be relied on for regulatory purposes.

282. We acknowledge that the SFA-TLG short model suffers from monotonicity violations for all of the Australian DNSPs and, therefore, would not have been used by the AER to assess the efficiency of base year opex. However, that is beside the point. It is precisely because there are so many

monotonicity violations and some unrealistically low efficiency estimates that the AER should have been alerted to the fact that the SFA-TLG model is seriously misspecified.

Figure 26: The effect of model misspecification on period average efficiency estimates



Source: Frontier Economics

283. The misspecification of the SFA-TLG models is not restricted to the short sample SFA-TLG model alone. Rather, the misspecification problem affects *all* of the econometric benchmarking models used by the AER. In particular, the long sample SFA-TLG model exhibits a negative *mu* estimate and implausibly low efficiency estimates as well. However, there are no monotonicity violations associated with that model for Evoenergy and it *would* be included by the AER when assessing the efficiency of a Evoenergy's base year opex. In other words, the AER's approach of excluding models that exhibit monotonicity violations does not deal properly with the problem that all of the AER's models are misspecified and, therefore, are not fit-for-purpose.

284. In our view, the proper course of action would be for the AER to review the specification of the models. That review cannot (and should not) be resolved without proper stakeholder consultation. Until the AER has had an opportunity to conduct such a review and demonstrate a material improvement in the reliability of the models, the AER should exercise extreme caution when interpreting the benchmarking results from its econometric models.

Failure of the models to account adequately for changes in efficiency over time of the Australian DNSPs

Simulated impact on estimated average efficiency

285. As explained above, we suspect that a key source of the statistical problems associated with the AER's models is that they are misspecified in the sense that they all assume that DNSPs maintain a constant level of efficiency over time. However, there is strong *prima facie* evidence (including evidence from the AER) that a number of the DNSPs have become more efficient over time. In these circumstances, the constant efficiency assumption built into the AER's benchmarking models will tend to produce biased estimates of efficiency.

286. We note that efficiency estimates are used in the AER's benchmarking roll-forward model to infer the efficient average opex of a DNSP over the sample period, by adjusting actual opex by the efficiency score and the efficiency target. In principle, it might not matter if a DNSP's efficiency changes over time, provided the estimated (constant) efficiency is a good estimate of the average efficiency. (This also assumes that the cost function elasticities are appropriate and not affected by the misspecification).

287. A key question, therefore, is whether the AER's models, although misspecified with respect to changing efficiencies over time, might still produce acceptable estimates of each DNSP's average efficiency over the sample period. One simple way to test this is via simulation analysis.

288. In summary, the simulation analysis we performed involved the following steps:

a First, we assume a 'true' level of average efficiency for each DNSP over the long sample period;

b Next, we assume starting values for efficiency in 2006 for that each DNSP, and a constant rate of efficiency improvement per annum that results in the assumed true average level of efficiency over the long sample period.

c Then, we simulate the opex for each DNSP, for each year, using the assumed true (time-varying) efficiencies over the long sample period, and the AER's estimates of the parameters from the long sample SFA-TLG model.

d Finally, we fit the long sample SFA-TLG model to the simulated opex data and obtain efficiency estimates for each DNSP.

289. If the AER's long sample SFA-TLG model had accounted for the fact that the DNSPs had achieved constant efficiency improvements over time, then the estimated average efficiencies would match the assumed true level of efficiency that we had specified for each DNSP. In fact, what we found is that for most DNSPs, the higher the rate of efficiency improvement, the greater the extent to which the model underestimates the true level of average efficiency.

290. Since this simulation analysis is for illustrative purposes only, we focus on the long sample SFA-TLG model. Quantonomics' efficiency estimates from that model for the Australian DNSPs are presented in the second column of Table 13 below.

291. The third column of Table 13 specifies (for the purposes of the simulation analysis) the assumed true level of efficiency for each DNSP. The efficiencies in the third column are the same as those in the second column, except for Ausgrid, Endeavour Energy and Energex. For these DNSPs we specify more plausible assumed 'true' levels of efficiency than those presented in the second column, informed by the efficiency scores derived from the AER's other models.

Table 13: Efficiency estimates – long sample SFA-TLG, draft ABR dataset, Option 5 opex

DNSP	Quantonomics' estimated efficiencies	Assumed efficiencies in the simulation analysis
Evoenergy	54.19%	54.19%
Ausgrid	30.68%	55.00%
CitiPower	78.26%	78.26%
Endeavour Energy	48.80%	60.00%
Energex	44.97%	50.00%
Ergon Energy	74.41%	74.41%
Essential Energy	75.06%	75.06%
Jemena	76.14%	76.14%
Powercor	97.49%	97.49%
SA Power Network	90.99%	90.99%
AusNet	73.65%	73.65%
TasNetworks	96.06%	96.06%
United Energy	81.22%	81.22%

Source: Quantonomics estimates and Frontier Economics assumptions

292. We then allow the efficiency of each Australian DNSP to change over time. We specify an efficiency adjustment factor of x%, so that the DNSP's efficiency in 2006 is equal to the DNSP's specified average minus x% of the gap between their average and 100% and ending in 2022 at the average plus x% of the gap between their average and 100%. For example, if we set the adjustment factor to 25%, a DNSP with an average efficiency of 60% will have an efficiency of 60% in the middle of the sample period, increasing to 70%[82] at the end of the sample period (and starting at 50% at the beginning of the sample period).

