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Review of the AER’s Use of MPFP Modelling

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Introduction

As part of its periodic resets for Australia's Distribution Network Service Providers (DNSPs), the Australian Energy Regulator (AER) performs regular benchmarking analysis of companies' costs and outputs. To do so, it relies on an annual benchmarking report from its consultants Economic Insights (EI) (EI Benchmarking Report), the most recent of which was released to DNSPs on 25 August 2020.[1]

The AER is in the consultation phases of issuing a new reset for DNSPs in Victoria, and we understand that it will rely in part upon results from the 2020 EI Benchmarking Report in its final determinations.

In the EI Benchmarking Report, EI carries out several analyses, including econometric estimation of the operating expenditure (opex) cost function (cost function) and multilateral partial factor productivity (MPFP) modelling.

In the draft determinations for the DNSPs in Victoria, the AER uses results from the MPFP model to inform several components of DNSPs' opex allowance:

- The AER's appraisal of whether each company's base year opex is efficient is based in part on the results of MPFP benchmarking;
- The AER's determined output growth allowances depend in part on output weights derived from the MPFP model and
- The AER's determined productivity target draws on analysis from the MPFP model.

United Energy commissioned NERA to review the mechanics of, and the AER's reliance upon, the MPFP modelling in setting DNSPs' opex allowances.

We conclude that the MPFP modelling is based on a set of arbitrary assumptions and methodological choices. The resulting efficiency scores and output weights are therefore not a reasonable reflection of DNSPs' relative outputs, inputs and efficiency levels. Therefore, the AER can place no reliance upon the MPFP modelling in its opex assessment process. Instead, the AER should place greater reliance upon the econometric cost functions, which do not suffer from the same deficiencies.

Background of MPFP Modelling in Australia

Network Regulation in Australia

Since the National Electricity Rules (NER) were amended in 2008, the AER has been responsible for the economic regulation of electricity DNSPs of the National Electricity Market. As part of its role as the economic regulator, the AER carries out periodic price resets, where reviews DNSPs' proposed expenditure and chooses either to accept a DNSP's proposal or replace it with its own determination.

[1] Economic Insights (25 August 2020), Econometric Benchmarking Results for the Australian Energy Regulator's 2020 DNSP Annual Benchmarking Report.

In making a price determination, the National Electricity Law (NEL) stipulates that the AER "must take into account the revenue and pricing principles"[2], which themselves stipulate that a DNSP "should be provided with a reasonable opportunity to recover at least the efficient costs the operator incurs in" in providing distribution services.[3]

The NER sets out a more detailed framework for how the AER should assess DNSPs' proposals, and stipulates that the AER must accept a company's opex proposal if it is satisfied that it reasonably reflects the efficient costs of providing distribution services. If it is not satisfied that the company's proposal reasonably reflects the efficient costs of providing distribution services, the AER must replace the DNSP's proposal with its own determination.[4]

In determining whether it is satisfied with a DNSP's proposal, it must have regard to, among other factors, the annual AER Benchmarking Report.[5] The AER Benchmarking Report draws heavily on the results from the EI Benchmarking Report.

From these statutory obligations, it is clear that the analyses that the AER relies upon should themselves reflect the efficient costs of providing distribution services. If they do not, then the AER may fail to accept a proposal that reflects the efficient costs of providing distribution services, and substitute it with a determination that does not reflect efficient costs. This would be a violation of the NER.

If the AER does fail to accept a proposal that reflects efficient costs and replaces it with a determination that does not, then the affected DNSPs will not have "a reasonable opportunity to recover at least the efficient costs" of providing distribution services.[6] This would be a violation of the NEL.

We appraise the MPFP model and the AER's uses of it against the criterion that it is likely to reflect efficient operating costs. We find that it does not. Although no component of DNSPs' opex allowances are derived exclusively from the MPFP model, it dilutes the reliance upon models that are more likely to reflect efficient costs. In the best-case scenario, the MPFP modelling produces results similar to other techniques, in which case it does not add any new information.

Technical Description of MPFP Modelling

EI calculates MPFP efficiency scores as follows:

First, EI calculates output weights based on a Leontief regression technique, which explains opex, overhead lines (OHL), underground cables (UG) and transformers as a function of four output variables: Energy Throughput (Energy), Ratcheted Maximum Demand (RM Demand), Customer Numbers (Customers) and Network Length (Length), as well as time. It estimates 52 separate regressions: 4 input variables times 13 DNSPs. The regression model used is:

2 National Electricity (South Australia), Act 1996, Schedule – National Electricity Law, Section 16(2).

3 National Electricity (South Australia) Act 1996, Schedule – National Electricity Law, Section 7A(2).

4 National Electricity Rules, v150, clause 6.5.6(c)-(e).

5 National Electricity Rules, v150, clause 12.1(4).

6 National Electricity (South Australia) Act 1996, Schedule – National Electricity Law, Section 7A(2).

$$x_{ift} = (1 + b_{if}t)[a_{if1}^2 y_{1ft} + a_{if2}^2 y_{2ft} + a_{if3}^2 y_{3ft} + a_{if4}^2 y_{4ft}]$$

where i indexes the input (one per regression); f indexes the firm (one per regression); and t indexes time (13 years). The level of the input at time t is x_{ift} and the level of output 1 at time t is y_{1ft} (outputs 2-4 are analogous). The output coefficients are a_{if1}^2 through a_{if4}^2, which capture the contribution of the relevant output to input demand (the model forces the coefficient to be positive by requiring it to be a square). The time coefficient b_{if} captures how the relationship between the input and output changes over time.

The contribution of each output to explaining each input for each output is then aggregated across the 52 models to give a single set of output weights. The MTFP output weights from the 2020 EI Report are in Table 1 below:[7]

Table 1: MTFP Output Weights

	Energy	RM Demand	Customers	Length
MTFP	8.58%	33.76%	18.52%	39.14%

Source: EI[8]

These output weights then define an output index for each company in each year. EI then divides the output index by each company's opex. The resulting ratio in each year is the company's opex MPFP score.

EI calculates the multi-year (2006-19) comparative efficiency of companies in this model by calculating each company's average MPFP score as a proportion of that of the top performing DNSP.

Recent Developments in the AER's MPFP Modelling

As first introduced in 2014, the MPFP model had few uses. The AER used the multi-year benchmarking results as one piece of evidence in deciding whether to accept a company's base year opex proposal, but did not use it for any other purpose.

Since its introduction in 2014, the AER has placed increasing weight on MPFP modelling in the overall price reset process, without presenting any evidence that it is suitable for its increased role.

First, the AER now places more emphasis on the MPFP model when assessing a DNSP's efficiency, relying not only on the company's relative performance over an extended period of time, but also assessing efficiency on an individual year basis. Second, the MTFP output weights feed directly into the output growth allowance, along with weights derived from the cost functions. Finally, the AER relies in part on MPFP analysis to inform a productivity target of 0.5 per cent per year.

7 These weights are used for other components of Multilateral Total Factor Productivity (MTFP) modelling, so we refer to them as MTFP weights.

8 Economic Insights (25 August 2020), Econometric Benchmarking Results for the Australian Energy Regulator's 2020 DNSP Annual Benchmarking Report, p.3.

As a result of the AER's recent increasing reliance on the MPFP modelling as described above, the models have been subject to greater scrutiny from DNSPs and their advisors, and EI has responded in turn.

In December 2018, we wrote a report criticising the introduction of the MTFP weights into the output growth allowance. We argued that the econometric techniques underpinning the calculation of the weights were unreliable and produced weights which were highly arbitrary.[9]

In early 2019, EI responded in the form of a memo to the AER. It responded to and attempted to rebut each of our criticisms.[10] As we demonstrate throughout this report, its response failed to adequately defend its modelling techniques.

In December 2019, Frontier Economics reviewed both our report and EI's response, and concluded that the Leontief econometric model had statistical problems "so severe that they cannot be overcome by taking weighted averages".[11] Frontier also identified a coding error in EI's econometric models.

In April 2020, EI responded to Frontier's criticisms, and corrected its coding error. It argued that in correcting its coding error, it had removed the statistical problems with the Leontief regression and could therefore continue relying upon it. This is not the case. [12]

Appraisal of MPFP Modelling

In this section, we review the mechanics of the MPFP modelling. We find that, due to numerous statistical failings and other methodological shortcomings, the AER's use of it is unlikely to reflect the efficient costs of providing distribution services. Therefore, in relying upon it, the AER violates its obligations under the NEL and the NER.

Assessment of the Leontief Econometric Models

We first assess the Leontief econometric equations which estimate the relationship between outputs (the independent variable) and each of four inputs (the dependent variables), across four inputs and 13 DNSPs. Even when correcting for the coding error described above, there are numerous technical problems with this econometric specification, such that the coefficients and resulting output weights are effectively meaningless.

1. We have not been able to identify any use of this econometric specification other than by EI or its affiliates (i.e. Dr Denis Lawrence and entities associated with him), and EI has not cited any. In combination with the substantial statistical problems we identify (see below), this suggests that they have not been properly validated and subject to rigorous peer review.

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9 NERA (18 December 2018), Review of AER's Proposed Output Weightings – Prepared for CitiPower, Powercor, United Energy and SA Power Networks.

10 Economic Insights (30 April 2019), Review of NERA report on output weights.

11 Frontier Economics (5 December 2019), Review of Econometric Models Used by the AER to Estimate Output Growth – A report prepared for CitiPower, Powercor and United Energy, p.1-2.

12 Economic Insights (18 May 2020), Review of reports submitted by CitiPower, Powercor and United Energy on opex input price and output weights, p.17.

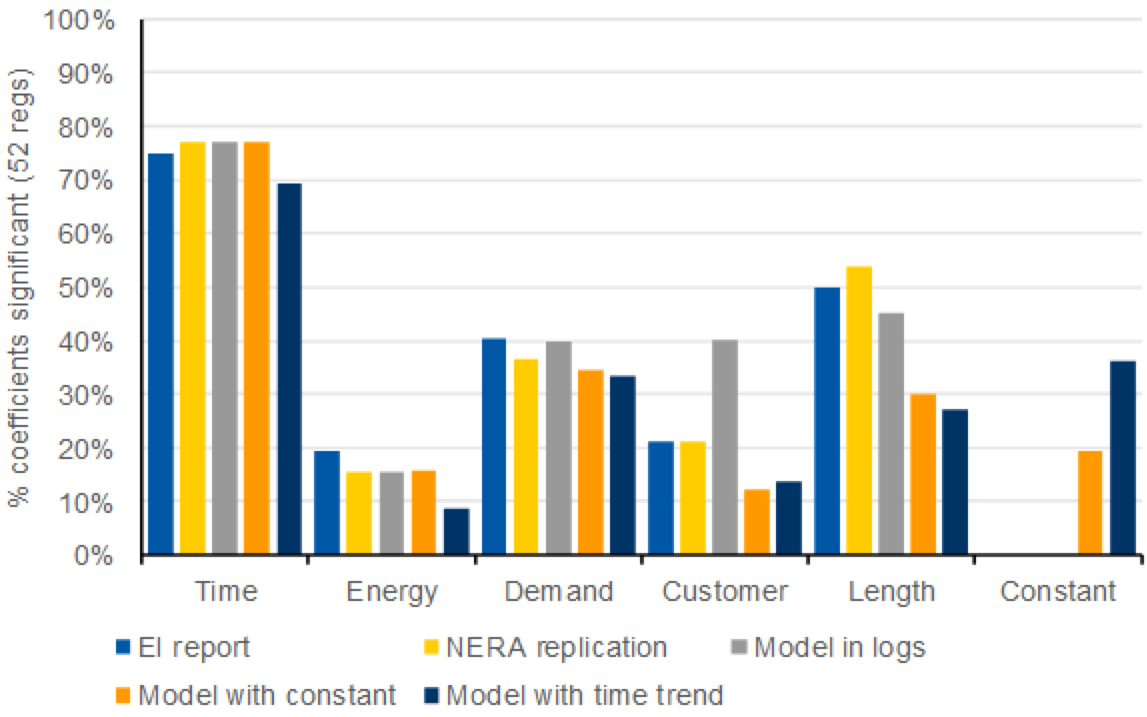
2. The Leontief model specification does not have a constant. Because all outputs and inputs are substantially larger than zero relative to their level of variation, this specification guarantees that at least one output coefficient will be statistically significant, or that multiple will be jointly significant if no single coefficient is individually significant. This is true even if there is no relationship between any of the output variables and the input variable in question, or if there is insufficient data to estimate that relationship.
3. Time enters into the specification as a multiplicative rather than additive term. This is non-standard and illogical. First, the estimated coefficients on time and outputs depend on whether time is counted from 0 to 12 or from 2006 to 2013 (or indeed any other range), which has no intuitive explanation. Second, the coefficients on outputs are biased, because the model fails to capture additional effects of time which do not relate to the levels of the outputs.
4. There is very little evidence that the true values of any or all coefficients are not zero (meaning they should have zero output weights). It is standard in econometrics to assess whether regression coefficients are significantly different from zero. By EI's own calculations, 66 per cent of the coefficients EI estimates are not significant. Additionally, EI uses an overly generous evaluation of significance, which ignores the fact that, when assessing many coefficients, some of them will appear significant simply by chance. Using a more appropriate evaluation we find that 80 per cent of coefficients are not significant. Additionally, of those that are, it is not possible to say whether they are significant because they drive costs, or because they act as a proxy for the omitted constant term.

We estimate the sensitivity of the coefficients to the following changes in this specification:

- We introduce a constant term;
- We introduce a linear rather than multiplicative time trend;
- We re-specify the input and output variables as natural logarithms, consistent with the specification of the cost functions, as well as econometric benchmarking models worldwide;
- We pool together the data across the 13 DNSPs and run four panel fixed effects models, which estimates the effect of each output on the relevant input across all 13 companies simultaneously.

In Figure 1 below, we show how the percentage of statistically significant coefficients on each output changes under the different specifications, excluding the panel fixed effects model because each variable only appears four rather than 52 times.

Figure 1: Fewer coefficients are significant using alternative model specifications



Source: NERA analysis

As the figure shows, most outputs are less likely to be statistically significant in each of the sensitivities we test, with Customers and Length appearing to be especially sensitive to the specification.

We do not advocate for any one of the alternative regression models that we try, as they are all variants on an econometric specification that is deeply flawed. Rather, these sensitivities demonstrate that the approach is sensitive to the underlying regression specification, and there is no reason to use EI's particular variant over any of those that we consider. Thus, it is not reasonable to use them as the basis for MPFP calculations.

Process of Combining Coefficients into Output Weights

The model weights vary counterintuitively between companies

The process of combining coefficients into output weights involves aggregating the contribution of each output to the fitted level of each input variable across the 52 regressions. We present the contribution of each variable to the fitted value of each input this in Table 2 below, separated by input and DNSP.

Table 2: Contribution of Outputs to Inputs

Input: Opex	Energy	RM Demand	Customers	Length
ACT	0%	8%	0%	93%
AGD	0%	100%	0%	0%
AND	0%	100%	0%	0%
CIT	100%	0%	0%	0%
END	90%	0%	0%	11%
ENX	0%	100%	0%	0%
ERG	0%	10%	0%	90%
ESS	0%	0%	100%	0%
JEN	0%	0%	100%	0%
PCR	0%	11%	0%	89%
SAP	0%	100%	0%	0%
TND	100%	0%	0%	0%
UED	94%	6%	0%	0%

Input: Overhead Lines	Energy	RM Demand	Customers	Length
ACT	0%	82%	0%	19%
AGD	0%	0%	0%	100%
AND	0%	1%	0%	99%
CIT	0%	0%	21%	79%
END	0%	29%	0%	71%
ENX	0%	4%	0%	96%
ERG	0%	25%	0%	75%
ESS	24%	0%	0%	76%
JEN	0%	3%	28%	69%
PCR	0%	0%	62%	38%
SAP	11%	0%	17%	72%
TND	19%	0%	0%	81%
UED	0%	12%	88%	0%

Input: Underground Cables	Energy	RM Demand	Customers	Length
ACT	0%	36%	0%	64%
AGD	0%	0%	0%	100%
AND	0%	0%	100%	0%
CIT	13%	0%	0%	87%
END	0%	0%	0%	100%
ENX	0%	100%	0%	0%
ERG	0%	100%	0%	0%
ESS	0%	61%	0%	39%
JEN	0%	0%	0%	100%
PCR	0%	87%	13%	0%
SAP	0%	29%	0%	71%
TND	0%	0%	32%	68%
UED	0%	16%	40%	44%

Input: Transformers				
	Energy	RM Demand	Customers	Length
ACT	20%	0%	0%	80%
AGD	0%	100%	0%	0%
AND	0%	58%	31%	11%
CIT	51%	4%	0%	46%
END	0%	10%	0%	91%
ENX	0%	38%	0%	62%
ERG	0%	0%	100%	0%
ESS	0%	0%	100%	0%
JEN	0%	20%	0%	80%
PCR	0%	8%	0%	92%
SAP	28%	10%	0%	62%
TND	0%	0%	100%	0%
UED	0%	29%	71%	0%

Source: NERA analysis

The contribution of each output to the fitted level varies substantially and counterintuitively across the 52 regressions.

The opex regressions suggest that all companies have a single primary driver of opex, but it appears effectively random what that driver is. That each company has a different driver of opex according to EI's analysis undermines the basis for estimating a single cost-function and common set of output weights in the first place: EI's evidence suggests that the companies have different drivers of costs and entirely different output weights.

If the OHL and UG regressions have some basis in actual cost relationships, they should be driven primarily by Length with a secondary contribution from RM Demand, since the dependent variable is measured in MVAkm, effectively a linear combination of length and capacity. However, while the OHL regressions are mostly primarily driven by Length, not all of them are, and RM Demand is no more important as a secondary driver than the other two outputs. The UG regressions are even less closely driven by Length and RM Demand – Length is the primary driver in only 7 of 13 models, and a secondary driver in 2 others.

EI argues that it "minimise[s] the risks associated with the limited degrees of freedom per regression and the fixed propositions nature of the Leontief cost function [by taking] a weighted average of the derived output cost shares across all the Australian DNSP observations".[13] However, this relies on an assumption that the probability that the model will assign a high weight to a particular output variable is equal to that output's importance in driving costs. As we demonstrate above, this is unlikely to be the case.

Arbitrary weight is placed on the OHL, UG and Transformer models

It is unclear why the capital input models (OHL, UG and Transformers) are even relevant to determining opex MPFP outputs, and EI provides no explanation as such. These output weights are used to define aggregate output, which is used to assess MPFP and MTFP across all inputs, including capital inputs such as lines and transformers.

[13] Economic Insights (30 April 2019), Review of NERA Report on Output Weights, p.6.

Our analysis shows that opex has a weight of only 36.9 per cent in the construction of the weights. As a result, opex productivity scores are set on the basis of output weights that are more than half determined by outputs' effect on non-opex inputs. Therefore, the AER fails to identify the drivers of efficient *opex*, which would require (at a minimum) an assessment of how outputs are related to opex. This would also be consistent with the cost function models, which only estimate opex as the dependent variable.

However, weights derived from just the opex Leontief regressions alone are not themselves reliable. Their calculation is still subject to all of the flaws associated with the econometric regression.

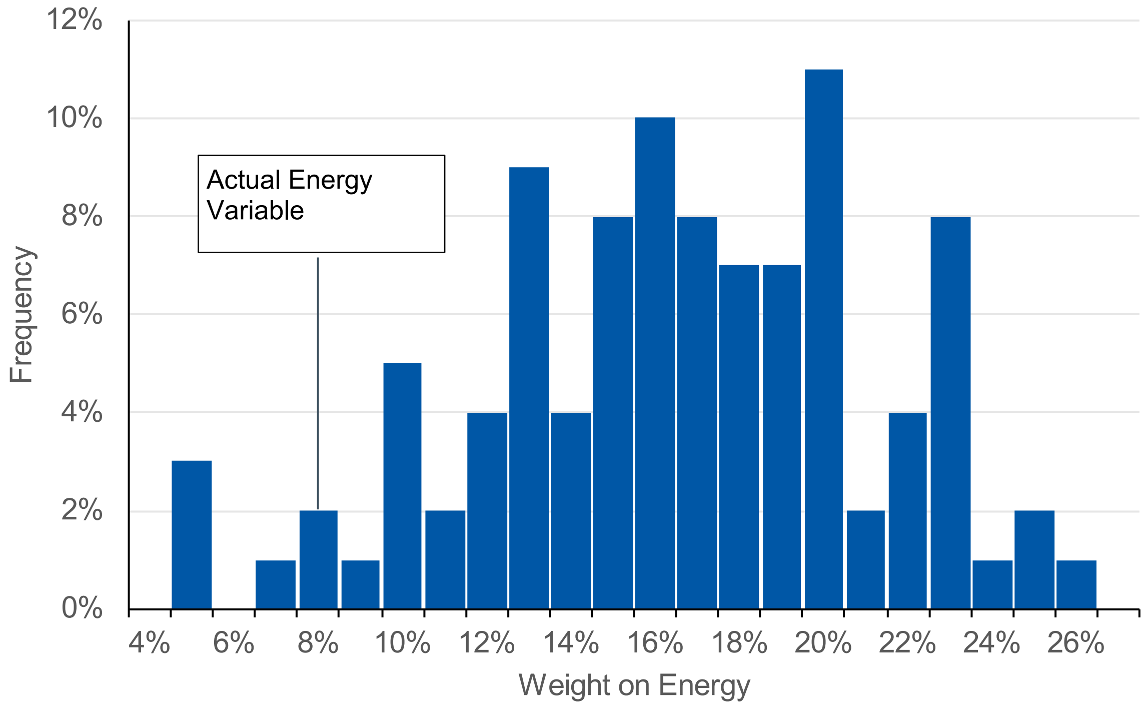
EI's approach gives weight to meaningless variables

By using squared coefficients, the EI Leontief model forces the output coefficients in each regression to be non-negative. In averaging across 52 regressions, as long as a variable receives a positive coefficient at least once, then it will receive a strictly positive weight in the final MTFP weights.

Due to the imprecision with which the model is estimated, with an illogical specification and very little data, it is incorrect to assume that a variable with a non-existent relationship would always receive a coefficient of zero. Even in a properly-specified regression equation with sufficient degrees of freedom, we would expect a meaningless variable to have a statistically significant coefficient about 5 per cent of the time, or two to three times out of 52 regressions.

We demonstrate that EI's method attributes positive weight to meaningless series by removing the Energy variable as reported by companies and replacing it with a random number generated based on the mean and standard deviation of each company's actual Energy value. In effect, this randomly generated variable resembles each company's energy variable in level and distribution but without any relation to cost in each year because random variations in it could not possibly explain variations in cost. We replicate this analysis 100 times and report weights resulting from each simulation in Figure 2 below.

Figure 2: Weight Assigned to Random Energy Variable



Source: NERA analysis

As the figure shows, the output weight assigned to this random variable is larger than the weight assigned to the actual Energy in 95 per cent of cases, even though it clearly bears no relation to variations in cost. This suggests that Energy is no stronger a driver of cost than a random number with a similar average level.

A similar story emerges if we remove Energy as a driver in the 52 regressions and replace it with a variable that we know to be spurious. We have done this using the following data series in place of Energy: (i) Annual flights to and from Melbourne Airport; (ii) The exchange rate between British Pounds Sterling and New Zealand Dollars (expressed as GBP per NZD);(iii) The number of girls born in the Republic of Ireland each year named Zoe. This variable receives 19 per cent weight; and (iv) Energy delivered by a different DNSP. In (i)-(iii), the spurious variable receives higher weight than the company's Energy variable. In 7 of 12 degrees of offset (i.e. Degree 1 is AGD's Energy explaining ACT's costs; Degree 2 is AND's Energy explaining ACT's costs, etc), the other company's Energy variable receives higher weight than the same company's Energy variable.

With ample time and computational resources, it is possible to data-mine any number of spurious relationships in any context. We have carried out no such exercise in this case. In fact, our analysis demonstrates that virtually any spurious variable will receive a positive weight, so long as it is positive and exhibits similar levels of variation around its mean as the MTFP input variables. The restrictive econometric specification (i.e. forced non-negative coefficients and no constant) means that variables with negative values or large variation relative to its mean are unlikely to receive positive coefficients and, hence, MTFP weights.

In fact, all of the spurious data series above (including the randomly-generated Energy variables above) have one key feature in common: they all exhibit similar levels of variation relative to their mean levels. Due to the restrictions of the econometric specification (non-negative coefficients and no constant), most regressions only have one variable with only one non-zero output coefficients. Therefore, a variable with any negative values or with large variation relative to its mean would be very unlikely to explain opex or the capital inputs, which exhibit relatively little variation relative to their means in each year.

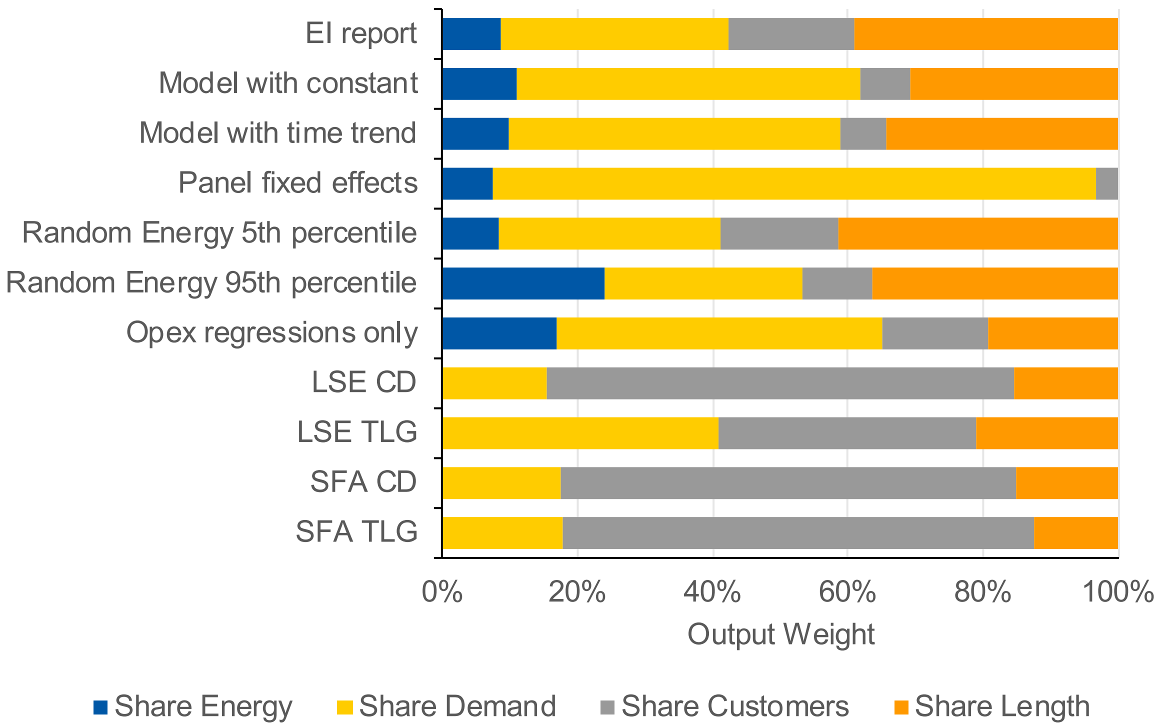
The same is not true in a less restrictive specification: an independent variable's negative values could be captured by a negative coefficient and a volatile variable to could receive a smaller coefficient plus a positive constant. Our analysis demonstrates that, once we have accounted for the restrictive econometric specification, it is very easy to find variables that apparently drive MTFP inputs.

In short, the flaws of the econometric specification coupled with the small sample sizes means that the finding of a positive econometric relationship does not suggest a positive causal relationship, even if it is statistically significant. Because the approach places excessive weight on meaningless variables, and weights must sum to 100 per cent, EI's approach also assigns insufficient weight to meaningful variables.

Different econometric specifications yield different output weights

The weights allocated to each of the four outputs depend on the regression specification used. In Figure 3, we demonstrate the sensitivity of the ultimate weights to each of the alternative econometric specifications discussed above, as well as the 5th and 95th percentile iterations (in terms of weight on Energy) from the Random Energy simulation above. We also show the weights from the cost functions for comparison.

Figure 3: Output weights vary with regression specifications



Source: NERA analysis

The sensitivity of the output weights to the regression specification is clear. The output weight allocated to energy is halved when moving from the EI model to the panel fixed effects model. The weight allocated to customer numbers shrinks to less than a third of its previous value in all alternative specifications. In the EI model, circuit length is the greatest contributor to output costs; in all alternative specifications, demand is the greatest contributor.

Overall, this analysis illustrates that the output weights derived from the Leontief regressions are not reliable because they are volatile and precarious to changes in model specification. Alternative, more plausible specifications of the regressions yield very different weights.

In short, we conclude that the weights that actually come out of the Leontief specification are effectively random. EI could select four weights at random and not be further from the truth than it is under these output weights.

Implications of Output Weight Calculations

The MPFP model has three direct uses in the opex assessment process: (1) the AER uses it to assess whether a DNSP's base year opex is efficient; (2) the AER bases the output growth allowance in part on the MTFP weights; and (3) the AER applies a productivity adjustment derived in part from MPFP analysis.

Each of these uses is sensitive to the choice of output weights. Hence, the use of the MPFP model reduces the likelihood that the AER correctly identifies a DNSP's efficient opex. Therefore, its use runs contrary to the NEL and the NER.

First, in Table 3 below, we demonstrate how each company's rank in the MPFP benchmarking assessment changes with different weights, when measured over 2006-2019.

Table 3: MPFP Efficiency Ranks Under Alternative Weights

	EI Weights	Model w Cons.	Model w Time Trend	Panel Fixed Effects	Random Energy (5th)	Random Energy (95th)	Opex Models Only	Cost Function Avg
ACT	12	12	12	10	12	12	9	10
AGD	13	13	13	11	13	13	11	11
AND	6	8	9	9	7	10	10	9
CIT	3	1	2	1	3	3	1	1
END	10	6	5	8	10	6	6	8
ENX	8	7	7	6	8	5	7	6
ERG	9	9	8	13	6	9	12	13
ESS	5	10	10	12	5	8	13	12
JEN	11	11	11	5	11	11	8	5
PCR	1	2	1	3	1	1	2	3
SAP	2	3	3	4	2	2	3	4
TND	4	4	4	7	4	4	5	7
UED	7	5	6	2	9	7	4	2

Source: NERA analysis

While the differences are unlikely to change the AER's conclusions about the relative efficiency of the most and least efficient DNSPs – CIT, PCR and SAP are among the top four, while ACT and AGD are in the bottom four, regardless of output weights – the rankings could influence the AER's conclusions on the efficiency for companies in the middle.

For instance, under different weights, ERG's rank varies from 6^{th} to 13^{th}, ESS's rank varies from 5^{th} to 12^{th}, JEN's rank varies from 5^{th} to 11^{th}, and UED's rank varies from 2^{nd} to 9^{th}. When considering whether a DNSP is among the top performing firms, these dramatically different rankings could plausibly be the difference between the AER deciding to accept the company's opex proposal and not.

Second, different MTFP output weights would yield different overall output weights for the output growth allowance. We show these in Table 4 below, which already take into account the weights derived from the cost functions.

Table 4: Average Output Weights Under Different MPFP Approaches

Model	Energy	RM Demand	Customers	Length
EI report	1.72%	25.11%	52.52%	20.66%
w/ constant	2.17%	28.55%	50.29%	18.98%
w/ time trend	1.99%	28.13%	50.19%	19.69%
Fixed Effects	1.48%	36.18%	49.50%	12.83%
Rand. Energy (5^{th})	1.66%	24.93%	52.30%	21.11%
Rand. Energy (95^{th})	4.79%	24.21%	50.86%	20.14%
Opex Models Only	3.37%	27.98%	51.94%	16.70%
Cost Function Avg	0.00%	22.94%	61.02%	16.04%

Source: NERA analysis

The differences in the average output weights compound annually. Assuming that each company's outputs grow at the same rate they did between 2015 and 2019, each DNSP's total opex allowance varies by 0.6-1.3 per cent by the end of a hypothetical five-year reset.

Given EI's method for estimating them, the output weights selected by EI are arbitrary, and bear little resemblance to the true drivers of opex: even if the econometric specification were robust, the weights primarily capture the effect of outputs on OHL, UG and Transformers rather than opex. Therefore, variation in companies' opex allowances due to variation in these output weights is unlikely to reflect variations in efficient costs.

Third, the choice of MTFP weights has a material impact on the AER's appraisal of long-term productivity trends of the top four most efficient companies. The long-term average MPFP growth amongst these firms varies by 0.66-0.67 per cent, simply as a result of the choice of weights. However, this is only one of several pieces of evidence on which the AER holistically relied to set a productivity target, so it is not possible to say whether the AER would have reached a different conclusion with different weights.

Cost Functions in Place of MPFP Models

As we describe throughout this report, the MPFP modelling is part of the AER and EI's toolkit, and has become increasingly so in the last two to three years. We therefore understand that it represents a methodological shift to discontinue its use, and that the AER may be hesitant to do so if it were to sacrifice analysis and evidence that it could appraise by no other means.

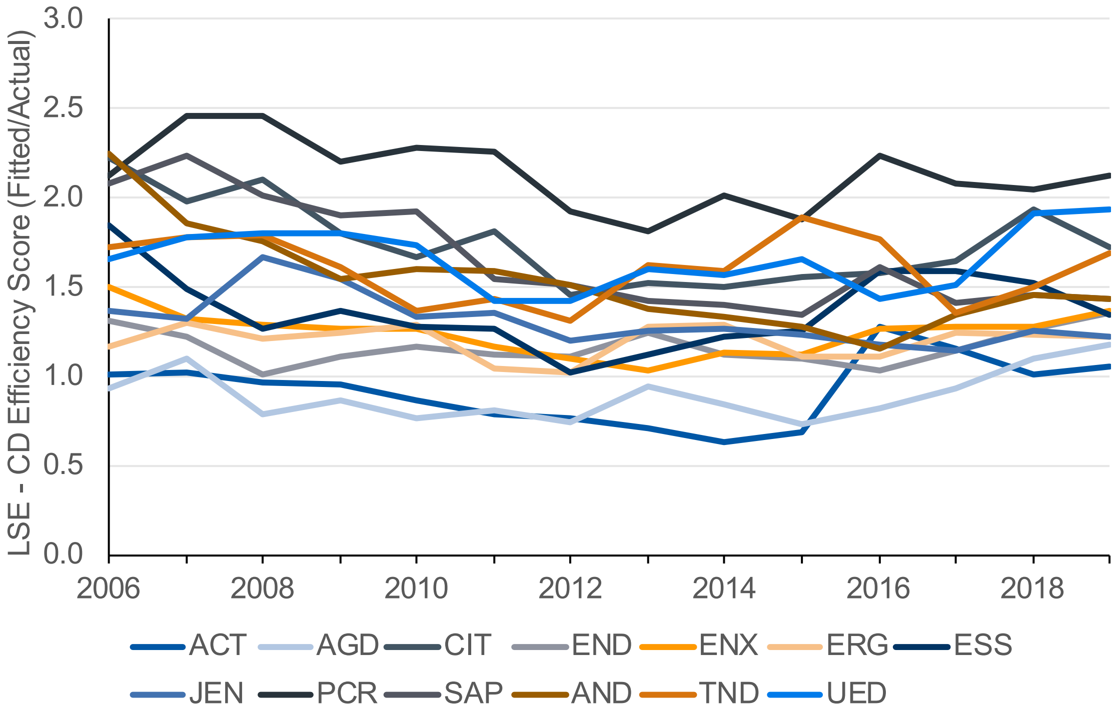
However, the existing cost functions can be used in place of the MPFP model for each of the AER's uses of it. Indeed, relying on its cost functions and eliminating the MPFP model (at least as currently conducted) would improve the rigour of the AER's determinations by eliminating essentially meaningless and arbitrary analysis.

First, the AER uses the MPFP model as one of five benchmarking techniques to assess the efficiency of DNSPs' opex over an extended historical window (e.g. 2006 to 2018 or 2012 to 2018). The AER could place more emphasis on its other efficiency assessment approaches by omitting the MPFP analysis from this part of the assessment.

Second, the AER uses the MPFP model to assess companies' year-on-year changes in efficiency. Whilst EI has not set up the cost function models to present this level of detail, it is simple to do so in the form of a ratio of fitted opex to actual opex.

To demonstrate, we carry out this analysis of the cost functions. Figure 4 shows the annual efficiency scores from LSE-CD model – we show the equivalents for the other three cost models in the body of this report.

Figure 4: Annual Efficiency Scores - LSE CD

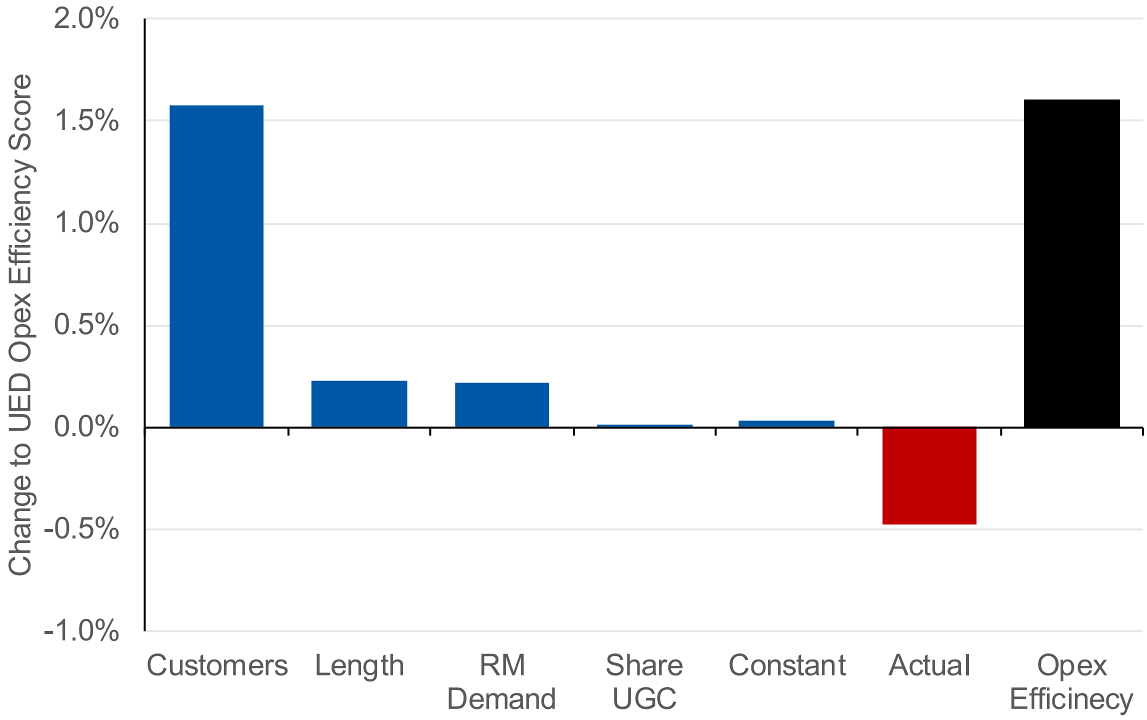


Source: NERA analysis

In these figures, we can see each firm's efficiency relative to its peers on an annual basis, and also relative to itself in previous years.

The data can also be modified to decompose the drivers of change to a company's opex efficiency from one year to the next. We demonstrate this in Figure 5 below, which decomposes changes to UED's LSE-CD efficiency score from 2018-19 due to changes in output drivers and actual opex.

Figure 5: UED 2018-19 Changes in Opex Efficiency



Source: NERA analysis

Other uses of the MPFP model are even simpler to adapt to the cost functions:

- *Output growth weights*: The AER could simply remove the MTFP weights from this calculation and place 25 per cent weight on the weights from each of the cost functions.
- *Productivity:* The AER could simply place greater consideration on the other pieces of evidence and ignore the results of the MPFP model.

Conclusions

We have carried out a thorough review of EI's Leontief modelling, the MPFP modelling based upon it, and the AER's use of various components of EI's outputs. We find that EI's method for deriving output weights is arbitrary, poorly justified, and highly likely to result in weights that are unrelated to drivers of efficient opex.

The AER's conclusions from its uses of the MPFP modelling are highly sensitive to the choice of output weights. Therefore, the AER's price control parameters which rely upon MPFP modelling are unlikely to reasonably reflect the efficient cost of providing distribution services, as is stipulated by the NER, or to allow companies a reasonable opportunity to recover efficient costs, as stipulated by the NEL. Moreover, by using MPFP modelling as a supplement to other forms of modelling, the AER reduces weight on modelling techniques which may reflect the efficient costs of providing distribution services, and the final price control parameters are less likely to satisfy the opex criteria.

Therefore, the AER fails to satisfy the opex criteria of the NER as well as the RRP in the NEL by relying in part on the MPFP model. The AER could better satisfy the opex criteria by placing no reliance on the MPFP model.

1. Introduction

As part of its periodic resets for Australia's Distribution Network Service Providers (DNSPs), the Australian Energy Regulator (AER) performs regular benchmarking analysis of companies' costs and outputs. To do so, it relies on an annual benchmarking report from its consultants Economic Insights (EI) (EI Benchmarking Report).

In the EI Benchmarking Report, EI carries out several analyses, including econometric operating expenditure (opex) cost function benchmarking (cost function) and multilateral partial factor productivity (MPFP) modelling.

Each DNSP's price control period lasts for five years, but timings of each control period are staggered by state. In Victoria, for instance, the next price control period is scheduled to run from 1 July 2021 to 30 June 2026. In forming its final determination for the Victorian DNSPs, we understand that the AER will rely on the results of the most recent EI Benchmarking Report, dated 25 August 2020, which has been provided to us by United Energy.[14]

In keeping with its past use of the results of the MPFP modelling, we anticipate that the AER is minded to use MPFP modelling for three purposes in the draft determination:

- Each company's productivity level as measured by the MPFP model feeds into the AER's overall assessment of DNSPs' "base year" opex efficiency, alongside the opex benchmarking models;
- The MPFP model relies on "output weights" as derived from a set of Leontief models to define a composite level of outputs. The AER uses these weights to estimate the "trend" in DNSPs' opex resulting from changes in DNSPs' outputs within each reset period; and
- The average change in industry-wide MPFP is one piece of evidence which the AER has relied upon recently to set a target for ongoing productivity growth and therefore to set the trend in efficient opex within each reset period.

We have been commissioned by United Energy to review the mechanics of, and the AER's reliance upon, the MPFP modelling in setting DNSPs' opex allowances.

This report proceeds as follows:

- In Chapter 2, we set out the factual background to the remainder of the report, including a discussion of the AER's statutory obligations, a technical description of the MPFP modelling and a detailed description of the AER's reliance upon it.
- In Chapter 3, we analyse each step of the MPFP modelling process, and appraise the AER's reliance upon it against its statutory obligations.
- In Chapter 4, we describe how the AER could use other modelling techniques for the same purposes that the AER currently uses the MPFP modelling.
- In Chapter 5, we conclude.