293. We then simulate opex for each DNSP for each year by applying the specified true level of efficiency (time varying for Australian DNSPs) to the production function and applying random shocks (using the distribution of the random error term from the initial estimation). Thus, we obtain an alternative (simulated) opex for each of the 1,137 observations in the 2023 Draft Annual Benchmarking Report dataset.

294. We then apply the SFA-TLG model estimation procedure, and obtain efficiency estimates for the Australian DNSPs, as well as the *mu* (mean of the distribution used for the inefficiency term).

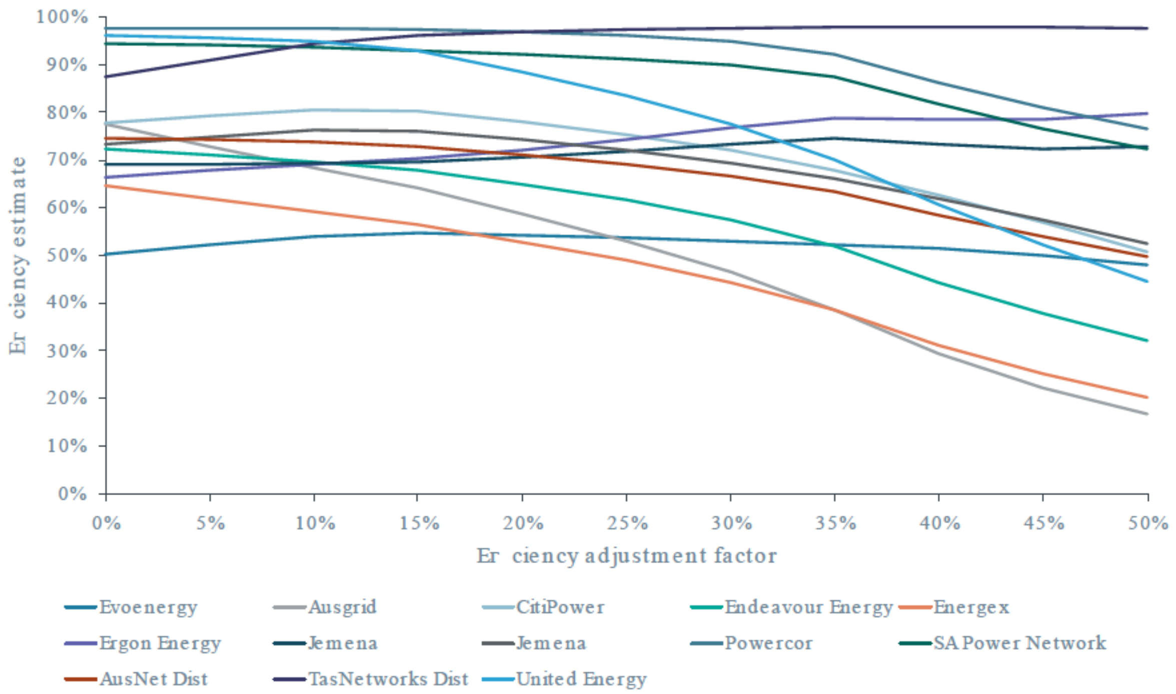
[82] Derived as 60% + 25% x (100% – 60%).

295. The results of the simulation analysis are presented in Figure 27. The figure shows that the estimated average efficiency for Ausgrid falls dramatically as the efficiency time trend increases. By way of example, Ausgrid's true average efficiency is assumed to be 55%. In the scenario where the efficiency trend coefficient is 40%, Ausgrid's true efficiency rises from 37% in 2006 to 73% in 2022.[83] However, the estimated constant efficiency is only 27%, well below the assumed true average efficiency of 55%.

296. Furthermore, as Figure 28 shows, the estimated *mu* parameter becomes negative and large as the efficiency trend increases. As explained above, when this occurs, the SFA-TLG models will tend to produce excessively low efficiency estimates for DNSPs.

297. This simulation analysis suggests that the AER's models cannot estimate the average efficiency of DNSPs correctly when efficiency varies over time (because the models assume constant efficiency over time), and in fact may understate average efficiency by a considerable margin for firms that have improved their efficiency the most.