[14] Economic Insights (25 August 2020), Econometric Benchmarking Results for the Australian Energy Regulator's 2020 DNSP Annual Benchmarking Report.

Overall, we find that the MPFP modelling is based on a set of arbitrary assumptions and methodological choices. The resulting efficiency scores and output weights are therefore not a reasonable reflection of DNSPs' relative outputs, inputs and efficiency levels. Therefore, we recommend that the AER place no reliance upon the MPFP modelling in its opex assessment process. Instead, the AER should place greater reliance upon the econometric cost functions, which do not suffer from the same deficiencies.

2. Background of MPFP Modelling in Australia

As part of its suite of econometric models and benchmarking techniques, the AER has relied upon MPFP modelling carried out by EI since 2014. EI first carried out an assessment of DNSPs' relative efficiency as part of the 2014-19 price control decisions for DNSPs in New South Wales and ACT.[15] Since 2017, EI has updated its analysis annually, with the 2020 EI Benchmarking report released in August 2020.

Based primarily on the EI report, the AER also releases an annual benchmarking report (AER Benchmarking Report), with the most recent version released in November 2019.[16] We understand that the 2020 version of the AER Benchmarking Report, based on the 2020 EI Benchmarking Report, will be released in November 2020. We also understand that the 2020 version of the AER Benchmarking Report will inform the final determinations for the DNSPs in Victoria.

In this chapter, we set out the factual background to the use of MPFP modelling in Australia. In particular, we cover the following:

- In Section 2.1, we provide a brief overview of electricity network regulation in Australia, including a discussion of the role and duties of the AER in regulating the electricity DNSPs;
- In Section 2.2, we describe the uses of EI's MPFP modelling as part of the price control process;
- In Section 2.3, we set out the mechanics of the MPFP modelling, from the calculation of output weights to calculation of final price control parameters; and
- In Section 2.4, we discuss recent developments in the use of MPFP modelling, including an ongoing methodological debate between NERA, EI and Frontier Economics.
- In Section 2.5, we summarise and conclude.

2.1. Network Regulation in Australia

2.1.1. The role and responsibilities of the AER in regulating electricity networks are set out in the NEL and the NER

The AER has been responsible for the economic regulation of electricity DNSPs of the National Electricity Market (NEM) – i.e. all of Australia except Northern Territory and Western Australia – since 1 January 2008, when the National Electricity Rules (NER) were amended to give that responsibility to the AER in place of jurisdictional regulators.[17]

[15] Economic Insights (17 November 2014), Economic Benchmarking Assessment of Operating Expenditure for NSW and ACT Electricity DNSPs.

[16] AER (November 2019), Annual Benchmarking Report – Electricity distribution network service providers.

[17] National Electricity Rules, v18, clause 6.1.1.

The NER is itself granted force of law by the National Electricity Law (NEL).[18] The NEL and the NER together guide the AER's regulation of electricity DNSPs, and set out the functions, responsibilities and powers of the AER.

As we demonstrate in Chapter 3, the continued reliance upon the MPFP models does not comply with the AER's responsibilities set out in the NEL and the NER the models do not capture DNSPs' efficient costs or changes to DNSPs' efficient costs. Therefore, in relying upon these models, the AER makes it *less* likely that a company will have an opportunity to recover its efficient costs, which is not compliant with the AER's responsibilities in the NEL or the NER.

2.1.1.1. The National Electricity Law defines the principles of network regulation

The goal of the NEL, set out in the National Electricity Objective, is:

> "… to promote efficient investment in, and efficient operation and use of, electricity services for the long term interests of consumers of electricity with respect to—
>
> (a) price, quality, safety, reliability and security of supply of electricity; and
>
> (b) the reliability, safety and security of the national electricity system."[19]

The Revenue and Pricing Principles (RPP) of the NEL further stipulate that a network service provider "should be provided with a reasonable opportunity to recover at least the efficient costs the operator incurs in (a) providing direct control network services; and (b) complying with a regulatory obligation or requirement or making a regulatory payment".[20]

According to the NEL, when performing a regulatory function or power, the "AER must […] perform or exercise that function or power in a manner that will or is likely to contribute to the achievement of the national electricity objective".[21] Furthermore, the AER "must take into account the revenue and pricing principles when exercising a discretion in making those parts of a distribution determination […] relating to direct control network services".[22]

2.1.1.2. The National Electricity Rules sets out the duties of the AER

While the NEL sets out the AER's statutory duties, the NER provides a more detailed framework that the AER is required to follow in meeting those requirements.

The NER requires that a DNSP's opex proposal must achieve the operating expenditure objectives (opex objectives), which are: to meet or manage expected demand; comply with all

18 National Electricity (South Australia) Act 1996, Schedule – National Electricity Law

19 National Electricity (South Australia), Act 1996, Schedule – National Electricity Law, Section 7.

20 National Electricity (South Australia) Act 1996, Schedule – National Electricity Law, Section 7A(2).

21 National Electricity (South Australia), Act 1996, Schedule – National Electricity Law, Section 16(1).

22 National Electricity (South Australia), Act 1996, Schedule – National Electricity Law, Section 16(2).

regulatory obligations or requirements; maintain quality, reliability and security of supply; and maintain the safety of the distribution network.[23]

The NER also defines the criteria against which the AER assesses whether a DNSP's proposal achieves the operating expenditure objectives (the opex criteria):[24]

> "The *AER* must accept the forecast of required operating expenditure of a *Distribution Network Service Provider* that is included in a *building block proposal* if the *AER* is satisfied that the total of the forecasting operating expenditure for the *regulatory control period* reasonably reflects each of the following (the *operating expenditure criteria*):
>
> (1) the efficient costs of achieving the *operating expenditure objectives*: and
>
> (2) the costs that a prudent operator would require to achieve the *operating expenditure objectives*; and
>
> (3) a realistic expectation of the demand forecast and cost inputs required to achieve the *operating expenditure objectives*."

If, having regard to the most recent AER Benchmarking Report (among several other factors), the AER is "satisfied that the total of the forecast operating expenditure for the *regulatory control period* reasonably reflects" the opex criteria, then the AER must accept the forecast.[25] If it is not satisfied that the DNSP's proposal satisfies the opex criteria, it must not accept the forecast and instead provide its own estimate of required opex that does "reasonably reflect" the opex criteria.[26]

Additionally, under clause 6.12.2, when replacing a DNSP's proposal with its own estimate, the AER must "set out the basis and rationale of the determination, including: (1) details of the qualitative and quantitative methods applied in any calculations and formulae made or used by the AER".[27]

2.2. The AER's Approach to Setting Opex Allowances

At each reset, the AER sets the level of efficient opex that each DNSP is allowed to recover for the subsequent five-year reset period. The five-year reset periods are staggered by jurisdiction as to when they begin and end.

Drawing on the requirements set out in the NER, the AER assesses whether the DNSP's proposed opex satisfies the opex criteria. If it finds that the DNSP's proposed opex does not satisfy the opex criteria, it rejects the company's proposal and replaces it with its own analysis.

23 National Electricity Rules, v150, clause 6.5.6(a).

24 National Electricity Rules, v150, clause 6.5.6(c). Italics in original.

25 National Electricity Rules, v150, clause 6.5.6(c)-(e). Italics in original.

26 National Electricity Rules, v150, clauses 6.5.6(d) & 6.12.1(4).

27 National Electricity Rules, v150, clause 6.12.2.

The AER uses a "base-step-trend" approach to determining its view of efficient opex. This approach defines base opex for a recent year, and then applies a yearly rate of change and step changes to set the overall level of allowed opex.[28]

2.2.1. The base opex allowance defines a DNSP's allowed opex before the beginning of the reset period

To assess base opex, the AER evaluates the DNSP's historical opex in a recent year, relying on the AER Benchmarking Report which compares opex efficiency across all 13 DNSPs in the NEM.[29] In assessing the efficiency of the DNSP's historical opex, the AER considers especially "its performance over time (using a period–average efficiency score from our econometric and opex multilateral partial factor productivity (MPFP) models)."[30] In particular, these models comprise:

- A Least Squares Econometrics (LSE) Cobb-Douglas (CD) econometric model, which estimates opex as a function of three output variables: ratcheted maximum demand (RM Demand), customer numbers (Customers), and network length (Length). Additionally, this model includes the company's share of underground lines, time, and a company-specific "dummy" variable. The dummy variable captures costs incurred by each company that is not explained by the assumed output variables, share of underground lines and time. The AER estimates the efficiency of each company by comparing the level of the dummy variable for each company with the lowest dummy variable across the sample;
- An LSE Translog (TLG) model, which differs from the LSE CD model in that it allows for a more complex relationship between the output variables (including squared and cross-product terms);
- A Stochastic Frontier Analysis (SFA) CD model, which differs from the LSE CD model in that it estimates a stochastic company-specific inefficiency term rather than a dummy variable. The model decomposes each company's unexplained costs into random variation (which is normally distributed) and company-specific inefficiency (which is strictly non-negative);
- An SFA TLG model, which combines the SFA estimation technique with the TLG functional form; and
- The opex MPFP model, described further in Section 2.3. In addition to the three output variables described above, this model also includes energy throughput (Energy) as an output variable.

We refer to the first four models above collectively as the "cost functions", which do not include the MPFP model. In its 2020 draft determinations, the AER assesses the cost functions over a 2006-18 window as well as a 2012-18 window. It assesses the MPFP model over the 2006-18 period.

28 (1) AER (November 2013), Better Regulation – Expenditure Forecast Assessment Guideline for Electricity Distribution, p.22.

29 See, e.g., AER (November 2019), Annual Benchmarking Report – Electricity distribution network service providers

30 AER (September 2020), Draft Decision – Powercor, Distribution Determination 2021 to 2026, Attachment 6: Operating expenditure, p.6-23.

The AER uses these assessments to conclude whether each DNSP's historical opex is efficient and hence whether it can accept the company's base year opex level.

For example, in its September 2020 draft determinations for DNSPs in Victoria, the AER concludes that "Powercor has consistently been amongst the better performers in our benchmarking results and that it has operated within the opex forecast set by us", and it therefore accepted Powercor's 2019 opex as its base year assumption.[31]

For Jemena, by contrast, the AER finds that "[t]he results from our productivity index techniques [i.e. MPFP] and econometric opex cost function modelling indicate […] the presence of material inefficiency in Jemena's 2018 base year opex". Regarding the MPFP modelling in particular, the AER finds that "[i]n base year 2018, Jemena is placed equal last […]. This is an indicator that Jemena's base year opex likely contains a material degree of inefficiency".[32] As a result, the AER adjusts Jemena's 2018 opex based on its findings from the four econometric benchmarking models, assessed both from 2006-18 and 2012-18 (excluding the SFA TLG model from the latter period due to insufficient data).[33]

2.2.2. The rate of change allowance captures changes to opex pressures during a reset period

The AER applies a rate of change to base opex to forecast yearly changes in opex in the subsequent regulatory period. The rate of change is a percentage growth term to the base opex which reflects expected growth in efficient opex due to changes in output drivers, input prices and productivity.

2.2.2.1. The output growth allowance captures changes in efficient opex due to changes in outputs delivered

The output growth component of the rate of change reflects the forecast annual increase in the selected output variables (RM Demand, Customers, Length and Energy). The AER estimates the impact on costs by multiplying the growth in each output by a corresponding weight for each output in operating costs.

The AER calculates weights on each output by taking an unweighted average of measures of output weight from each of the five models described in Section 2.2.1 above:

- For the four cost functions, the AER uses the three "first order"[34] output coefficients estimated from 2006-18, scaled so each model's coefficients sum to 1.00; and
- For the MPFP model, the AER uses output weights on each of the four output variables included in that model (i.e. the three outputs included in the cost functions, plus Energy). EI estimated these output weights using the Leontief regression technique described in Section 2.3 below. These are the same weights used for multilateral *total* factor

31 AER (September 2020), Draft Decision – Powercor, Distribution Determination 2021 to 2026, Attachment 6: Operating expenditure, p.6-25.

32 AER (September 2020), Draft Decision – Jemena, Distribution Determination 2021 to 2026, Attachment 6: Operating expenditure, p.6-36.

33 AER (September 2020), Draft Decision – Jemena, Distribution Determination 2021 to 2026, Attachment 6: Operating expenditure, p.6-47.

34 i.e. excluding the coefficients on the squared and cross-product terms in the TLG models.

productivity (MTFP), which considers productivity as well, so we refer to these weights as MTFP weights (as does EI).

We list the AER's preferred weights in Table 2.1 below.

Table 2.1: AER's Preferred Output Weights

	Energy	RM Demand	Customers	Length
MTFP	8.58%	33.76%	18.52%	39.14%
LSE CD	0.00%	15.48%	68.95%	15.56%
LSE TLG	0.00%	40.89%	37.95%	21.16%
SFA CD	0.00%	17.50%	67.43%	15.08%
SFA TLG	0.00%	17.90%	69.73%	12.37%
Overall	**1.72%**	**25.11%**	**52.52%**	**20.66%**

Source: EI[35]

For each DNSP, the AER forecasts the percentage growth of each output in each year of the reset period, based on its assessment of company forecasts. The AER then uses these weights to combine into a consolidated output growth rate and associated opex allowance.

2.2.2.2. The input price growth allowance captures changes in efficient opex due to changes in input prices

Each DNSP's rate of change allowance includes a component which captures changes in input prices above the level of inflation, particularly labour costs. This component of the allowance is not related to the use of the MPFP model and we do not describe it further.

2.2.2.3. The productivity allowance captures changes in efficient opex due to changes in productivity

Finally, the AER assumes that companies will achieve a 0.5 per cent annual reduction in efficient opex due to ongoing improvements in productivity. This assumption itself comes from a holistic review of seven different pieces of evidence, the following three of which derive directly from the AER's benchmarking techniques:[36]

- Opex MPFP for the top four companies (CIT, PCR, SAP and UED) between 2011 and 2017 shows annual productivity growth of 0.35, using a geometric mean (i.e. end-point to end-point) averaging technique, and 0.97 per cent, based on the slope of a linear regression on the natural logarithm of the MPFP levels in each year;
- The time trends on the cost functions show annual productivity growth of 1.2 – 2.2 per cent when estimated between 2011 and 2017; and
- The econometric coefficient on the undergrounding variables, combined with an assumed continuation of undergrounding work, suggests annual opex cost reductions (i.e. productivity) of 0.1 – 1 per cent.

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35 Economic Insights (20 May 2020), Review of reports submitted by CitiPower, Powercor and United Energy on opex input price and output weights, Table 4.

36 AER (March 2019), Final decision paper – Forecasting productivity growth for electricity distributors, Table 12.

The other four sources relate to other industries (gas and water) or countries.

From the range of estimates assessed, the AER selects 0.5 per cent as a central estimate, though it does not derive mechanically from any combination of the different estimates.

2.2.3. Step changes

The AER accounts for the possibility of further modifications to opex forecasts whenever there are opex components that are not compensated for in the base opex or in the rate of change. These step changes do not relate to MPFP modelling, so we do not discuss them further.

2.3. Technical Description of MPFP Modelling

In this section, we briefly summarise the mechanical approach that EI uses to calculate the MPFP models. Broadly speaking, this comprises three steps:

- EI calculates output weights based on a Leontief regression technique. There are 52 unique regression models, separately for 13 DNSPs multiplied by four input variables. The input variables comprise opex, OHL, UG and transformers. EI refers to the latter three of these as "capital" inputs, and uses them as the inputs to measure "capital MPFP"[37];
- Based on the output weights, EI calculates an output index which measures the aggregate level of outputs delivered by DNSP and by year. Dividing this index by an input index (opex in the case of the opex MPFP model or opex and capital inputs in the case of the MTFP model), EI calculates a productivity index by DNSP and by year. The opex MPFP specifically shows opex productivity. These indices can be aggregated across firms to show state-level or industry-level productivity (or any other aggregation of firms);
- EI calculates the relative efficiency of DNSPs by comparing their productivity scores over an extended period of time.

To aid in our interrogation of the results, we have replicated each of the above steps. EI performs all of the steps in Shazam. We have estimated output weights using Stata and the remaining two steps in Microsoft Excel. Our replications are virtually identical to those reported by EI, with the exception that our t-statistic values (which measure statistical significance) are sometimes higher and sometimes lower than EI's. The differences in the t-statistics are only large when the t-statistics themselves are extremely large (e.g. 90 vs 60), and so do not influence our qualitative conclusions if we use either set.

The discrepancy between t-statistics is likely due to differences in the maximisation algorithm employed by Shazam compared to Stata. Maximum Likelihood Estimators, as must be used to estimate EI's Leontief regressions, cannot be solved analytically. Therefore any programme must rely on heuristic algorithms which come to slightly different results.

Where these distinctions are relevant (i.e. when discussing statistical robustness of different model specifications), we report both EI's values and our replications of them. Where only

[37] See for example: Economic Insights (25 August 2020), Economic Benchmarking Results for the Australian Energy Regulator's 2020 DNSP Annual Benchmarking Report, p.10.

the coefficients themselves are important, we use our replication, but the differences are negligible.

We describe each of these steps in more detail in Appendix A.

2.4. Recent Developments in AER's MPFP Modelling

The AER has relied upon MPFP modelling conducted by EI since its 2014 price control decision for DNSPs in New South Wales and ACT.[38] In that decision, the AER used the MPFP model only as part of the base year efficiency assessment, alongside econometric opex cost function benchmarking models and simple partial performance indicators (e.g. opex per customer plotted against customer density).[39]

The AER states that the MPFP model "has the advantage of producing robust results with small datasets". EI found that "the similarity in results despite the differing methods used and datasets used reinforces our confidence in the results".[40]

However, while it was used in assessing the efficiency of DNSPs' submitted base year opex, it did not feed directly into the AER's alternative base year opex estimates, which the AER substituted in place of DNSPs' submissions: The AER instead based its substituted value solely on the results of the SFA CD model. In short, the MPFP model as originally introduced was used for a qualitative appraisal of efficiency. The AER argued that it was valid because it showed relatively similar overall efficiency results as the econometric opex cost function benchmarking models (though the standard of similarity was not defined).

2.4.1. The AER has recently started to place more weight on MPFP modelling

Since its introduction in 2014, the AER has placed increasing weight on MPFP modelling in the overall price reset process. The AER has not shared any additional analysis that would suggest that the MPFP modelling is sufficiently accurate to bear this additional burden. One can see this expanded importance in three ways.

First, as part of the base year opex assessment process, the AER has placed increasing importance on the results of the MPFP modelling in deciding whether the DNSP's proposed base opex level is efficient. In 2014, it used the MPFP modelling primarily as a cross-check to the opex benchmarking. The AER did not carry out detailed analysis of the MPFP modelling beyond the average efficiency score it produces.[41]

In the 2020 draft determinations for Victoria, by contrast, the AER now relies heavily on a the MPFP modelling to determine the efficiency of each company's base year opex. As described in Section 2.2.1, the AER cites the MPFP results in determining that Jemena's

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[38] Note: The final decisions for the 2014-19 price control period were released in 2015, after the period had already started. We nonetheless refer to these decisions as 2014 decisions.

[39] AER (November 2014), Draft decision – Essential Energy distribution determination 2015–16 to 2018–19, Attachment 7: Operating expenditure, p.7-30 - 7-31

[40] (1) AER (November 2014), Draft decision – Essential Energy distribution determination 2015–16 to 2018–19, Attachment 7: Operating expenditure, p.7-69; (2) Economic Insights (17 November 2014), Economic Benchmarking Assessment of Operating Expenditure for NSW and ACT Electricity DNSPs, p.46-47

[41] AER (April 2015), Final Decision –Essential Energy distribution determination 2015−16 to 2018−19, Attachment 7 – Operating expenditure, p.7-33.

proposed base year opex is inefficient on an individual-year basis. Therefore, the AER is relying on not just the broad trend implied by the MPFP modelling or rank-ordering of comparators but relying on the accuracy of individual pairings of companies and years.

Second, in 2014, the AER based the output weights used to inform the output growth assumption (part of the rate-of-change allowance) only on the coefficients of the SFA CD model.

In its decisions for the 2019-24 reset periods in New South Wales, ACT and Tasmania, in response to the Consumer Challenge Panel 10 (CCP10) and the Australian Competition Tribunal (ACT), the AER expanded its approach to include coefficients from the other cost functions as well as the MTFP output weights.[42] At the time, it did not consider the SFA TLG model to be sufficiently robust, so the output weights were based on the three other cost functions plus the MTFP weights.

Finally, before 2019, the AER applied a productivity growth assumption of 0 per cent. In 2019, the AER estimated that DNSPs could achieve 0.5 per cent productivity growth per year, informed in part by the MPFP modelling as described in Section 2.2.2.3. The AER first used its assumption on the level of productivity growth as part of the 2020-25 decisions for DNSPs in South Australia and Queensland

2.4.2. Ongoing debate on the robustness of the MPFP models

As a result of the AER's recent increasing reliance on the MPFP modelling as described above, the models have been subject to greater scrutiny from DNSPs and their advisors, and EI has responded in turn. We summarise the state of the debate thus far below.