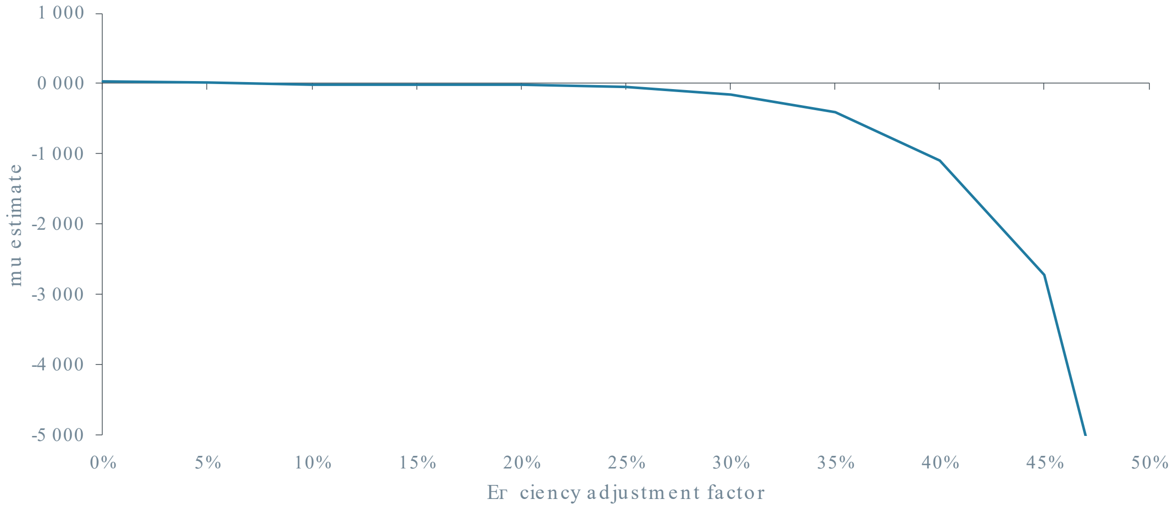
Figure 27: Estimates of efficiency for different efficiency adjustment factors



Source: Frontier Economics analysis

[83] Taking the gap between the actual and predicted opex as a proxy for efficiency, more specifically using the exponent of the negative of the residual, Ausgrid's estimated efficiency rises from 28% in 2006 to 54% in 2022. Thus, such a trend factor is not unreasonable and reflects the large improvements that some DNSPs have made.

Figure 28: Estimates of mu for different efficiency trend factors



Source: Frontier Economics analysis

Alternative LSE specification

298. As a further illustration of the potential for time-varying efficiencies to lead to biased estimates of sample average efficiency, we consider a simple modification to the LSE models to include a time varying efficiency trend for each Australian DNSP.

299. Instead of only including dummies for each Australian DNSP in the LSE models, we also include DNSP specific time trends for the Australian DNSPs. To achieve this, the DNSP dummy D_i is multiplied by the sum of α_i and the time trend variable t multiplied by the DNSP's yearly change in the dummy variable coefficient, β_i, resulting in the following specification:

$$logRealOpex_{it} = X_t\beta + (\alpha_i + t\beta_i)D_i + \epsilon_{it}$$

300. These factors can be converted into efficiency scores. For each year, we find the lowest factor across DNSPs, and then average these factors over the sample period. Individual efficiencies are then calculated with respect to this factor. We then average the year specific efficiencies for each DNSP.

301. The results for the four LSE models are presented in Table 14 through Table 17. Some substantial differences can be observed between the estimates of average efficiency under the AER's existing LSE models and the modified LSE models that incorporate a DNSP-specific time trend. For example, Ausgrid's estimated efficiency for the short sample LSE-TLG model increases substantially (by more than seven percentage points).

Table 14: Efficiency score comparison, long LSE-CD

Efficiency	Quantonomics specification	Alternative model with time-varying efficiency
Evoenergy	48.0%	46.6%
Ausgrid	58.0%	57.3%
CitiPower	80.0%	77.1%
Endeavour Energy	66.0%	64.1%
Energex	68.7%	66.6%
Ergon Energy	55.6%	54.3%
Essential Energy	66.0%	64.0%
Jemena	72.9%	70.4%
Powercor	100.0%	96.9%
SA Power Networks	93.7%	90.7%
AusNet	82.2%	79.8%
TasNetworks	83.0%	80.4%
United Energy	94.2%	91.3%

Source: Frontier Economics analysis

Table 15: Efficiency score comparison, long LSE-TLG

Efficiency	Quantonomics	Alternative
Evoenergy	43.1%	41.0%
Ausgrid	55.5%	57.7%
CitiPower	73.0%	69.8%
Endeavour Energy	66.0%	64.6%
Energex	66.8%	67.0%
Ergon Energy	57.9%	52.4%
Essential Energy	73.1%	68.1%
Jemena	57.0%	55.2%
Powercor	100.0%	96.2%
SA Power Networks	97.0%	92.1%
AusNet	76.0%	75.1%
TasNetworks	78.2%	72.9%
United Energy	75.1%	74.8%

Source: Frontier Economics analysis

Table 16: Efficiency score comparison, short LSE-CD

Efficiency	Quantonomics	Alternative
Evoenergy	45.1%	46.2%
Ausgrid	58.7%	61.1%
CitiPower	71.5%	71.6%
Endeavour Energy	65.2%	66.2%
Energex	65.9%	66.8%
Ergon Energy	58.6%	59.4%
Essential Energy	66.3%	68.4%
Jemena	66.5%	66.5%
Powercor	100.0%	100.3%
SA Power Networks	87.5%	88.2%
AusNet	77.2%	77.4%
TasNetworks	80.5%	81.6%
United Energy	92.1%	92.8%

Source: Frontier Economics analysis

Table 17: Efficiency score comparison, short LSE-TLG

Efficiency	Quantonomics	Alternative
Evoenergy	43.9%	43.3%
Ausgrid	55.1%	62.5%
CitiPower	71.9%	70.9%
Endeavour Energy	67.9%	68.3%
Energex	63.4%	67.8%
Ergon Energy	69.1%	60.4%
Essential Energy	79.3%	75.4%
Jemena	52.2%	55.3%
Powercor	100.0%	100.3%
SA Power Networks	94.7%	91.1%
AusNet	68.5%	73.7%
TasNetworks	81.6%	77.4%
United Energy	72.2%	80.1%