When the AER proposed expanding its output weight methodology to include the other cost functions and the MTFP weights, we wrote a report appraising some of the proposed techniques.[43] Our report covered other elements beyond the MTFP modelling (namely, the use of Energy as a cost driver and the interpretation of the TLG coefficients), but we summarise our findings relating to the MTFP models below:

1. The process for deriving weights from the MPFP modelling was opaque;
2. The drivers included in the MPFP modelling were chosen based on tariff structure, not by assessing their effect on DNSPs' costs;
3. The weights in the MPFP model are artificially constrained to be positive, masking possible misspecification of the model; and
4. The MPFP weights are estimated with very little data, suggesting the weights are estimated imprecisely.

[42] AER (November 2018), Draft Decision – Essential Energy Distribution determination 2019–24, Attachment 6 – Operating expenditure, p.6-28 – 6-29.

[43] NERA (18 December 2018), Review of AER's Proposed Output Weightings – Prepared for CitiPower, Powercor, United Energy and SA Power Networks.

At the request of the AER, EI responded directly to our criticisms, concluding overall that its approach remained sound.[44] We summarise EI's arguments regarding MPFP modelling below, along with our reactions to each of those arguments:

1. *Transparency:* EI claims it has demonstrated "near unprecedented" levels of transparency by providing the input and output code from its Shazam modelling.[45] While it is true that its results are replicable from the input and output code, the code itself is poorly annotated and requires some knowledge of Shazam syntax to find the relevant terms.[46] It is an exaggeration to suggest that this level of transparency is "near unprecedented". In similar regulatory proceedings in the energy and water sectors in Great Britain, for example, Ofgem and Ofwat routinely publish modelling files which are much easier to interrogate.
2. *Billed vs functional outputs:* With respect to our claim that the choice of output weights derives at least in part from output variables which are "billed" (particularly Energy), EI states that "nothing could be further from the truth". In attempting to rebut our argument, EI states that one reason for including Energy as an output variable is that it "is what consumers see directly *and pay for*. […] In other words, energy throughput scores highly on the second selection criterion".[47] While EI cites other justifications for using Energy as an output variable, one of them does relate to the fact that customers pay for it directly in their bills. Hence, it is a billed output and this influences EI's decision to include it. Therefore, in spite of EI's claims to the contrary, many things could be, and in fact are, "further from the truth". We do not list them exhaustively below for reasons of brevity.

3. *Negative output weights:* EI emphasises that, the coefficients are forced to be non-negative in individual Leontief regressions, but would not provide a positive value if the estimated relationship were negative (and would instead find a value of 0). We agree with this claim. However, as discussed in Section 3.2.1, the process of aggregating coefficients into output weights across multiple regressions still does put *positive* weight on output variables, even if the relationship between outputs and costs is non-existent in reality. EI also states that it has never estimated these equations without using squared coefficients. The fact that it has not changed this approach does not make it correct.
5. *Precision of estimates:* EI claims that:
   A. It improves the precision of its estimates through aggregating across 52 regressions. We explain that this is not a valid claim in Sections 3.1 and 3.2 below.
   B. Its output shares are corroborated by the results of a translog opex model estimated across all four outputs. EI only provides half a page in an appendix of its 2018 benchmarking report describing its translog specification, but does not present the output or any interpretation as to how the output corroborates the MPFP weights.[48] We assume the raw output is in published Shazam code somewhere, but cannot we

44 Economic Insights (30 April 2019), Review of NERA report on output weights.

45 Economic Insights (30 April 2019), Review of NERA report on output weights, p.3.

46 Although it was among the first econometric software packages when it was launched in 1977, Shazam is not among the more commonly used packages today, with econometricians generally preferring to use R, Stata, SAS or SPSS.

47 Economic Insights (30 April 2019), Review of NERA report on output weights, p.6.

48 Economic Insights (9 November 2018), Economic Benchmarking Results for the Australian Energy Regulator's 2018 DNSP Annual Benchmarking Report, p.110.

have not appraised whether it corroborates the MPFP weights or not, nor has EI explained how it does.

C. It has increased its sample size by around 50 per cent from when it first estimated its output weights. The current Leontief models using 13 years' data (or 12 at the time of EI's response) are insufficient to yield precise estimates (see discussion in Section 3.1 below). EI's original Leontief models had only eight years of data, which is even less adequate for estimating five coefficients.

In December 2019, Frontier Economics (Frontier) reviewed our 2018 Outputs report as well as EI's response to it. It concluded that "the AER should discontinue its reliance on the Leontief model in the setting of opex allowances", based on statistical problems "so severe that they cannot be overcome by taking weighted averages".[49]

Frontier also identified a coding error in EI's Leontief regression commands. Whereas EI had intended for the time variable to be equal to 0 in 2006 (1 in 2007, etc) for all DNSPs, it failed to reset for subsequent DNSPs. Therefore, for the second DNSP in the set, time in 2006 equalled 12, and 13 in 2007, etc, while for the third DNSP, time in 2006 equalled 24.

EI responded to Frontier's criticisms in a memo to the AER in April 2020. In short, it corrected the coding error that Frontier identified. It argued that as a result, many of Frontier's criticisms of the statistical robustness of the Leontief modelling were thus mitigated, namely that many more of the coefficients were statistically significant and intuitive.[50] It concluded that "there is no case for not including the MTFP/MPFP weights in the output growth component in applications of the rate of change formula".[51] As we explain in Section 3.1, numerous other statistical failings continue to exist in the Leontief models, which present a strong case for not including the MPFP model in the AER's suite of cost assessment methods.

In its 2020 Benchmarking Report, having corrected this coding error, EI lists its 52 updated Leontief regression results. It finds that "28 of the 52 regressions now have one significant output coefficient, 17 have two significant output coefficients and 2 have 3 significant output coefficients", or, put another way, 47 of 52 with at least one significant output variable.[52] It treats this as evidence that the Leontief models are robust. As we discuss, in Chapter 3, this high proportion of models with at least one statistically significant variable is a virtual certainty based on how the models are specified (having corrected the coding error), rather than any indication that the output variables are actually correlated with costs: One can obtain similar degrees of significance using randomly-generated series that have no underlying relationship whatsoever to costs.

49 Frontier Economics (5 December 2019), Review of Econometric Models Used by the AER to Estimate Output Growth – A report prepared for CitiPower, Powercor and United Energy, p.1-2.

50 Economic Insights (18 May 2020), Review of reports submitted by CitiPower, Powercor and United Energy on opex input price and output weights, p.16-17.

51 Economic Insights (18 May 2020), Review of reports submitted by CitiPower, Powercor and United Energy on opex input price and output weights, p.17.

52 Economic Insights (25 August 2020), Economic Benchmarking Results for the Australian Energy Regulator's 2020 DNSP Annual Benchmarking Report, p.129

2.5. Summary and Conclusion

As described in Section 2.2, the MPFP model (and the wider MTFP model) serves several roles in the price control determination process. To summarise:

- The AER uses long-term average MPFP benchmarking results directly when assessing whether a company's base year opex proposal is efficient. It does not directly use the MPFP model in calculating its alternative base year estimate, but a company's performance in the MPFP model influences whether the AER accepts or instead replaces the company's base year proposal.
- The AER uses the MTFP output weights directly to calculate the output growth component of the rate of change allowance.
- The AER uses a variation on the MPFP modelling (i.e. the rate of change of four companies over the period from 2011 to 2017) as one piece of evidence in setting the productivity growth assumption. While the productivity assumption is not mechanically linked to any one piece of evidence, each piece of evidence influences the AER's holistic view.

Additionally, the AER uses companies' annual MPFP performance to assess qualitatively whether a company's efficiency improves or worsens over a period of time and to set the base-year opex at resets. For example, in deciding to perform an adjustment to the opex allowance in the base year for a recent price control adjustment for Jemena, the AER cites that its productivity in 2018 specifically is jointly last in the industry and therefore a reduction in base opex was proportionate.

When the AER has other occasions to consider a company's efficiency or productivity (or for a state or an industry) beyond those described above, it tends to refer first to the MPFP model. Indeed, in its 2019 Benchmarking report, the AER states that its primary benchmarking techniques to "measure the relative productivity of each DNSP in the NEM are multilateral total factor productivity (MTFP) and multilateral partial factor productivity (MPFP)".[53]

For the reasons stated above, we therefore conclude that the MPFP model is an important determinant of a company's opex allowance, and, therefore, is important to determining whether the AER's decision meets the opex criteria in any opex determination.

In appraising the MPFP model, as we do in Chapter 3, we therefore consider: (i) whether the MPFP model and the AER's various uses of it reasonably reflect the efficient costs of providing distribution services (i.e. meeting the opex objective); (ii) whether they represent a "realistic expectation of the […] cost inputs required to achieve" the opex objectives (as set out in the opex criteria); and (iii) whether they provide DNSPs with "a reasonable opportunity to recover at least the efficient costs" or providing distribution services (as set out the Revenue and Pricing Principles of the NEL).[54]

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[53] AER (November 2019), Annual Benchmarking Report – Electricity distribution network service providers, p.1.

[54] (i) National Electricity Rules, v150, clause 6.5.6(c); and (ii) National Electricity (South Australia) Act 1996, Schedule – National Electricity Law, Section 7A(2).

3. Appraisal of MPFP Modelling

In this chapter, we consider in detail whether the MPFP modelling is robust. Specifically, we demonstrate that the MPFP modelling and the AER's uses of it do not reasonably reflect the efficient costs of meeting the opex objective as set out in Section 2.1.1. Neither does reliance on the MPFP modelling allow the AER to determine an opex allowance which represents a "realistic expectation of the […] cost inputs required to achieve" the opex objectives. We focus especially on the process of calculating output weights, but also consider the wider implications of the MPFP approach as part of other components of the benchmarking process.

This chapter proceeds as follows:

- Section 3.1 discusses econometric shortcomings of the Leontief regressions which underpin the calculation of the weights;
- Section 3.2 discusses shortcomings in how EI combines the regression results into output weights;
- Section 3.3 discusses the implications of the shortcomings of the output weight calculations in terms of the final MPFP results as well as the price control parameters that derive from them; and
- Section 3.4 appraises the MPFP modelling against the Opex criteria set out in the NER.

3.1. Assessment of the Leontief Econometric Models

As described in Section 2.3, the MPFP output weights are based on an aggregation of 52 Leontief regressions. Each equation estimates the level of one input in one company as the function of four output levels and time. With only 13 data points per regression and five estimated coefficients, that leaves only eight degrees of freedom over which EI can estimate the relationships.

The regression specification is:

$$x_{ift} = \left(1 + b_{if}t\right)\left[a_{if1}^2 y_{1ft} + a_{if2}^2 y_{2ft} + a_{if3}^2 y_{3ft} + a_{if4}^2 y_{4ft}\right]$$

where i indexes the input (one per regression); f indexes the firm (one per regression); and t indexes time (13 years). The level of the input at time t is x_{ift} and the level of output 1 at time t is y_{1ft} (outputs 2-4 are analogous). The output coefficients are a_{if1}^2 through a_{if4}^2, which capture the contribution of the relevant output to input demand. The squares on the coefficients mean the contribution is forced to be positive (whether a is positive or negative, a^2 is always positive). The time coefficient b_{if} captures how the relationship between the input and output changes over time. EI runs 52 regressions of this form.

EI constructs the output weights using the output coefficients estimated from these regressions. There are so many problems with the regressions that the output coefficients estimated from them are not at all reliable, so the resulting output weights are also not at all reliable.

In the first part of this section, we explain several of the problems with EI's Leontief regressions. We list the problems here and then explain them in detail in sections 3.1.1 to 3.1.4.

1. We have not found evidence of widespread use of these Leontief regressions. In fact, the only place we have seen them used is in EI's reports. We are therefore concerned about the reliability of these models, as they have several non-standard features which have not been independently evaluated.
2. The regression models do not have a constant. It is textbook standard to include a constant in a regression model.[55] Without a constant, the coefficients on outputs will be biased.
3. The treatment of time in the regressions makes no sense. Time is multiplied by the outputs rather than added to them. This creates two problems. First, the estimated coefficients on time and outputs depend on whether time is counted from 0 to 12 or from 2006 to 2013 beyond just the scaling factor, which should not be the case. Second, the coefficients on outputs will be biased, because there are added effects of time which have been missed.
4. 80 per cent of the estimated output coefficients are statistically indistinguishable from zero, meaning that there is no evidence for a relationship between the output and the input. By EI's own calculations, 66 per cent of the coefficients EI estimates are statistically indistinguishable from zero. This is already poor, but EI's evaluation of does not account for the fact that when they estimate 208 coefficients, some will be different from zero just by chance. Using a more appropriate evaluation we find that 80 per cent of coefficients are statistically indistinguishable from zero.

In the second part of this section, we show that if we use alternative regression models which resolve some of these problems, the estimated output coefficients change. This means the output weights also change. The changes can be substantial: circuit length goes from having the highest output weight in EI's model to having zero output weight in one of the models we consider. We consider four models in total.

The first two models we consider are a model with a constant and a model with a time trend. These models improve on problems (2) and (3) above, and result in a substantial reduction in the output weight for customer numbers. However, they still suffer from problem (4): most of the coefficients are statistically indistinguishable from zero.

The third is a model with a log-log specification, rather than a specification in levels. Using logs rather than levels is in line with standard benchmarking techniques, such as econometric cost functions. Unfortunately, the algorithm used to estimate the Leontief regressions does not converge for almost half of these models, meaning that coefficient estimates cannot be generated. We attribute this to the small sample size.

The fourth model is a fixed effects panel model. This combines data on all DNSPs and estimates a single set of output coefficients for each input. This model overcomes the

[55] Davidson, R and McKinnon, J. (1993) *Estimation and Inference in Econometrics.* Oxford University Press. [Section 2.5]

problem of having too few observations to estimate the model, but still suffers from problem (3) because it uses EI's specification for time. This model places zero weight on circuit length, putting most of the weight on ratcheted maximum demand.

The point of this exercise is not to advocate for any one of the alternative regression models, as none of them resolves all the problems we identify with EI's Leontief regressions. Rather, the point is that to show this MPFP approach is very sensitive to the underlying regression specification.

Since the MPFP approach is very sensitive to the underlying regression specification, we should be confident that whatever specification produces reliable coefficient estimates. The various problems we have identified with EI's Leontief regression mean that we have no confidence in the coefficients estimated from those regressions. It is not reasonable to use these coefficients as the basis for MPFP calculations (or anything else).

3.1.1. There is no evidence for widespread use of this econometric model

There is no evidence for the use of this econometric model outside of reports produced by EI. The econometric model used is not standard in several respects.

First, the coefficients in the model are forced to be positive. This is done by specifying the coefficients as squares, e.g. a^2. Whether a is positive or negative, a^2 will always be positive.

Second, time is multiplied by the output variables, rather than added to them. Adding time to the model is the more standard approach. When time is multiplied by the output variables in this way, it acts to modify the relationship between the inputs and the outputs, rather than directly affecting the inputs. The problems created by doing this are described in Section 3.1.3.

Third, the way in which time modifies the effects of output variables is non-standard: rather than a set of interaction terms, the modification is assumed to be the same for all output variables.

When using a non-standard model, it is conventional to either carefully explain its behaviour, or refer to literature that does so.

EI does not explain the behaviour of the model. The only external reference it gives for the model is a 2003 report by Dr Denis Lawrence for the New Zealand Commerce Commission, but Dr Lawrence is also the lead author of EI's econometric work for the AER and hence does not represent an independent view from EI itself.[56] The 2003 report also provides no explanation of the econometric model, and instead refers to explanations in an earlier draft of it, which we could not find online. We also could not find literature explaining the behaviour of this non-standard econometric model either on EI's website or using standard search engines. Neither could we readily find evidence of it peer-reviewed journals.

56 Lawrence, D. (2003), Regulation of Electricity Lines Businesses, Analysis of Lines Business Performance – 1996–2003, Report prepared by Meyrick and Associates for the New Zealand Commerce Commission, Canberra, 19 December.

Even if EI were to identify a handful of references produced by external parties for its model to justify a model otherwise apparently of its own invention, that this model specification is so rarely-used raises questions about its reliability. The model may not have been carefully examined or subjected to rigorous testing. Therefore, we do not know what properties the estimated coefficients from the model will have, if the functional form of the model does not perfectly describe the real relationships between inputs and outputs. We do not know how badly biased the estimated coefficients will be.

To take one example, it is generally known that if we forced the coefficient on an output to be zero when it is not zero, then the coefficients on other outputs would be biased. This is called "omitted variable bias" and it can be quantified. [57] In the case of this model, if the true coefficients of the statistical relationship between inputs and outputs are not positive (as may be the case between, say, Energy, and the inputs costs), the estimates of other coefficients will also be biased.

Since EI has not provided any supporting evidence to explain its non-standard model, these concerns remain unaddressed. EI provides no independent evidence or testing of its assumed functional form which would afford any confidence in its specification or results.

3.1.2. The absence of an intercept term essentially guarantees that a regression will have at least one statistically significant output coefficient

The regression model does not have an intercept term, which means that estimated coefficients on the outputs are badly biased and are effectively forced to be significant.

The issue is a very simple one. In applied problems, it is the textbook standard to include an intercept.[58] This is because the mean value of the residual part of the input on the left-hand side of the regression may be different from zero. The residual part is the part not explained by the outputs on the right-hand side of the regression. The non-zero mean of the residual is the effect of other factors that influence the input but are not included in the model. The intercept coefficient picks this effect up.

If an intercept is not included in the model, the four outputs included in the right-hand side of the regression also pick up the effects of these factors not included in the model. This has two negative consequences.

First, the estimated coefficients on the outputs are biased: the estimates do not reflect the true contribution of the output to the input. Instead, they reflect a combination of the output and the other unmodelled factors.

Second, the estimated coefficients will be falsely reported as significant. This is because the coefficients must pick up the obvious feature of the input, that its mean is large compared to its variability around the mean. The resulting significant coefficient thus mainly tells us that

57 Camero, A. and Trivedi, P. (2005) *Microeconometrics: Methods and Applications.* Cambridge University Press. [Section 4.7.4]

58 Davidson, R and McKinnon, J. (1993) *Estimation and Inference in Econometrics.* Oxford University Press. [Section 2.5]

both the input and the output have relatively large means compared to their variation around those means, rather than that the variation is in any way related.

The lack of intercept term also means that the cost function is assumed to have constant returns to scale. This is fundamentally implausible for an electricity network, which has high fixed costs. The opex required for a small electricity network is likely to be larger than for a large network due economies of scale. An intercept is necessary to capture that initial opex requirement. If the constant is not included, the coefficient on the outputs will be biased upwards.

To address this problem, EI should include intercepts in its regressions or de-mean all variables.[59] It is surprising that EI does not already do this, given that it does include an intercept and de-mean all variables in its econometric opex cost function benchmarking models. The inclusion of an intercept is standard practice in regulatory benchmarking[60]

For example, compare the analysis of the relationship between Customers and OHL for UED with and without an intercept. In EI's original regression without an intercept, the coefficient on Customers is significant, and the predicted mean value of OHL based on Customers alone is 81,598 MVAkms. This is close to the true mean value of OHL for UED: 94,897 MVAkms.

We conducted an alternative regression with an intercept (see Table B39 in the Appendix). In our revised specification, the coefficient on Customers is not significant. The predicted value of OHL based on the intercept alone is 79,570 MVAkms. Meanwhile, the predicted contribution of Customers to OHL is 0 MVAkms. When we add a constant to EI's original analysis, we find that only 52 of 208 output coefficients are significant, reduced from EI's 68.

A model without an intercept is effectively guaranteed to produce a large, statistically significant coefficient on at least one output variable. Before we add a constant to the model, 47 of the regressions have at least one significant output coefficient.[61] Of the five that did not have any statistically significant output variables, this is because the model used multiple output variables to proxy for the coefficient, each with enough uncertainty *individually* to be statistically insignificant. However, a simple test for *joint* statistical significance indicates a very high level of joint significance, as is virtually guaranteed by the model specification.[62]

After adding a constant, 38 regressions have at least one significant output coefficient.

The above analysis of the importance of an intercept can also explain why EI found more significant coefficients after correcting the coding error identified by Frontier Economics.[63]

59 De-meaning a variable involves calculating the mean level of that variable within the sample (i.e. for all years of a single DNSP), and subtracting the mean from each observation. This achieves a similar level effect as introducing an intercept term.

60 E.g. All econometric models relied upon by energy and water regulators Great Britain and Northern Ireland include a constant term.

61 The five which have no significant coefficients are: opex for ACT, ERG, and PCT; OH for JEN; and UG for ESS.

62 We performed a Wald test of joint significance. The p-values of these tests were all numerically equivalent to zero, indicating that the output coefficients were jointly highly significant.

63 Frontier Economics (5 December 2019), Review of Econometric Models Used by the AER to Estimate Output Growth – A report prepared for CitiPower, Powercor and United Energy, p.1-2.

With the original coding error in place, some DNSPs had values for time ranging between e.g. 100 and 112, rather than 0 and 12. In the models for these DNSPs, the fact that time had a large positive average value meant that the time coefficient could act as a constant, and so fewer output coefficients were significant. Once the coding error was corrected, time could no longer act as a constant, so more output coefficients became significant.

3.1.3. Relationships are only significant due to time trends

EI does not account for time trends in the inputs and outputs. Time trends are a particular feature of time series data, that is, data recorded on a single entity (here DNSP) over multiple time periods. When time trends are not accounted for, the estimated coefficients will be biased and their significance of coefficients will be overstated.

In regressions using time series data, time trends are accounted for by either including time as an explanatory variable on the right-hand side or de-trending the data in advance. In this respect, including a time trend is similar to including an intercept, discussed in Section 0.

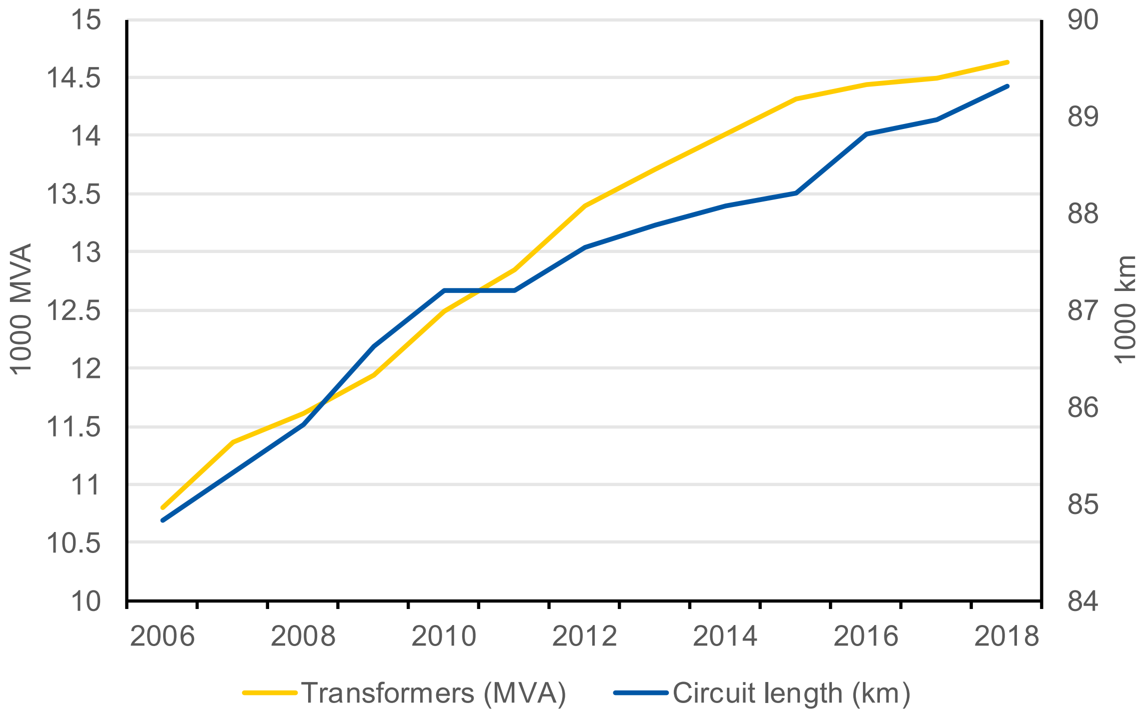
EI does include time on the right-hand side of the regression, but it is multiplied by the output coefficients rather than added to them. This means that EI allows time to modify the relationship between inputs and outputs, but does not allow time to directly affect inputs.

This creates a problem very similar to the problem caused by omitting the intercept. There may be factors not included in the model which are increasing over time, and directly affect the input variable rather than modifying the relationship between the inputs and outputs. In EI's regression model, the effects of these factors will be picked up by the output coefficients. This means that the estimated output coefficients will be biased: they will combine the effect of the output, and the effect of the unmodelled time-trending factors. These coefficients will be falsely reported as significant.

To understand the problem, consider the relationship between Length and transformers for SA Power Networks (SAP) (see Figure 3.1). Both variables trend up over time. This means that a statistical test of the relationship between the two will produce a significant result. The t-value for the coefficient on Length in the model for transformers reported by EI is 5.43. This statistically significant result is obtained because both variables are related to time; it does not say anything about the relationship between the two variables.

Using an alternative regression where time enters as an explanatory variable rather than as a modifier, the t-value for the coefficient on Length in the model for transformers is 0.013. The t-value for the coefficient on time is 11.24, i.e. highly significant. This is evidence that the significant relationship detected by the original model was a false relationship.

Figure 3.1: SAP circuit length and transformers are time trending



Source: NERA analysis

Therefore, the results of the Leontief model are not robust because EI does not include time as an explanatory variable and therefore captures the effects of time within the output coefficients.

3.1.4. Over one-third of the coefficients EI reports as significant are not actually significant

EI reports the number of significant coefficients across the 52 models as evidence of the robustness of its models. They find that 68 of 208 of all output coefficients are significant, i.e. 33 per cent. However, EI have used the wrong standard to evaluate significance. Using a corrected standard, we find that only 41 of their coefficients are significant.

EI use the 5 per cent standard of statistical significance. The idea of this standard is to have only a 5 per cent probability that the test reports a significant relationship “by chance". When estimating many coefficients, then, 5 per cent of them will be significant “by chance”. EI estimates a total of 208 output coefficients across all regressions. Using the standard 5 per cent significance level, 10-11 of those coefficients will be significant by chance.[64]

The Bonferroni correction is a technique that is used to adjust the standard of significance tests when estimating many coefficients. Instead of considering each coefficient test separately and allowing a 5 per cent probability that the test reports a significant relationship

[64] i.e. 208 x 0.05.

"by chance", it considers all coefficient tests together and allows a 5 per cent probability that any one test reports a significant relationship "by chance".[65]

Typically, we use a p-value of 0.05 to test at the 5 per cent standard level. To find the Bonferroni-corrected p-value, we divide 0.05 by the number of coefficients estimated, i.e. 260 (208 output coefficients plus 52 time coefficients).[66] The Bonferroni-corrected p-value is thus .0002. Given this p-value, we calculate the critical value which the t-statistics on EI's estimated coefficients must exceed to be considered significant. This critical value is 6.44.[67]

Using the Bonferroni correction, we find that 41 of 208 estimated output coefficients are significant (i.e. 20 per cent, a reduction of 13 percentage points), and 22 of 52 time coefficients are significant (i.e. 42 per cent, a reduction of 33 percentage points). We demonstrate this in Figure 3.2 below.

The reverse implication should be noted: 80 per cent of the estimated output coefficients are insignificant. That means that the MPFP output weights are based on estimated coefficients which, 80 per cent of the time, are statistically indistinguishable from zero.

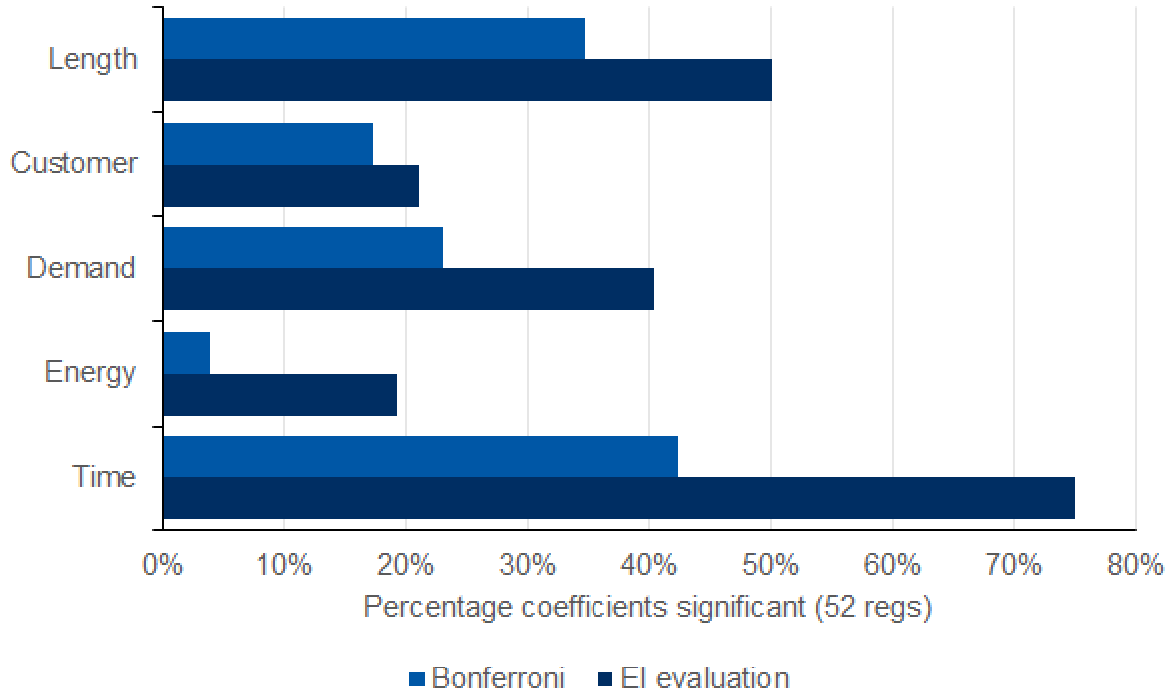
These levels of significance ignore uncertainty over the functional form. In other words, these coefficients will be significant by chance *assuming that the underlying model* is true. In practice, given the weak justification for the functional form estimated, the reliability of EI's estimates is far worse than these measures of statistical significance would suggest.

65 Formally, the Bonferroni-corrected p-value is derived via a linear Taylor approximation of the relationship $p_{target} = 1 - \left(1 - p_{adj}\right)^N$. Here N is the number of coefficients to be tested, p_{target} is the overall p-value desired (here 0.05), and p_{adj} is the adjusted p-value against which each coefficient should be evaluated to achieve p_{target}. The relationship relies on an assumption of independence between statistical tests.

66 Romano J.P., Shaikh A.M., Wolf M. (2010) Multiple Testing. In: Palgrave Macmillan (eds) The New Palgrave Dictionary of Economics. Palgrave Macmillan, London. https://doi.org/10.1057/978-1-349-95121-5_2914-1

67 Based on a Student-t distribution with 8 degrees of freedom. Given the small sample size, the Student-t distribution is more appropriate than the standard normal distribution used by EI.

Figure 3.2: Few coefficients are statistically different from zero using Bonferroni



Source: NERA analysis

3.1.5. Alternative regression models yield different statistical results

We replicate EI's specification with four alternative models: a model based on natural logarithms (i.e. a log-log model), a model with a constant, a model with a time trend, and a fixed effects panel model. We describe each of these in turn in sections 3.1.5.1 to 3.1.5.4 below. To restate, EI's Leontief specification is as follows:

$$x_{ift} = (1 + b_{if}t)\left[a_{if1}^2 y_{1ft} + a_{if2}^2 y_{2ft} + a_{if3}^2 y_{3ft} + a_{if4}^2 y_{4ft}\right]$$

Each model has characteristics which are preferable to the specification chosen by EI in at least one dimension and are at least as reasonable or a more reasonable specification of the underlying relationships. Our analysis shows that EI's results are not robust to these changes in functional form and the significant coefficients that EI identifies turn out to be insignificant for minor changes in the specification. In other words, EI's results are not robust and are an artifice of the specific (and unjustified) relationship it models.

3.1.5.1. Model in natural logarithms

Our first alternative model is a model based on natural logarithms. This model replaces the variables in levels, $\{x_{ift}, y_{1ft}, \dots, y_{4ft}\}$, from the above model with the natural logarithm of each variable (i.e. a log-log model).

The log-log specification is a more realistic representation of the demand function, because it captures the interdependence of the various input-output conversion processes. The log-log specification is therefore the standard in regulatory benchmarking models. For example, EI uses log-log specification in its econometric opex cost function benchmarking models.

EI's specification in levels implies a Leontief, or additive, demand function. This means that demand for an input, e.g. opex, will increase linearly with an output, e.g. energy throughput, even if none of the other outputs are growing. In practice this is unrealistic: the rate increase in demand for opex as energy throughput increases is likely to depend on whether other outputs are also growing. The log-log model that we use implies a Cobb-Douglas demand function which captures this interdependence.

Using the model in logs, the results in terms of statistical significance of the coefficients differ substantially from those using EI's original additive model. This can be seen from Figure 3.3: the blue columns represent the proportion of coefficients reported significant in EI's original model, while the grey columns represent the proportion of coefficients reported significant in the log specification.

We find that in the log specification, the coefficients on time and customer numbers are more frequently significant, while those on energy, demand, and length are less frequently significant. The most substantial change is that the increase in the proportion of coefficients on customer numbers which are significant. This is primarily driven by the regressions for transformers and overhead lines.

It was not possible to estimate all 52 regression models in logs – only 28 models were estimated.[68] For the remaining regressions, the maximum likelihood algorithm did not converge. It is likely that this is due to the small sample size of each regression. However, this does not imply that EI's specification is preferable, but rather that there is insufficient data to carry out these regressions robustly.

3.1.5.2. Model with a constant

Our second alternative model adds a constant to EI's original model. This has two advantages as described in Section 0. First, it avoids the problem of bias and artificial significance in output coefficients, arising because both the outputs and inputs have large positive coefficients. Second, it is a more realistic representation of the demand function for this industry.

The model is specified as follows:

$$x_{ift} = \left(1 + b_{if}t\right)\left[a_{if0}^2 + a_{if1}^2 y_{1ft} + a_{if2}^2 y_{2ft} + a_{if3}^2 y_{3ft} + a_{if4}^2 y_{4ft}\right]$$

Here everything is exactly as an EI's model, except for the addition of the constant term, a_{if0}^2. This term is constrained to be positive to ensure comparability with the output coefficient estimates. The addition of a constant term reduces the degrees of freedom of the regression by one.

Using this model with a constant, the results are again quite different to those using EI's original model. In Figure 3.3, results from EI's original model are in blue while results from the model with a constant are in orange. A lower percentage of the coefficients on Energy, RM Demand, Customers, and Length are significant. Nearly 20 per cent of estimates for the

[68] The breakdown is: 11/13 opex models, 7/13 OH models, 5/13 UG models, 5/13 Transformer models

constant term are significant, which is more than the 16 per cent of Energy coefficients or 12 per cent of Customers coefficients. This indicates that the constant term is at least as important in explaining input demand as energy and customer numbers.

Despite the loss of degrees of freedom, it was possible to estimate 50 of the 52 regressions. For the other two regressions, the maximum likelihood algorithm did not converge.[69]

3.1.5.3. Model with a time trend

Our third alternative model changes the treatment of time. As outlined in Section 3.1.3, EI's model treats time as a modifier of the relationship between inputs and outputs. In the model presented here, time is treated as an explanatory variable. This avoids the problems of bias and artificial significance in output coefficients, arising because both inputs and outputs trend over time, which was discussed in Section 3.1.3.

The model is specified as follows:

$$x_{ift} = a_{if0}^2 + a_{if1}^2 y_{1ft} + a_{if2}^2 y_{2ft} + a_{if3}^2 y_{3ft} + a_{if4}^2 y_{4ft} + b_{if}^2 t$$

Here time, t, enters as an explanatory variable rather than a modifier. Since it enters as an explanatory variable, the coefficient on time b_{if}^2 is constrained to be positive for comparability with the coefficients on other explanatory variables. This model also includes a constant, a_{if0}^2.

Using this model where time enters additively rather than as a modifier, the results are again quite different to those from EI's original report. A lower proportion of coefficients are significant on all four outputs: energy, demand, customer numbers, and circuit length. The two variables with the most frequently significant coefficients are time and the constant, indicating that both are relatively more important to explaining input demand than are any of the outputs.

It was possible to estimate 45 of the original 52 regressions using this model. The remaining seven failed to converge.[70]

3.1.5.4. Fixed effects panel model

Our fourth alternative model combines the data from all DNSPs, running one regression for each of the four inputs instead of thirteen DNSP-specific regressions. That is, we treat the data as a panel rather than separate time series. This overcomes the problems arising due to the small sample size, for example, the failure of the maximum likelihood algorithm to converge for the specification in natural logarithms.

The specific panel data model we use is a fixed effects model. This model includes an DNSP-specific "fixed effect" to account for unique characteristics that create differences in the regression left-hand side variable which are constant over time. For example, in a model

[69] The regressions which did not converge were for provider END, with UG and transformers as the inputs.

[70] The regressions which failed to converge were: all four of the models for DNSP JEN, and all but the opex model for ACT.

where OHL is the left-hand side variable, the fixed effect captures the differences in scale of DNSP networks. The specification is:

$$x_{ift} = (1 + b_i t)\left[a_{i1}^2 y_{1ft} + a_{i2}^2 y_{2ft} + a_{i3}^2 y_{3ft} + a_{i4}^2 y_{4ft} + c_f^2\right]$$

The fixed effect is c_f^2, which is essentially a constant term that differs for each firm.

Note that the remaining coefficients are no longer indexed by f, indicating that the panel data model estimates a single coefficient for all thirteen DNSPs. We see this as an acceptable simplification, given that the share calculation in which these coefficients are used takes an average of the thirteen coefficients and produces a single index, which is then applied equally to all 13 DNSPs for the purposes of the MPFP and MTFP modelling.

We do not include a constant in this model, because the DNSP fixed effects perform the same role.

Using this fixed effect model, we find that the coefficient on time is significant for all four input variables; the coefficient on Energy is significant for OH only; and the coefficient on RM Demand is significant for opex, UG, and transformers. The coefficients on Customers and Length are never significant. Overall, therefore, 4 of 16 output coefficients are significant (25 per cent) and all time coefficients are significant (100 per cent).

3.1.5.5. Accounting for many coefficients in the alternative models

Like EI's original model, our alternative models face the problem that when estimating many coefficients, some of them will appear significant just by chance.

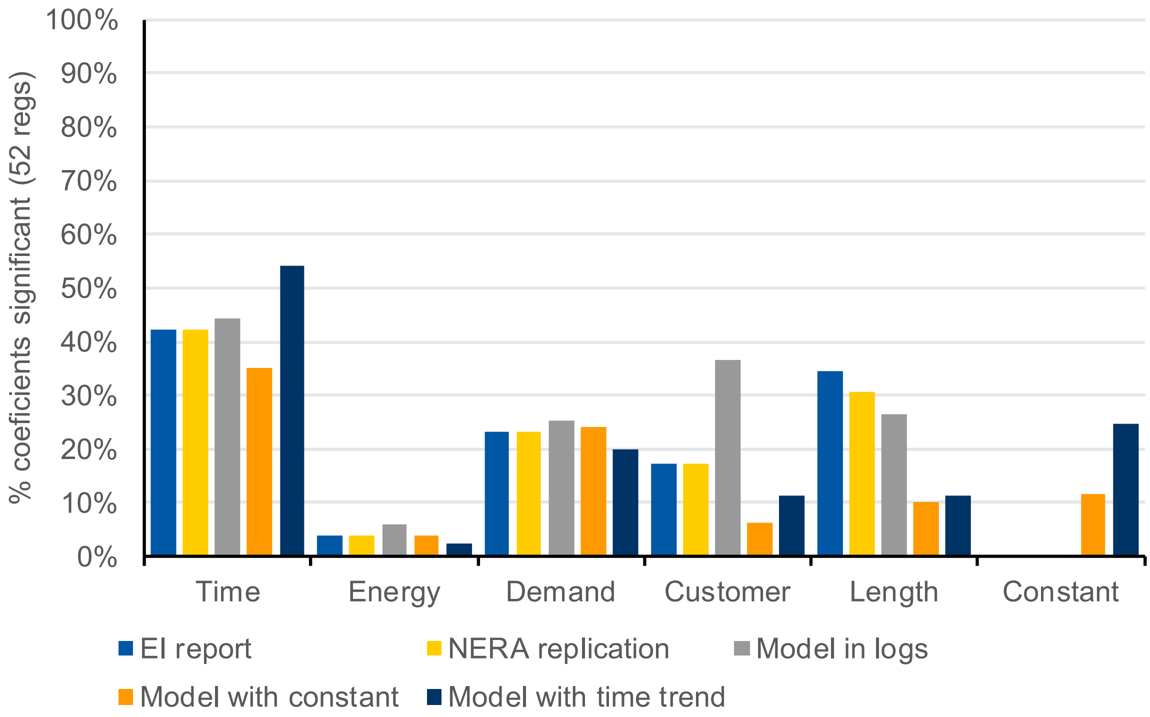
The solution to this problem is to apply a Bonferroni correction to the statistical tests. The results of applying this correction to EI's original model, the model in log-log, the model with a constant, and the model with a time trend are seen in Figure 3.3.

The fixed effects approach involves fewer coefficients; we estimate only 16 output coefficients rather than 208. Therefore it is not comparable to the other models and is not displayed in Figure 3.3. It is also less severely affected by the many coefficients problem or by the Bonferroni correction. Applying the Bonferroni correction to the fixed effects model, 4 of 16 (25 per cent) of output coefficients are significant. Energy is significant for OH only, and the coefficient on RM Demand is significant for opex, UG, and transformers.

The most important result from Figure 3.3 is that no matter what regression specification we use, less than 40 per cent of the coefficients on each output is significant. This means that over 60 per cent of estimated coefficients are statistically indistinguishable from zero. For energy in particular this is much lower: about 95 per cent of the coefficients are statistically indistinguishable from zero.

This means that we can have no confidence in output weights calculated using the coefficients from any of these specifications. Output weights calculated using zero, instead of the estimated output coefficients, would be statistically justified.

Figure 3.3: Fewer coefficients are significant using the Bonferroni correction



Source: NERA analysis

The second important result from Figure 3.3 is that the set of coefficients which are significant changes depending on which specification is used. This is particularly noticeable for customer numbers and circuit length. The changes in significance reflect changes in the values of the estimated coefficients, which can be seen in the Tables in Appendix B. These changes result in changes in the output weights.

The implication is that output weights change depending on the regression model specification. Therefore, we must have confidence that the regression specification used provides a good approximation to the statistical relationship between inputs and outputs. Because of the problems outlined in Sections 3.1.1 through 3.1.4, we do not have this confidence in EI's Leontief regressions.

In short, these coefficients should not be relied upon as inputs to further calculations. By extension, the EI coefficients, which are based on a less robust specification, should also not be relied upon as inputs to further calculations.