Source: Frontier Economics analysis

302. We also find that modifying the Translog models to allow for different time trends for individual DNSPs reduces the number of monotonicity violations that occur. By way of example, Table 18 shows the effect of allowing separate time trends for the individual Australian DNSPs on the monotonicity violations associated with the LSE models. The table shows that:

   a Under the AER's 'standard' specification, the short sample LSE-CD model is not excluded due to monotonicity violations for any of the DNSPs. This does not change if individual time trends are allowed for the Australian DNSPs; and

   b Under the AER's standard specification, the short sample LSE-TLG model is excluded due to monotonicity violations for all of the DNSPs. However, the introduction of individual time trends for the Australian DNSPs results in the exclusion of the short sample LSE-TLG model for only two DNSPs.

Table 18: Effect of allowing individual Australian DNSP time trends on monotonicity violations

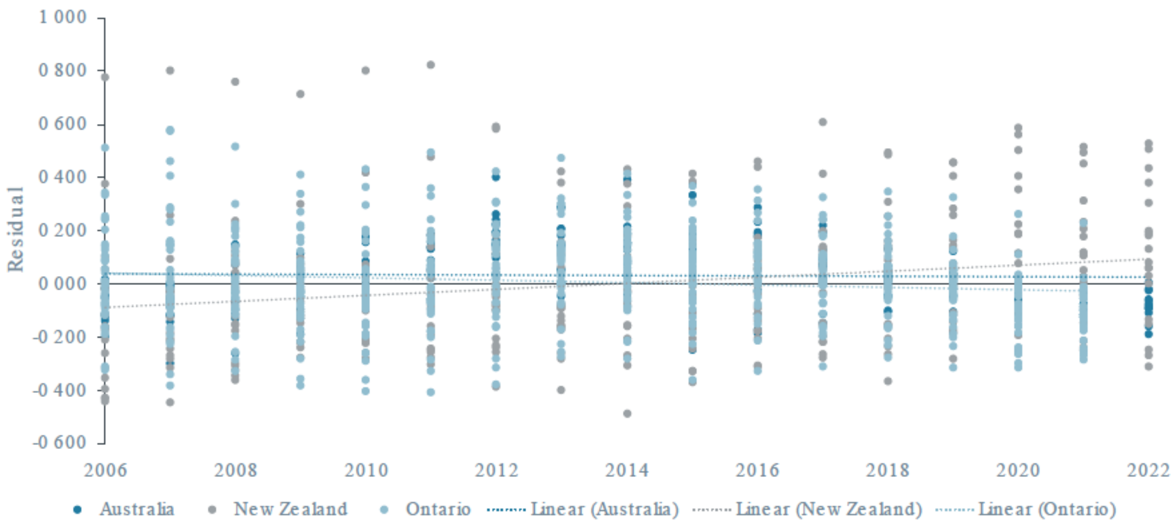
	LSE-CD short		LSE-TLG short	
DNSP	Standard	Alternative	Standard	Alternative
Evoenergy	45%	46%	44%	43%
Ausgrid	59%	61%	55%	62%
CitiPower	71%	72%	72%	71%
Endeavour Energy	65%	66%	68%	68%
Energex	66%	67%	63%	68%
Ergon Energy	59%	59%	69%	60%
Essential Energy	66%	68%	79%	75%
Jemena	66%	67%	52%	55%
Powercor	100%	100%	100%	100%
SA Power Networks	88%	88%	95%	91%
AusNet Dist	77%	77%	69%	74%
TasNetworks Dist	80%	82%	82%	77%
United Energy	92%	93%	72%	80%

Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Note: Green indicates that the model is included due to satisfying the monotonicity requirement

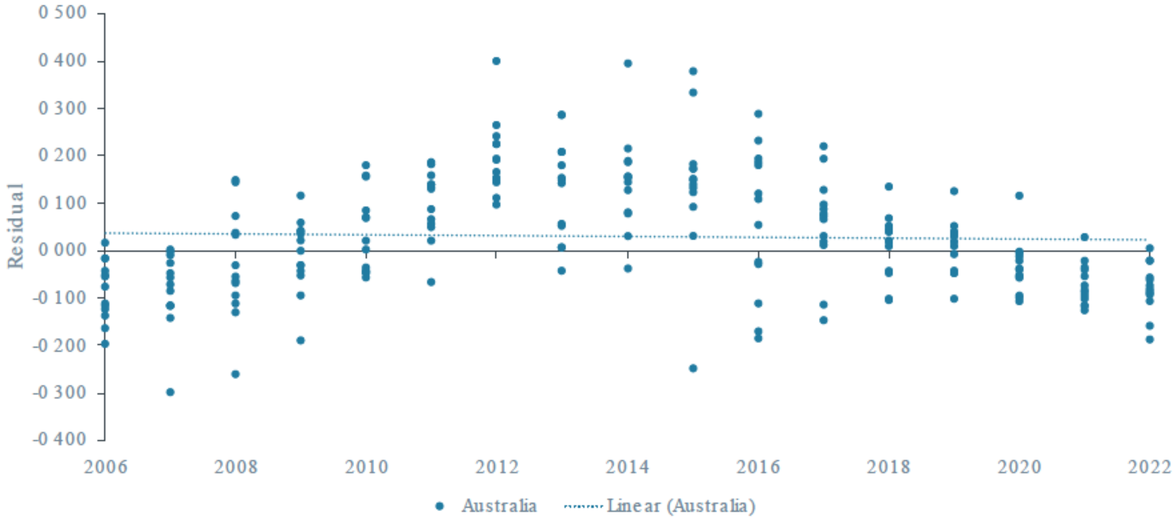
We also find that the residual plots for these alternative models are improved compared to the original specifications, with the residuals of Australian DNSPs having a flat trendline.