3.2. Process of Combining Coefficients Into Output Weights

In this section, we appraise the second part of EI's process in determining output weights in the MPFP modelling: converting regression coefficients into output weights. We describe this process in Appendix A.1.2 below. In short, we conclude that the MTFP weights which inform the MPFP model do not reflect a mix of outputs which drive opex.

3.2.1. The model weights vary counterintuitively between companies

In assuming a single set of weights which apply to all companies, EI implicitly assumes that all companies have the same drivers of efficient opex. However, this is directly contradicted by the inconsistency of the coefficients and hence output weights when considering companies separately. For each of 52 regressions, we have calculated the share of the fitted input cost which is driven by each output variable – effectively the coefficient multiplied by the variable level, accounting for the multiplicative effect of time. We show these in Table 3.1, separated by input variable.

Table 3.1: Contribution of Outputs to Inputs

Input: Opex				
	Energy	RM Demand	Customers	Length
ACT	0%	8%	0%	93%
AGD	0%	100%	0%	0%
AND	0%	100%	0%	0%
CIT	100%	0%	0%	0%
END	90%	0%	0%	11%
ENX	0%	100%	0%	0%
ERG	0%	10%	0%	90%
ESS	0%	0%	100%	0%
JEN	0%	0%	100%	0%
PCR	0%	11%	0%	89%
SAP	0%	100%	0%	0%
TND	100%	0%	0%	0%
UED	94%	6%	0%	0%

Input: Overhead Lines				
	Energy	RM Demand	Customers	Length
ACT	0%	82%	0%	19%
AGD	0%	0%	0%	100%
AND	0%	1%	0%	99%
CIT	0%	0%	21%	79%
END	0%	29%	0%	71%
ENX	0%	4%	0%	96%
ERG	0%	25%	0%	75%
ESS	24%	0%	0%	76%
JEN	0%	3%	28%	69%
PCR	0%	0%	62%	38%
SAP	11%	0%	17%	72%
TND	19%	0%	0%	81%
UED	0%	12%	88%	0%

Input: Underground Cables				
	Energy	RM Demand	Customers	Length
ACT	0%	36%	0%	64%
AGD	0%	0%	0%	100%
AND	0%	0%	100%	0%
CIT	13%	0%	0%	87%
END	0%	0%	0%	100%
ENX	0%	100%	0%	0%
ERG	0%	100%	0%	0%
ESS	0%	61%	0%	39%
JEN	0%	0%	0%	100%
PCR	0%	87%	13%	0%
SAP	0%	29%	0%	71%
TND	0%	0%	32%	68%
UED	0%	16%	40%	44%

Input: Transformers				
	Energy	RM Demand	Customers	Length
ACT	20%	0%	0%	80%
AGD	0%	100%	0%	0%
AND	0%	58%	31%	11%
CIT	51%	4%	0%	46%
END	0%	10%	0%	91%
ENX	0%	38%	0%	62%
ERG	0%	0%	100%	0%
ESS	0%	0%	100%	0%
JEN	0%	20%	0%	80%
PCR	0%	8%	0%	92%
SAP	28%	10%	0%	62%
TND	0%	0%	100%	0%
UED	0%	29%	71%	0%

Source: NERA analysis

These tables illustrate the instability of EI's approach to aggregating output weights.

First, the opex regressions suggest that, for four DNSPs, Energy is the sole or primary driver of opex. For four companies, RM Demand is the sole driver of opex. For two companies, Customers is the sole driver of opex. For three companies, Length is the sole or primary driver of opex.

Of course, this does not reflect the actual cost function for opex, which likely does not vary so dramatically between companies and will not be univariate. However, the modelling arbitrarily assigns weight to a single variable over the others due to problems in the model specification, especially the lack of a constant.

In the case of the opex models especially, the fitted opex is driven by a single dominant driver in all models. The smallest dominant driver still receives 89 per cent weight, and 8 of 13 models are entirely explained by just a single output driver. This suggests that the Leontief specification assigns high weight to a single variable as a means of proxying for the omitted constant term rather than to explain *variation* in costs.

Second, the dependent variable in the OHL and UG regressions is the product of network length and network capacity of OHL or UG (denominated in MVAkm). Given that the dependent variables are a linear combination of one actual output variable (Length) and a close proxy of another one (RM Demand as a proxy for network capacity), these inputs should only be driven by Length and RM Demand, out of the four output variables available.

For the OHL regressions, it is mostly true that Length is the primary driver of the dependent variable. However, the secondary driver is no more likely to be RM Demand than it is any other output variable. Additionally, in 3 of 13 models, Length is *not* the primary driver of OHL. For example, the model finds that UED's OHL is driven mostly by Customers, with a small secondary contribution from RM Demand. It finds that it is not driven *at all* by Length. This is clearly incorrect, and demonstrates the propensity of the Leontief regressions to identify false relationships at random.

For the UG regressions, the relationship between Length, RM Demand and UG is even less clear. Length is the primary driver barely more than half of the time, and fails to register at all in 4 of 13 regressions.

EI argues that it "minimise[s] the risks associated with the limited degrees of freedom per regression and the fixed propositions nature of the Leontief cost function [by taking] a weighted average of the derived output cost shares across all the Australian DNSP observations".[71] However, this relies on an assumption that the probability that the model will assign a high weight to a particular output variable is equal to that output's importance in driving costs. As we demonstrate above, this is unlikely to be the case.

3.2.2. EI's approach gives positive weight to meaningless variables

By using squared coefficients, the EI Leontief model forces the output coefficients in each regression to be non-negative. If the true relationship between the output variable and the input variable is negative, or if the observed data in the sample suggests a negative relationship, the MLE process finds a coefficient of 0 on that variable.

In its response to our December 2018 report on the calculation of output weights,[72] EI highlights this point, explaining that "[i]f the relationship in the database is non–existent then the regression will return a zero estimate for the output coefficient. If the relationship in the database is negative then the regression will force the estimated coefficient to zero as it is the least cost way it can satisfy the non–negativity constraint that is being imposed".[73]

However, due to the imprecision with which the model is estimated, with an illogical specification and only eight degrees of freedom, it is incorrect to assume that a variable with a non-existent relationship would always receive a coefficient of zero.

In a properly-specified regression equation with sufficient degrees of freedom, we would expect a meaningless variable to have a statistically significant coefficient about 5 per cent of

71 Economic Insights (30 April 2019), Review of NERA Report on Output Weights, p.6.

72 NERA (18 December 2018), Review of AER's Proposed Output Weightings – Prepared for CitiPower, Powercor, United Energy and SA Power Networks.

73 Economic Insights (25 August 2020), Economic Benchmarking Results for the Australian Energy Regulator's 2020 DNSP Annual Benchmarking Report, p.8.

the time, or two to three times out of 52 regressions. This is even more likely in the particular models in question, because:

- The forced relationship does not match the actual relationship between outputs and inputs. For example, by omitting a constant, the model assumes constant returns to scale rather than increasing returns to scale empirically observed in network industries. Additionally, the non-additive specification of time means that the regressions capture movements in input and output variables that are both driven by time.
- With only eight degrees of freedom to estimate five independent variables, it is unlikely that a meaningful relationship would be identified separately from other potential relationships. This is compounded by the fact that the output variables are correlated with one another, meaning that more data is generally necessary to identify separate effects from them.
- Because there is no constant term, the econometric specification guarantees that at least one variable will be statistically significant, or that multiple variables will be jointly significant.

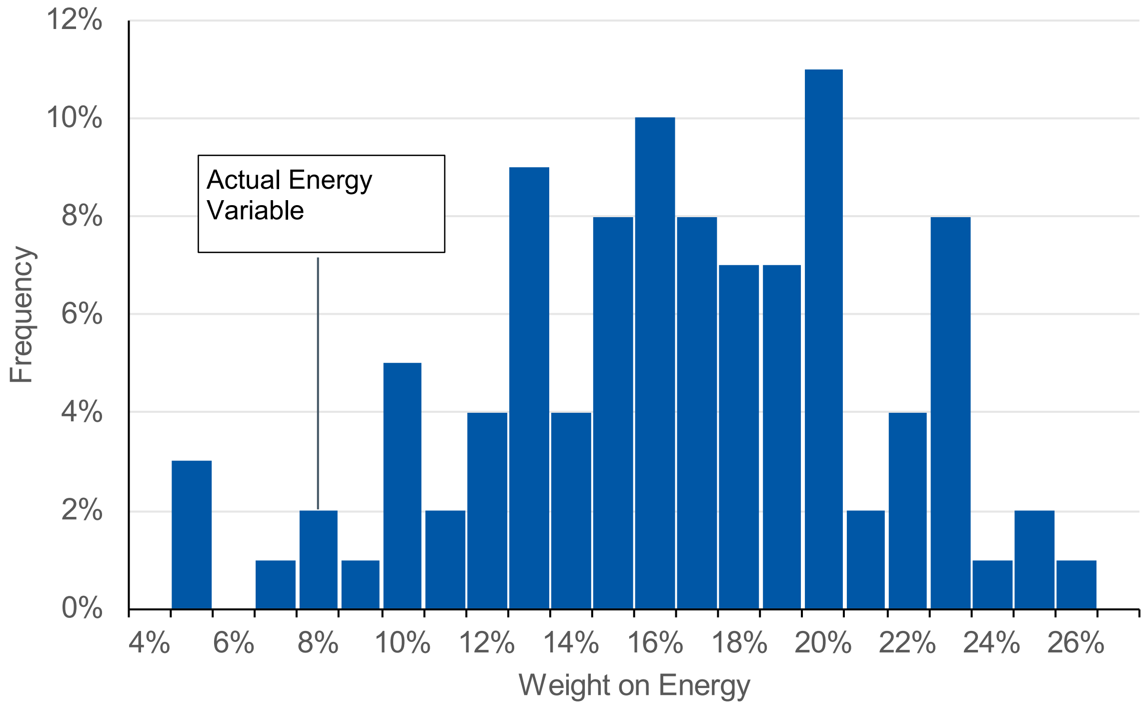
For the three reasons above, it becomes effectively random which variables actually receive weight in a given regression. We show this above in Table 3.1, which shows the weight that each output variable has in determining opex. There is no economic reason to believe that Energy is the primary driver of opex for four companies, Ratcheted Maximum for four companies, Network Length for three companies, and Customer Numbers for two companies. The model has simply assigned full or nearly full weight to these variables essentially by chance. In any case, that EI's regressions suggest that the cost function for these companies are so different undermines its case for benchmarking at all: The AER has no reason to use common output weights to forecast changes in costs if each company has an entirely different cost function.

In the absence of a squared coefficient term, we would expect some coefficients to be negative some of the time, especially if the relationship between that variable and the input variable is weak or non-existent. If negative coefficients were possible, it may be true that, when aggregating across all 52 models, the poor explanatory variables would receive smaller or no weight.

However, as the models are currently designed, these variables will never receive a negative coefficient. They will receive a positive coefficient some of the time simply due to chance, and a 0 coefficient when they would otherwise receive a negative coefficient. As a result, when averaging across 52 regressions, such a variable will receive a positive output weight even when it does not explain changes in cost whatsoever.

We demonstrate this effect by removing the Energy variable as reported by companies and replacing it with a random number generated based on the mean and standard deviation of each company's actual Energy value. In effect, this randomly generated variable resembles each company's energy variable in level and distribution but without any relation to cost in each year because random variations in it could not possibly explain variations in cost. We replicate this analysis 100 times and report weights resulting from each simulation in Figure 3.4 below.

Figure 3.4: Weight Assigned to Random Energy Variable



Source: NERA analysis

As the figure shows, the output weight assigned to this random variable is larger than the weight assigned to the actual Energy in 95 per cent of cases, even though it clearly bears no relation to variations in cost. This suggests that Energy is no stronger a driver of cost than a random number is.

A similar story emerges if we remove Energy as a driver in the 52 regressions and replace it with a variable that we know to be spurious. We have done this using the following data series in place of Energy:

- Annual flights to and from Melbourne Airport. This variable receives around 37 per cent weight, larger than any of the other included output variables.
- The exchange rate between British Pounds Sterling and New Zealand Dollars (expressed as GBP per NZD). This variable receives 19 per cent weight.
- The number of girls born in the Republic of Ireland each year named Zoe. This variable receives 19 per cent weight.
- Energy delivered by a different DNSP. We have run all 12 degrees of offset (e.g. Offset 1 uses the Energy variable from the next company alphabetically, Offset 2 uses the Energy variable from the second company down alphabetically, etc.). In seven instances, the weight assigned to Energy is higher than when the company's own Energy variable is used, while in the remaining five cases the regressions do not converge (i.e. the maximum likelihood algorithm was unable to find a solution).

With ample time and computational resources, it is possible to data-mine any number of spurious relationships in any context. We have carried out no such exercise in this case, with each of the variables above manually downloaded and individually run through our Stata code.

In fact, all of the spurious data series above (including the randomly-generated Energy variables above) have one key feature in common: they all exhibit similar levels of variation relative to their mean levels. Due to the restrictions of the econometric specification (non-negative coefficients and no constant), most regressions only have one variable with only one non-zero output coefficients. Therefore, a variable with any negative values or with large variation relative to its mean would be very unlikely to explain opex or the capital inputs, which exhibit relatively little variation relative to their means in each year.

The same is not true in a less restrictive specification: an independent variable's negative values could be captured by a negative coefficient and a volatile variable to could receive a smaller coefficient plus a positive constant. Our analysis demonstrates that, once we have accounted for the restrictive econometric specification, it is very easy to find variables that apparently drive MTFP inputs.

In short, the flaws of the econometric specification coupled with the small sample sizes means that the finding of a positive econometric relationship does not suggest a positive causal relationship, even if it is statistically significant.

Moreover, EI's approach of combining the results of 52 regressions does not add confidence in its findings, because its averaging approach only captures positive coefficients and not offsetting negative coefficients. Because the approach places excessive weight on meaningless variables, and weights are constrained to sum to 100 per cent, EI's approach also assigns insufficient weight to meaningful variables.

3.2.3. Excess and arbitrary weight is placed on OHL, UG and transformer models

EI provides no explanation for why it uses capital inputs in its calculation of weights that are ultimately used to determine opex allowances.

The calculation of output weights depends on the contribution of the outputs to opex, OHL, UG, and transformers. Of these, only opex is opex; the remaining three are capital inputs. EI explicitly acknowledges this in its report, writing that the Leontief regression is intended to provide "an approximation to any underlying production structure" and stating that "MTFP levels are an amalgam of opex MPFP and capital MPFP levels".[74] However, EI does not explain how this "underlying production structure" is appropriate for measuring *opex* productivity in its own right.

It would therefore be reasonable to expect that the calculation of the opex MPFP index would make use of output weights calculated using the opex regressions only. One would expect that only the calculation of the full MTFP index would be based on regressions for all four inputs. This would also be consistent with the cost functions, which econometrically calibrate the weight of each output based on how it drives *opex* rather than opex and capital inputs together.

74 Economic Insights (25 August 2020), Economic Benchmarking Results for the Australian Energy Regulator's 2020 DNSP Annual Benchmarking Report, p.1 & p.24.

Instead, the opex MPFP index is calculated using output weights derived from all four inputs. Our analysis shows that opex has a weight of only 36.9 per cent in the construction of these indices. The implication is that opex allowances are being set on the basis of indices that are more than half determined by non-opex inputs.

In Table 3.2, we compare the weights as derived from Opex models only with the weights reported in EI's analysis.

Table 3.2: MTFP Output Weights

	Energy	RM Demand	Customers	Length
Opex Only	16.87%	48.13%	15.66%	19.34%
MTFP	8.58%	33.76%	18.52%	39.14%
Delta	+8.29%	+14.37%	-2.86%	-19.80%

Source: NERA analysis and EI

As the Table demonstrates, the weights resulting from models which are more directly relevant to DNSPs' *opex* efficiency show very different weights from those that seek to explain capital inputs as well. The weights outlined for opex alone are not themselves reliable. Their calculation is subject to all of the criticisms previously outlined in Section 3.1.

Analysis based on opex alone should be used to determine opex allowances, not analysis which also incorporates capital inputs. However, the weaknesses of the MPFP method outlined in Section 3.1 mean that a revised MPFP analysis using weights based on only the opex regressions is not correct either.

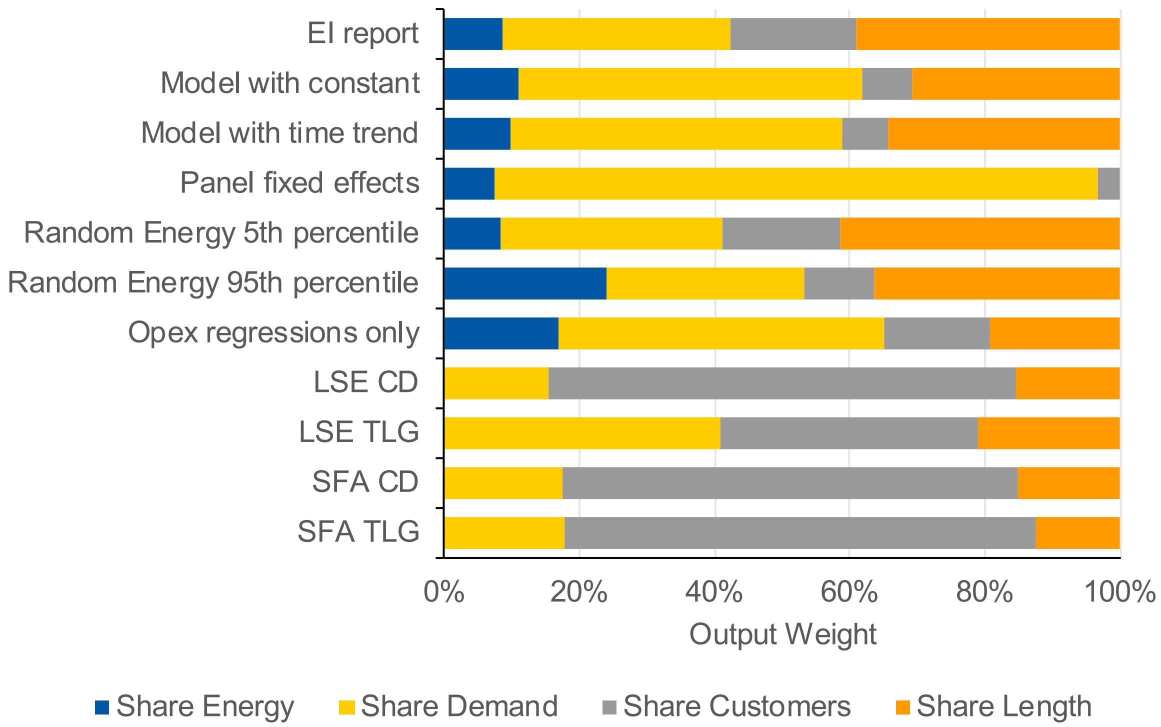
3.2.4. Different econometric specifications yield different output weights

The weights allocated to each of the four outputs depend on the regression specification used. We illustrate this by comparing the weights derived in EI's original analysis with the weights derived from the more appropriate alternative models considered in Section 3.1.5. We also show the weights derived from the "Random Energy" models described in Section 3.2.1, and the weights if derived only from the models with Opex as the dependent variable.

Finally, for comparison, we include the weights derived from the cost functions, and used in the Draft Determinations in Victoria. These do not include Energy as a variable. While we have not furthered our arguments on this matter in this report, the inclusion of Energy as an output variable in the MPFP model has been a subject of debate between us, Frontier Economics and EI. The cost functions consistently place considerably higher weight on Customers than the Leontief models. As the statistical sample is much more robust (with several hundred degrees of freedom), these models give an indication of what weights might be expected for the MPFP model using more robust econometric methods.

The weight allocated to each of the four outputs under different regression specifications is seen in Figure 3.5. The underlying numbers are given in Table 3.3.

Figure 3.5: Output weights vary with regression specifications



Source: NERA analysis

Table 3.3: Output weights from different regression specifications

Model	Energy	RM Demand	Customers	Length
EI report	8.58%	33.76%	18.52%	39.14%
w/ constant	10.85%	50.99%	7.41%	30.75%
w/ time trend	9.94%	48.90%	6.88%	34.27%
Fixed Effects	7.40%	89.14%	3.46%	0.00%
Rand. Energy (5^{th})	8.32%	32.86%	17.46%	41.36%
Rand. Energy (95^{th})	23.95%	29.28%	10.23%	36.54%
Opex Models Only	16.87%	48.13%	15.66%	19.34%
LSE CD	0%	15.48%	68.95%	15.56%
LSE TLG	0%	40.89%	37.95%	21.16%
SFA CD	0%	17.50%	67.43%	15.08%
SFA TLG	0%	17.90%	69.73%	12.37%
Bench. Models Avg.	0%	22.94%	61.02%	16.04%

Source: NERA analysis

The first bar of Figure 3.5 shows the output weights allocated by EI's original analysis.

The second through fourth bars show the output weights allocated by our alternative regression specifications, where the weights on the output variables have been re-scaled to sum to 100 per cent (i.e. excluding the weight on the constant term).

The final two bars show the output weights allocated using EI's original model but replacing the energy variable with a randomly generated variable. We considered 100 random energy variables; this figure shows only those at the 5th and 95th percentile, ranked by output weight allocated to the random energy variable.

The sensitivity of the output weights to the regression specification is clear. The output weight allocated to energy is halved when moving from the EI model to the panel fixed effects model. The weight allocated to customer numbers shrinks to less than a third of its previous value in all alternative specifications. In the EI model, circuit length is the greatest contributor to output costs; in all alternative specifications, demand is the greatest contributor.

The effect of the random energy variable on output weights especially demonstrates how arbitrary the weighting process is.

First, the fact that a random variable can be allocated a weight of nearly 25 per cent calls the validity of the entire procedure into question.

Second, the use of the Leontief cost function presupposes that the contribution of each output to cost is unrelated to the contributions of other outputs. We therefore expect that when the contribution of Energy to costs increases (moving from the 5th to 95th percentile of Random Energy), the contribution of the other three outputs should fall in equal proportions. However, this is not what we see. Moving from the 5th to the 95th percentile of Random Energy, the contribution of customers to costs shrinks by more, in both absolute and relative terms, than the contributions of either RM Demand or Length. This suggests that the contribution of Customers to costs depends on the contribution of Energy to costs, invalidating the underlying Leontief specification.

Overall, this analysis illustrates that the output weights derived from the Leontief regressions are not reliable because they are volatile and precarious to changes in model specification. Alternative, more plausible specifications of the regressions yield very different weights. The results from the Random Energy analysis call the validity of the entire procedure into question.

In short, we conclude that the weights that actually come out of the Leontief specification are effectively random. EI could select four weights at random and not be further from the truth than it is under these output weights.

3.3. Implications of Output Weight Calculations

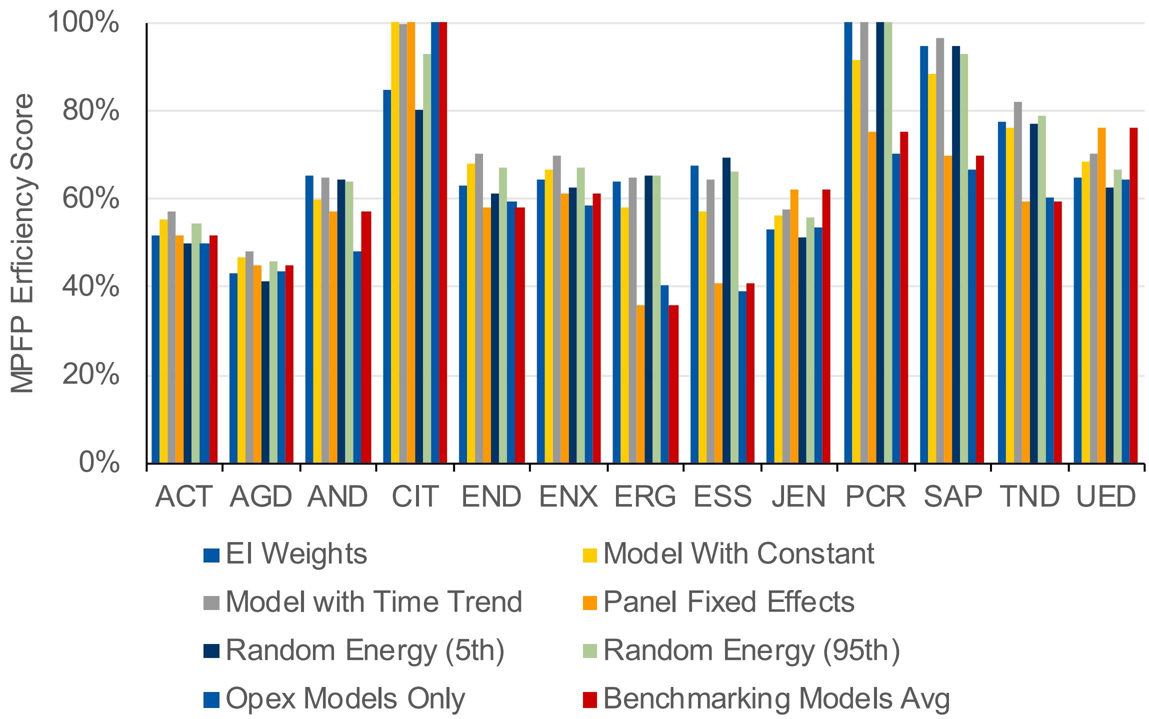
As we establish in the previous sections of this chapter, the output weights from the Leontief modelling are effectively random, with no bearing to actual drivers of cost. In this section, we set out the implications of these random output weights across the uses of the MPFP model. For each of these uses, we calculate alternative values and figures using the range of output weights set out in Table 3.3 above. For brevity, we include the average weights of the cost functions rather than all four separately.

3.3.1. Base Year Efficiency Assessment

As described in Section 2.2.1, the MPFP efficiency score is one piece of evidence that the AER uses to assess whether a DNSP's base year opex proposal is efficient.

In Figure 3.6 below, we demonstrate how each DNSP's MPFP efficiency score varies under the full range of output weights. In Table 3.4 we present the rank of each company in each model.

Figure 3.6: MPFP Efficiency Scores Under Alternative Weights



Source: NERA analysis

Table 3.4: MPFP Efficiency Ranks Under Alternative Weights

	EI Weights	Model w Cons.	Model w Time Trend	Panel Fixed Effects	Random Energy (5th)	Random Energy (95th)	Opex Models Only	Cost Function Avg
ACT	12	12	12	10	12	12	9	10
AGD	13	13	13	11	13	13	11	11
AND	6	8	9	9	7	10	10	9
CIT	3	1	2	1	3	3	1	1
END	10	6	5	8	10	6	6	8
ENX	8	7	7	6	8	5	7	6
ERG	9	9	8	13	6	9	12	13
ESS	5	10	10	12	5	8	13	12
JEN	11	11	11	5	11	11	8	5
PCR	1	2	1	3	1	1	2	3
SAP	2	3	3	4	2	2	3	4
TND	4	4	4	7	4	4	5	7
UED	7	5	6	2	9	7	4	2

Source: NERA analysis

As the figure and the tables show, DNSPs' full-period efficiency scores are sensitive to the choice of output weights. While the differences are unlikely to change the AER's conclusions about the relative efficiency of the most and least efficient DNSPs – CIT, PCR and SAP are among the top four, while ACT and AGD are in the bottom four, regardless of output weights – the rankings could influence the AER's conclusions on the efficiency for companies in the middle.

For instance, under different weights, ERG's rank varies from 6th to 13th, ESS's rank varies from 5th to 12th, JEN's rank varies from 5th to 11th, and UED's rank varies from 2nd to 9th. When considering whether a DNSP is among the top performing firms, these dramatically different rankings could plausibly be the difference between the AER deciding to accept the company's opex proposal and not.

3.3.2. Output weight indexation

As discussed in Section 2.2.2.1, the MTFP weights are one of five weights that feed into the average output weight indexation process, along with coefficients from the four cost function models . Therefore, the rate of change allowance is directly dependent on the MTFP weights, and hence, on the quality of the Leontief regressions and approach to averaging across companies and inputs.

In Table 3.5 below, we restate the output weights from the cost functions as included in the Victorian draft determination (though these will be updated in advance of the Victorian final determinations). In Table 3.6, we show the *overall* output weights from using each of the MTFP weights shown in Table 3.3 (i.e. the unweighted average of the four cost function models and each of the alternative MTFP weights. We illustrate these in Figure 3.7 below.

Table 3.5: Cost Function Model Weights

	Energy	RM Demand	Customers	Length
LSE CD	0.00%	15.48%	68.95%	15.56%
LSE TLG	0.00%	40.89%	37.95%	21.16%
SFA CD	0.00%	17.50%	67.43%	15.08%
SFA TLG	0.00%	17.90%	69.73%	12.37%

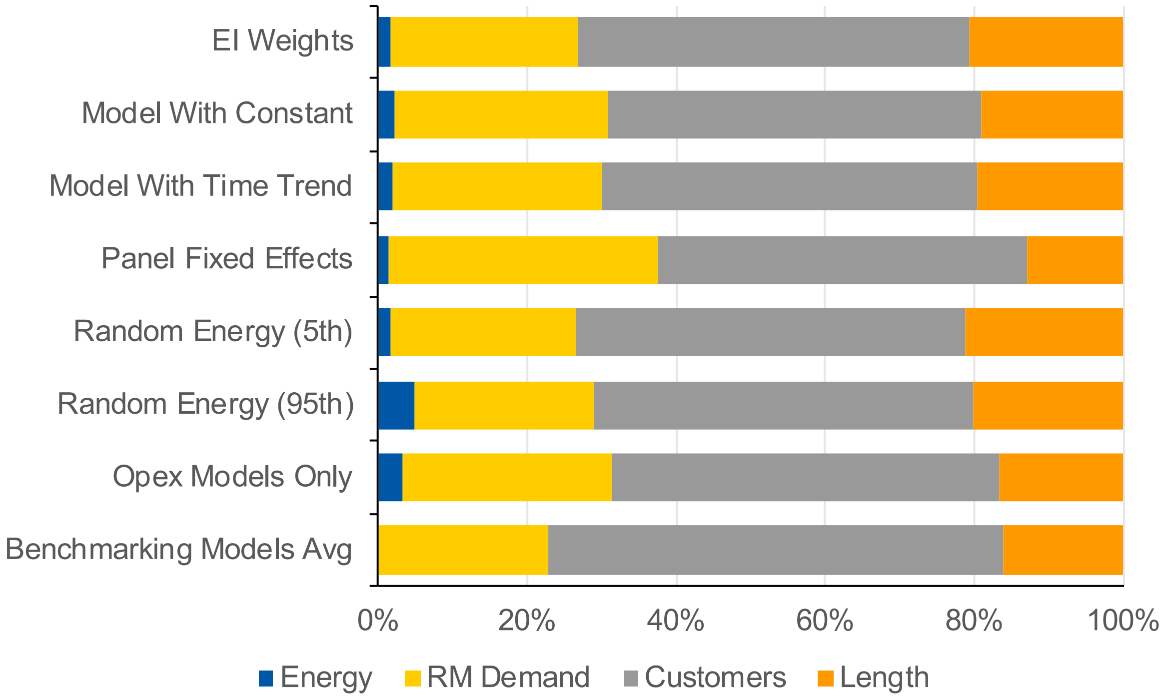
Source: AER

Table 3.6: Average Output Weights Under Different MPFP Approaches

Model	Energy	RM Demand	Customers	Length
EI report	1.72%	25.11%	52.52%	20.66%
w/ constant	2.17%	28.55%	50.29%	18.98%
w/ time trend	1.99%	28.13%	50.19%	19.69%
Fixed Effects	1.48%	36.18%	49.50%	12.83%
Rand. Energy (5th)	1.66%	24.93%	52.30%	21.11%
Rand. Energy (95th)	4.79%	24.21%	50.86%	20.14%
Opex Models Only	3.37%	27.98%	51.94%	16.70%
Cost Function Avg	0.00%	22.94%	61.02%	16.04%

Source: NERA analysis

Figure 3.7: Average Output Weights Under Different MPFP Approaches



Source: NERA analysis

Because each of these outputs is expected to grow at different rates during the coming reset periods, the different relative weights on each output has material implications on companies' revenue allowances, especially when compounded over multiple years.

We show a stylised example of this in Table 3.7 below, which demonstrates what each DNSP's allowance would be in Year 5 of a reset period relative to the base year (Year 0), assuming that each output grew at the DNSP-specific average rate from 2015-2019 and that there are no other components to the rate of change allowance. We show the highest and lowest Year 5 allowances based on the weights in Table 3.6 above (which already incorporate the weights from the cost functions), and the difference between them.

Table 3.7: Impact of Different Output Weights on Year 5 Opex Allowance

DNSP	Max	Min	Delta
ACT	110.9%	110.2%	0.7%
AGD	104.2%	103.2%	1.0%
AND	107.2%	106.1%	1.1%
CIT	105.3%	104.7%	0.6%
END	107.1%	106.2%	0.9%
ENX	105.4%	104.2%	1.1%
ERG	104.5%	103.4%	1.0%
ESS	103.9%	103.6%	0.3%
JEN	106.8%	105.5%	1.3%
PCR	106.9%	106.0%	0.9%
SAP	103.7%	102.8%	0.8%
TND	103.3%	102.6%	0.7%
UED	104.4%	103.5%	0.9%

Source: NERA analysis

As the table demonstrates, most DNSPs' opex allowances in the final year of a five year reset period vary by around 1 per cent, due exclusively to the arbitrary choice of output weights from the MTFP model.

As we establish in Sections 3.1 and 3.2, the MTFP weights do not reflect a mix of outputs which are robustly estimated and relevant to opex. In particular, these weights are primarily based on the (poorly estimated) effect of outputs on *capital inputs* (i.e. the OHL, UG and Transformer models), so they bear little resemblance to the effect of outputs on efficient opex, even if they did not suffer from econometric shortcomings. Therefore, the output growth allowance is not likely to reflect changes in efficient opex.

3.3.3. Industry-wide productivity trends

As discussed in Section 2.2.2.3, the AER uses the MPFP improvements of the top four firms as one piece of evidence to inform its productivity target of 0.5 per cent per annum. In its final decision on productivity, the AER estimated that the top four performing firms (CIT, PCR, SAP and UED) improved their MPFP by an average of 0.37 to 0.97 per cent between 2011 and 2017, based on geometric mean and regression averaging techniques, respectively.

In Table 3.8 below, we demonstrate how these same pieces of analysis would vary based on different MTFP weights. Note that this is based on the dataset relied upon in EI's 2020 Benchmarking report, and "EI Weights" refers to the most recent set of weights after correcting for the error in encoding time. Therefore, we do not replicate the numbers presented in the final productivity decision.

Table 3.8: Top Four DNSP Productivity Trends under Alternative Weights

	2011-17 Geometric Mean	2011-17 Regression
EI Weights	-0.59%	0.28%
Model With Constant	-0.77%	0.10%
Model with Time Trend	-0.75%	0.12%
Panel Fixed Effects	-0.14%	0.70%
Random Energy (5th)	-0.59%	0.28%
Random Energy (95th)	-0.81%	0.04%
Opex Models Only	-0.77%	0.08%
Benchmarking Models Avg	-0.14%	0.70%
Max	-0.14%	0.70%
Min	-0.81%	0.04%
Delta	0.67%	0.66%

Source: NERA analysis

As the table shows, the choice of MTFP weights has a material impact on the AER's appraisal of long-term productivity trends of the top four most efficient companies. Under both averaging techniques, the long-term average varies by 0.66-0.67 per cent, simply as a result of the choice of weights.

This piece of analysis was just one of seven that informed the 0.5 per cent productivity target, and that target is not derived mechanistically from any one piece of evidence. Therefore, it is not possible to determine with certainty whether the AER's chosen productivity target would have been different with a higher or lower value from this piece of evidence. However, this piece of evidence is clearly highly sensitive to the choice of weights, and we therefore can also not say with certainty that the AER would *not* have selected a different productivity target under different weights.

3.4. Assessment of MPFP Models with Respect to the NER and the NEL

In appraising the MPFP modelling, we evaluate whether the MPFP model and the AER's uses of it reasonably reflect the efficient costs of providing distribution services (i.e. meeting the opex objectives), and whether they represent a "realistic expectation of the […] cost inputs required to achieve" the opex objectives,[75] and whether it allows DNSPs a reasonable opportunity to recover its efficient costs, as set out in the NEL.[76]

We find that the MTFP output weights do not reflect the relative importance of outputs that an efficient operator would deliver. Therefore, in relying upon the MPFP model in determining whether a DNSP's proposed opex is efficient, or in calculating an alternative value to substitute in place of the DNSP's proposal, the AER fails to reasonably reflect the

[75] National Electricity Rules, v150, clause 6.5.6(c).

[76] National Electricity (South Australia) Act 1996, Schedule – National Electricity Law, Section 7A(2).

efficient costs of providing distribution services. Its methods which use the MPFP model do not represent a realistic expectation of the cost inputs required to achieve the opex objectives.

More specifically:

- Numerous technical flaws and data limitations mean that the output weights are effectively random and assign positive weight to potentially meaningless variables.
- The MPFP model is unreliable in assessing whether a DNSP's base year opex is efficient. The results of the MPFP model benchmarking do not reflect the cost efficiency of a DNSP because they are based on an arbitrary and inaccurate set of output weights. Different, and equally valid, sets of output weights may suggest different conclusions regarding the DNSP's base year efficiency. Hence it is unlikely that the results based on the set of weights actually employed represent the services that DNSPs actually deliver.
- When used as part of the output growth portion of the rate of change allowance, the MTFP weights are unlikely to reflect changes in outputs which drive changes in efficient costs. By placing excessive weight on some outputs and, as a result, insufficient weight on other outputs, the AER will provide excess and inefficient remuneration to DNSPs whose output growth is concentrated in the over-represented output categories. It will fail to provide adequate remuneration to efficient DNSPs whose output growth is concentrated in the under-represented output categories. While the MTFP weights represent only 20 per cent of the overall output weight methodology, they serve to dilute rather than strengthen the accuracy of the overall approach.
- For more *ad hoc* uses of the MPFP modelling, including the 0.5 per cent productivity target, the MPFP modelling is likely to distract rather than add to other pieces of analysis which could be used in its place.

Therefore, we conclude that the use of the MPFP model is inconsistent with the AER's statutory obligations as set out in the NEL and the NER, and should not be relied upon for future regulatory decision-making.

4. Cost Functions in Place of MPFP

As we describe throughout this report, the MPFP modelling is part of the AER and EI's toolkit, and has become increasingly so in the last two to three years. We therefore understand that it represents a major methodological shift to discontinue its use, and that the AER may be hesitant to do so if it were to sacrifice analysis and evidence that it could appraise by no other means.

There is no reason to believe that the AER would lose information or insight as a result of dropping the MPFP modelling. As we set out in this chapter, the AER could use its cost functions in its place for all current uses of the MPFP model. Indeed, relying on its cost functions and eliminating the MPFP model (at least as currently conducted) would improve the rigour of the AER's determinations by eliminating essentially meaningless and arbitrary analysis.

In Section 4.1, we set out how the cost functions can be used for the base year efficiency assessment. In Section 4.2, we set out how greater emphasis can be placed on the cost functions in its other uses.

4.1. Base Year Opex Efficiency Assessment

The AER uses the MPFP model as one of five benchmarking techniques to assess the efficiency of DNSPs' opex over an extended historical window (e.g. 2006 to 2018 or 2012 to 2018). The AER could place more emphasis on its other efficiency assessment approaches by omitting the MPFP analysis from this part of the assessment.

As presented by EI, the MPFP model has an additional advantage over the cost functions in that it can be used to assess a DNSP's efficiency on an individual year basis. As we describe in Section 2.2.1, Jemena's poor MPFP performance in 2018 *specifically* was one reason why the AER decided to substitute Jemena's base year opex proposal for its own. The EI benchmarking reports do not allow for similar annual analysis from the cost functions.

Although (to our knowledge) EI has never presented annual results for individual companies from the cost functions, it is trivial to adapt the modelling output to do so. Based on the modelling coefficients estimated over the relevant modelling period combined with annual driver levels, one simply needs to calculate the "fitted value" of opex and divide by the company's actual opex (scaled as appropriate by the opex price index).

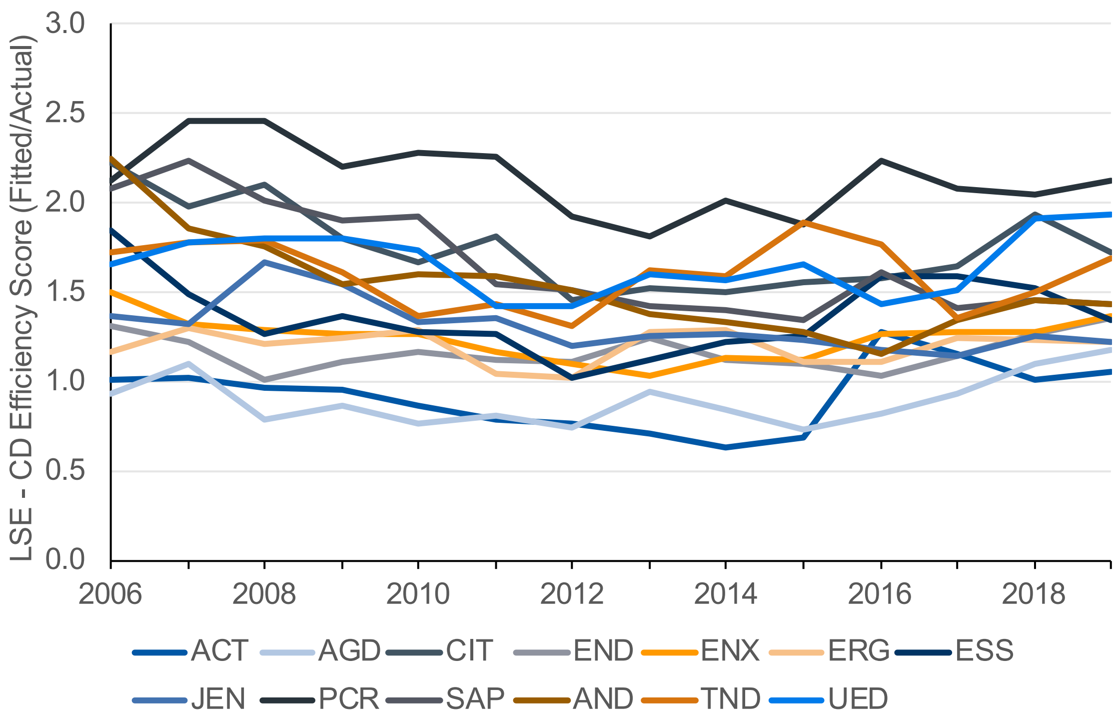
In order to maximise its usefulness, some adjustments should be made in calculating fitted values:

- In the LSE models, the fitted values should exclude the DNSP-specific dummy variables, which capture inefficiency. If these are included, then all DNSPs will appear to be similarly efficient, negating the usefulness of this analysis for any comparative analysis.
- In all models, EI would need to hold the time trend fixed. If the time trend is allowed to increase normally over time, then the annual efficiency score will only be appropriate for comparison with the rest of the industry, rather than to measure absolute improvements in

efficiency.[77] We hold time fixed at 2006. the first year of the benchmarking assessment, but any other year would demonstrate similar results.