Figure 29: Residuals – LSE-CD long model – time varying efficiency



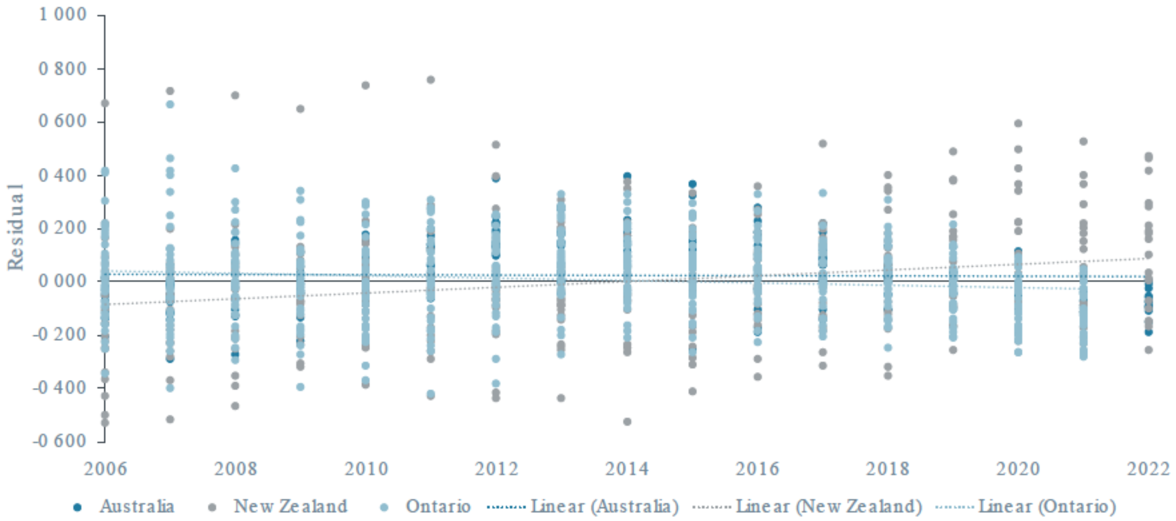
Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 30: Residuals for Australian DNSPs – LSE-CD long model – time varying efficiency



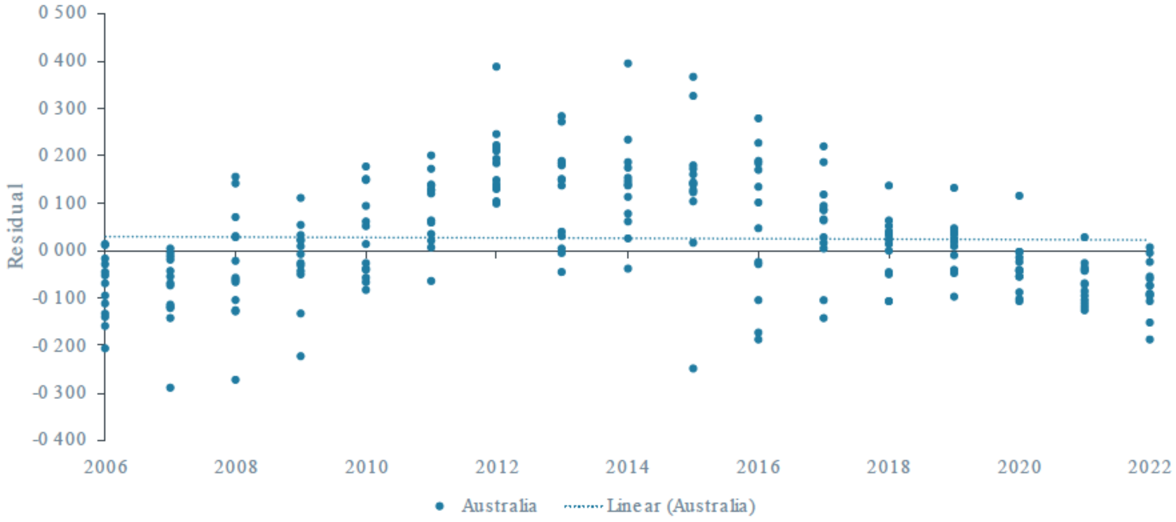
Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 31: Residuals – LSE-TLG long model – time varying efficiency



Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 32: Residuals for Australian DNSPs – LSE-TLG long model – time varying efficiency



Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

303. To avoid any doubt, we are not suggesting that the alternative model specification presented above (for illustrative purposes only) should be adopted by the AER. We simply show that making modest improvements to its models can reduce the misspecification problem and can also reduce the prevalence of monotonicity violations.

304. Our key recommendation is that the AER must rethink its econometric benchmarking models to reduce the misspecification problems that those models currently suffer from. A key focus of any such review should be how to allow for the fact that individual Australian DNSPs have made significant improvements in efficiency, particularly since 2014 — a change that the existing benchmarking models are unable to capture effectively.

Assumption of uniform time trend for all jurisdictions in the AER's sample

305. The AER's existing models do incorporate a time trend term. However, the time trend is assumed to be the same across all three jurisdictions. In other words, the AER's models cannot account for the possibility that the efficiency of the Australian DNSPs may have changed differently over time the efficiency of the New Zealand and Ontarian DNSPs.

306. As demonstrated in the residual plots presented above, the pattern of residuals over time differs between DNSPs in the different jurisdictions. That is, the residual plots indicate that:

   a There is a factor that is currently unaccounted for in the AER's models that is negatively related to time with respect to the Australian DNSPs; and

   b There is a factor that is currently unaccounted for in the AER's models that is positively related to time with respect to the New Zealand DNSPs.

307. A simple way to account for this is to add further time trend variables so that each jurisdiction has its own time trend. The 2023 Draft Annual Benchmarking Report notes that the AER intends to explore and consult further on this issue.

308. As the AER notes in the 2023 Draft Annual Benchmarking Report, the time trend in the models is intended to capture the effects of technical change on opex (i.e., 'frontier shift'/productivity improvements) over time. However, it is also likely to capture other factors that vary over time (e.g.,

improvements in efficiency/catch-up to the efficient frontier) but which are not accounted for explicitly in the model. For this reason, the time trend effect may differ between jurisdictions.

309. For illustrative purposes only, we have investigated an extension to the AER's standard model that allows for different time trends between jurisdictions. The resulting estimates of the time trends are presented in Table 19 below. The table also presents the estimated common time trend in the AER's current models. The resulting time trends estimates are consistent with what we would expect based on the residual plots in Figure 10 through Figure 13 above.

310. Table 19 also presents the results of a test of the null hypothesis that there is no difference in the time trends across the three jurisdictions. This null hypothesis is rejected convincingly for all eight models, with a p-value of 0.00% in every case. That is, the statistical evidence indicates that the efficiency of DNSPs in Australia are changing over time at a different rate to the DNSPs in New Zealand and Ontario—contrary to the uniform time trend assumed in the AER's existing models.

Table 19: Estimated time trends

	SFA CD short	SFA TLG short	LSE CD short	LSE TLG short	SFA CD long	SFA TLG long	LSE CD long	LSE TLG long
Standard model	0.33%	0.63%	0.30%	0.51%	1.19%	1.14%	1.03%	1.17%
Extended model - Australia	-3.34%	-3.38%	-3.02%	-2.90%	-0.28%	-0.52%	-0.18%	-0.25%
Extended model - NZ	2.89%	2.93%	2.79%	2.93%	2.45%	2.40%	2.58%	2.76%
Extended model - Ontario	-0.32%	-0.30%	0.08%	0.27%	0.76%	0.64%	0.61%	0.76%
Test								
ChiSq(2)	434.37	402.89	84.9	89.68	166.66	162.79	42.33	50.12
p-value	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Source: Frontier Economics analysis

311. Since there is *prima facie* evidence that the Australian DNSPs have become more efficient over time (particularly since 2014), the assumption of a uniform time trend could result in biased estimates of efficiency.

312. As shown in Table 20, the resulting efficiency estimates are more plausible for the short and long SFA-TLG model (results highlighted in red).

Table 20: Comparison of efficiency scores – standard model vs including separate time trends for each jurisdiction

	Short SFA-CD		Short SFA-TLG		Short LSE-CD		Short LSE-TLG		Long SFA-CD		Long SFA-TLG		Long LSE-CD		Long LSE-TLG	
DNSP	Standard	Alternative	Standard*	Alternative	Standard	Alternative	Standard	Alternative	Standard	Alternative	Standard	Alternative	Standard	Alternative	Standard	Alternative
Evoenergy	50%	48%	46%	47%	45%	45%	44%	43%	47%	46%	54%	44%	48%	47%	43%	43%
Ausgrid	59%	58%	3%	58%	59%	59%	55%	61%	55%	54%	31%	59%	58%	57%	55%	60%
CitiPower	77%	70%	37%	77%	71%	71%	72%	71%	83%	76%	78%	77%	80%	78%	73%	74%
Endeavour Energy	69%	65%	14%	63%	65%	65%	68%	68%	65%	63%	49%	62%	66%	65%	66%	67%
Energex	68%	67%	8%	65%	66%	66%	63%	68%	66%	66%	45%	69%	69%	68%	67%	71%
Ergon Energy	60%	52%	83%	59%	59%	58%	69%	60%	56%	52%	74%	59%	56%	55%	58%	53%
Essential Energy	66%	64%	96%	80%	66%	68%	79%	75%	60%	61%	75%	69%	66%	66%	73%	71%
Jemena	66%	69%	33%	64%	66%	67%	52%	55%	69%	71%	76%	71%	73%	73%	57%	59%
Powercor	96%	95%	58%	95%	100%	100%	100%	100%	96%	97%	97%	95%	100%	100%	100%	100%
SA Power Networks	89%	88%	57%	91%	88%	88%	95%	92%	88%	90%	91%	93%	94%	93%	97%	96%
AusNet Dist	73%	78%	38%	75%	77%	77%	69%	73%	74%	78%	74%	76%	82%	82%	76%	78%
TasNetworks Dist	87%	79%	97%	74%	80%	82%	82%	78%	85%	81%	96%	72%	83%	82%	78%	75%
United Energy	92%	94%	19%	88%	92%	93%	72%	81%	94%	94%	81%	96%	94%	95%	75%	80%

*Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset. Note: * These results presented here reflect the estimates presented in the final column in Table 12 above rather than the original estimates presented by Quantonomics.*

313. For example, under the short sample SFA-TLG:

a Ausgrid's estimated efficiency increases from 3% to 58%;

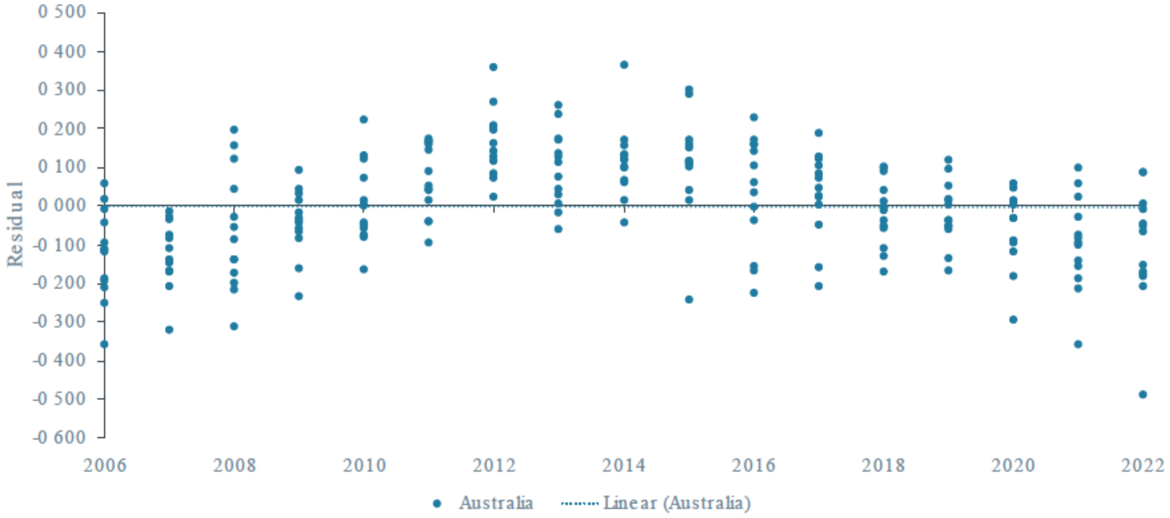
b Energex's estimated efficiency increases from 8% to 65%; and

c United Energy's estimated efficiency increases from 19% to 88%.

314. In every instance, the resulting efficiency estimates are more consistent with the efficiency estimates produced by the other models.

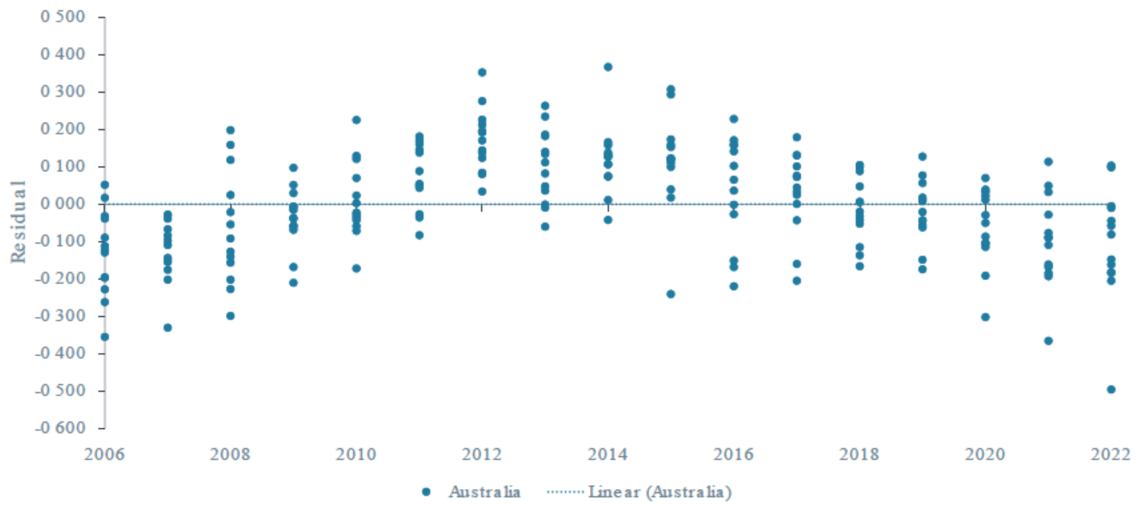
315. Analysis of the residual plots associated with the modified models, presented below in Figure 33 to Figure 36, illustrate that the residuals of Australian DNSPs no longer feature a time trend when differing time trends for New Zealand and Ontario DNSPs are allowed for.

Figure 33: Residuals for Australian DNSPs – SFA-CD model



Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 34: Residuals for Australian DNSPs – SFA-TLG model

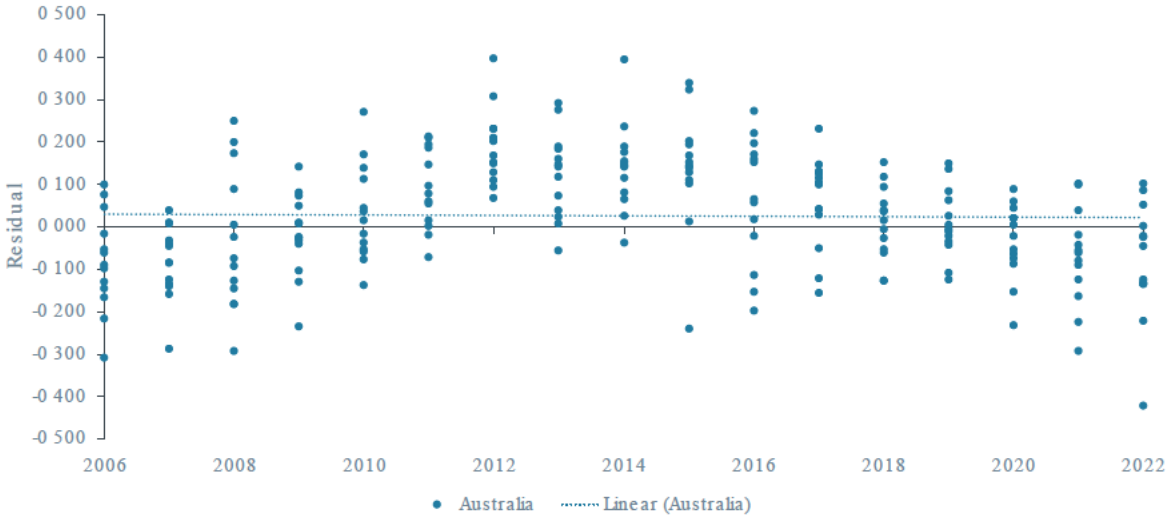


Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 35: Residuals for Australian DNSPs – LSE-CD model

Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Figure 36: Residuals for Australian DNSPs – LSE-TLG model



Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

316. Table 21 shows that allowing different time trends for the Australian, New Zealand and Ontarian DNSPs results in fewer of the short sample SFA-TLG models being excluded due to monotonicity violations.

Table 21: Effect of allowing jurisdiction-specific time trends on monotonicity violations

	Short SFA-CD		Short SFA-TLG		Short LSE-CD		Short LSE-TLG	
DNSP	Standard	TimeTrends	Standard	TimeTrends	Standard	TimeTrends	Standard	TimeTrends
Evoenergy	50%	48%	46%	47%	45%	45%	44%	43%
Ausgrid	59%	58%	3%	58%	59%	59%	55%	61%
CitiPower	77%	70%	37%	77%	71%	71%	72%	71%
Endeavour Energy	69%	65%	14%	63%	65%	65%	68%	68%
Energex	68%	67%	8%	65%	66%	66%	63%	68%
Ergon Energy	60%	52%	83%	59%	59%	58%	69%	60%
Essential Energy	66%	64%	96%	80%	66%	68%	79%	75%
Jemena	66%	69%	33%	64%	66%	67%	52%	55%
Powercor	96%	95%	58%	95%	100%	100%	100%	100%
SA Power Networks	89%	88%	57%	91%	88%	88%	95%	92%
AusNet Dist	73%	78%	38%	75%	77%	77%	69%	73%
TasNetworks Dist	87%	79%	97%	74%	80%	82%	82%	78%
United Energy	92%	94%	19%	88%	92%	93%	72%	81%

Source: Frontier Economics analysis of 2023 Draft Annual Benchmarking Report dataset

Note: Green indicates that the model is included due to satisfying the monotonicity requirement.

317. Again, we do not suggest that the AER should necessarily adopt the models specification presented above. The time trend term in the AER's models is intended to reflect an estimate of the rate of technical progress (i.e., frontier shift). However, it is likely that the estimated time trend in the modified model is capturing both the rate of frontier shift and catch-up efficiency achieved by the Australian DNSPs. If that is the case, the estimated time trend would not be suitable for rolling forward an estimate of efficient opex to the base year—since that would imply that DNSPs would need to achieve ongoing catch-up efficiency in addition to productivity improvements that reflect the shift in the efficient frontier over time.

318. Therefore, more work would need to be done to produce modified benchmarking model that disentangle the contributions of frontier shift and catch-up efficiency to the estimated time trend.

319. There are likely to be other issues that would need to be resolved before the modified model presented above could be considered for use to set regulatory allowances. The key point is that there is an imperative for the AER to give limited weight to the existing models, given the strong evidence that those models suffer from serious misspecification problems.

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