Figure 4.1 to Figure 4.4 below show annual efficiency scores by firm based on the four cost functions estimated between 2006 and 2019.

Figure 4.1: Annual Efficiency Scores - LSE CD



[77] By holding fixed the time trend, relative comparisons are still possible.

Figure 4.2: Annual Efficiency Scores - LSE TLG

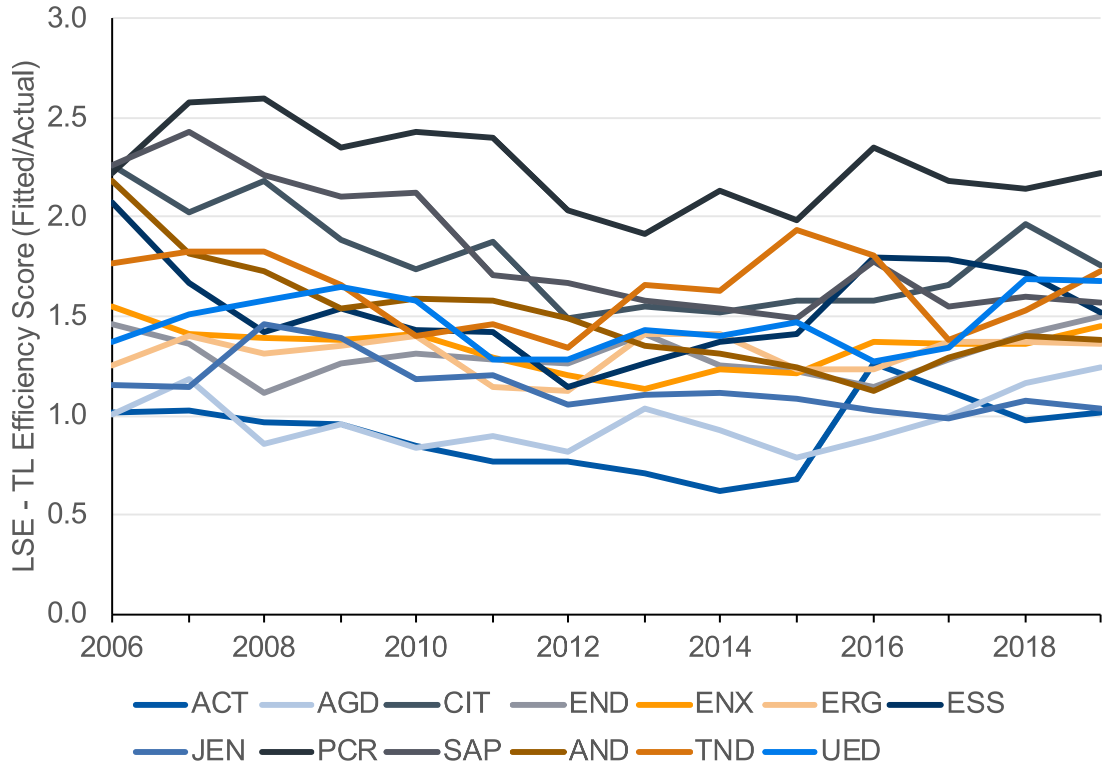


Figure 4.3: Annual Efficiency Scores – SFA CD

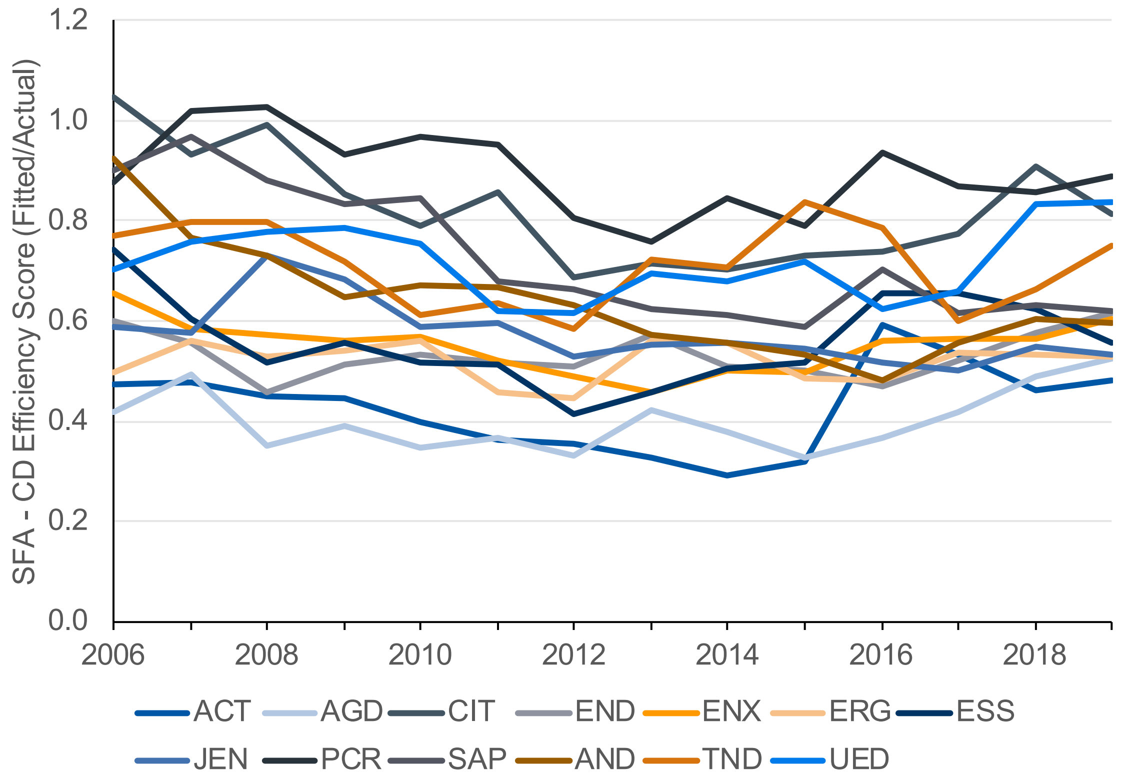
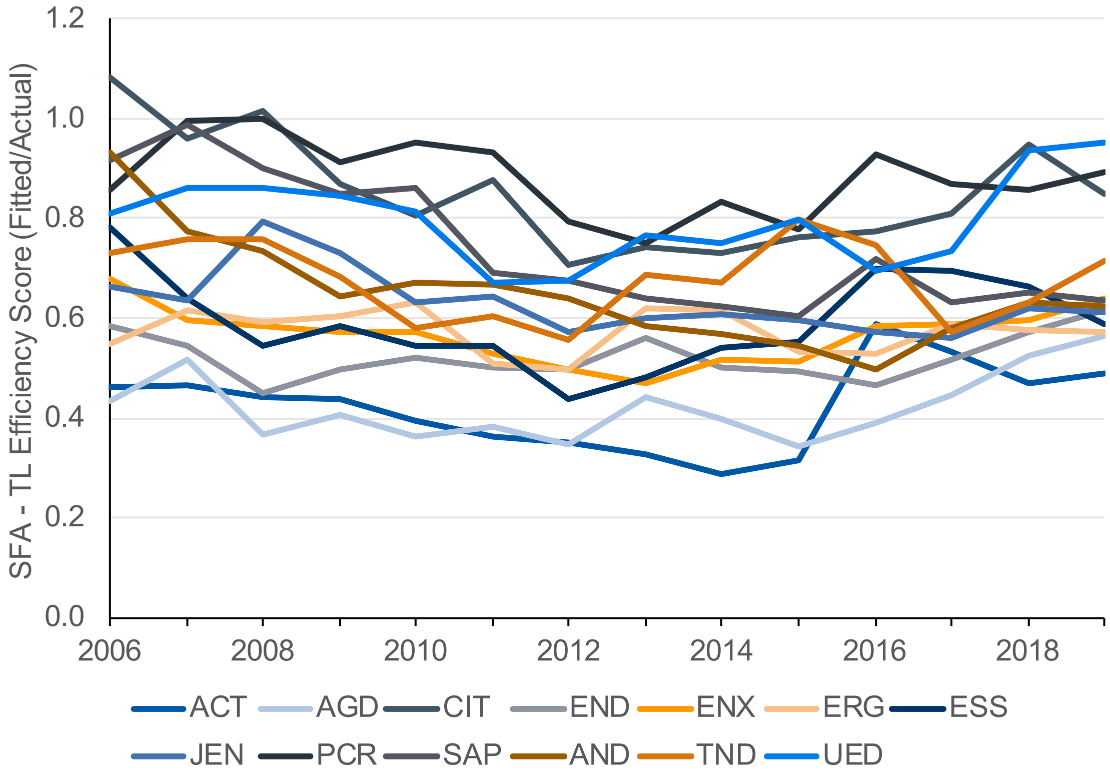


Figure 4.4: Annual Efficiency Scores – SFA TLG



Source: NERA analysis

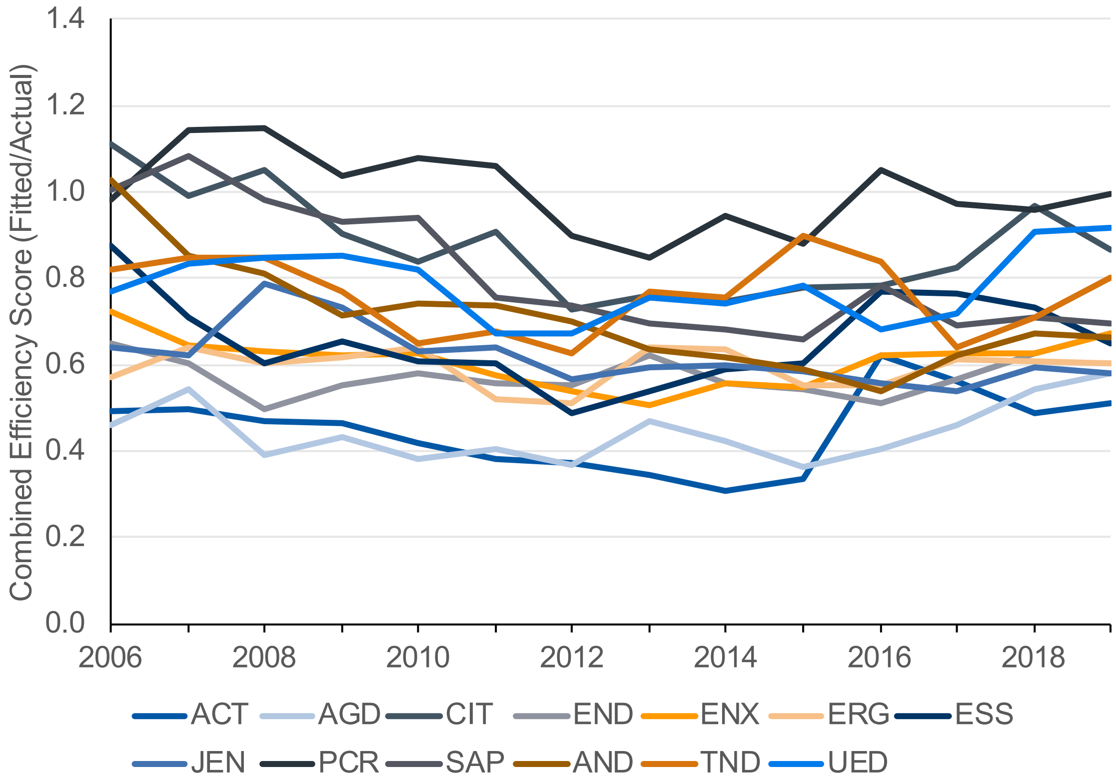
In these figures, we can see each firm's efficiency relative to its peers on an annual basis, and also relative to itself in previous years (since we exclude the effect of the time trend).

The absolute level of efficiency requires some interpretation or re-scaling as necessary. In the LSE models, efficiency is calculated relative to ACT's average efficiency, the DNSP whose dummy variable is omitted in modelling. ACT's average efficiency score is therefore 1.0 (or 100 per cent efficiency) by definition in 2006 (ignoring the industry-wide time trend which we hold constant). Because ACT is among the least efficient companies according to these models, other DNSPs' annual efficiency scores are higher than one (i.e. more than 100 per cent efficiency).

In the SFA models, the model specification puts the most efficient firm on the frontier with an efficiency score of 1.0 by definition (again ignoring the effect of time). All other firms have scores that are lower than this.

For cross-model comparisons between the LSE and the SFA models, the AER (or EI) would need to re-scale to a common base. In Figure 4.5, we present each firm's annual efficiency score on average across the four cost functions, with each function's scores re-scaled so that the best-performing firm in each model has an average efficiency score of 1.0.

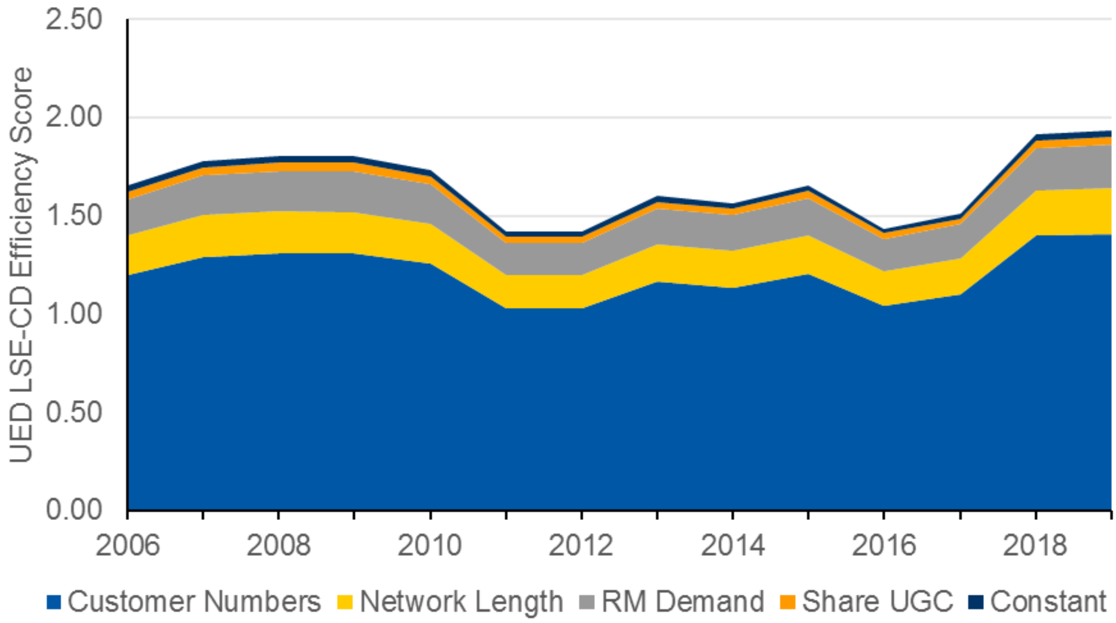
Figure 4.5: Annual Efficiency Scores – Average across cost models



These efficiency scores can be approximately decomposed between the different drivers as well. We have calculated this decomposition for the LSE CD model by estimating the share of each driver in contributing to the total fitted score by year and DNSP.[78] We present this below for UED, but this could be presented for any company or aggregation of companies (e.g. by state or across the industry).

78 In order to ensure positive values, we re-estimate the model without de-meaning the variables, and calculate the ratio of each coefficient multiplied by the logged output level, relative to the total fitted logged opex. This is only an approximation because, in a Cobb-Douglas specification (which is multiplicative), the contribution of one output to the total depends on the levels of all other outputs.

Figure 4.6: UED Decomposed Opex Efficiency



Source: NERA analysis

In this model, we see that UED became more efficient from 2006 to 2019, albeit with a decline in 2011. Were we to overlay this with the same from other companies (i.e. Figure 4.1), we could make comparative statements about UED's relative efficiency in any given year.

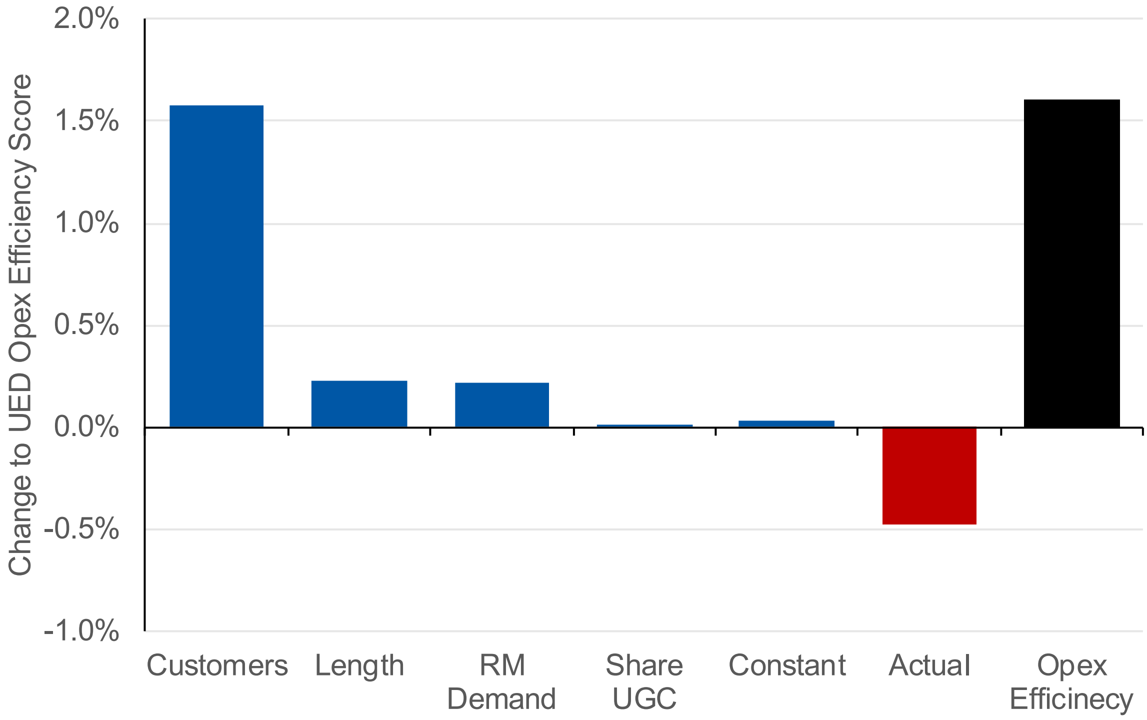
In this example, UED's output levels mostly grow slowly and steadily over the course of the modelling period, and hence so does UED's allowed opex. UED's actual opex is much more volatile. The troughs in the period represent times when UED's opex was higher than normal (and not explained by the relatively stable output levels), while the peaks (e.g. 2018-19) represent periods when opex was low.

When interpreting the decomposed levels included in the Figure, a trough in one colour (e.g. blue for Customers) represents a period when UED's customer-driven opex was high relative to the number of customers it actually served, and vice versa for the peaks.

As EI does with MPFP modelling, this can be modified to decompose the changes in efficiency from any year to any other year. We demonstrate this in Figure 4.7 below, which decomposes changes to UED's LSE-CD efficiency score from 2018-19, equivalent to Table 5.40 in the 2019 EI Benchmarking report.[79]

[79] See for example: Economic Insights (25 August 2020), Economic Benchmarking Results for the Australian Energy Regulator's 2020 DNSP Annual Benchmarking Report, Figure 5.40.

Figure 4.7: UED 2018-19 Changes in Opex Efficiency



Source: NERA analysis

As the figure shows, UED's outputs grew between 2018 and 2019, driven primarily by 1.8 per cent growth in Customers. Its opex also grew (hence the negative red bar), but by less than would be anticipated by the output growth. Therefore, its opex efficiency improved overall, as shown in the black bar.

While we have not done so, this analysis could be trivially extended to the SFA CD model. Further simplifying assumptions would be necessary to extend it to the TLG models, because TLG models include cross-product terms that are not straightforward to allocate to individual outputs.

4.2. Other Uses

Other uses of the MPFP model are even simpler to adapt to the cost functions:

- The output growth process uses weights from the four cost function models plus the MTFP weights (with 20 per cent weight each). The AER could simply remove the MTFP weights from this calculation and place 25 per cent weight on the weights from each of the cost functions.
- The AER relied on several different pieces of evidence in formulating its productivity assumption. The AER could simply place greater consideration on the other pieces of evidence and ignore the results of the MPFP model.

5. Conclusion

We have carried out a thorough review of EI's Leontief modelling, the MPFP modelling based upon it, and the AER's use of various components of EI's outputs. We find that EI's method for deriving output weights is highly arbitrary, poorly justified, and highly likely to result in weights that are unrelated to drivers of efficient opex.

The AER's uses of the MPFP modelling are highly sensitive to the choice of output weights. Therefore, the AER's price control parameters which rely upon MPFP modelling are unlikely to reasonably reflect the efficient cost of providing distribution services, as is stipulated by the NER. Moreover, by using MPFP modelling as a supplement to other forms of modelling, the AER reduces weight on modelling techniques which may reflect the efficient costs of providing distribution services, and the final price control parameters are less likely to satisfy the opex criteria.

Therefore, the AER fails to satisfy the opex criteria of the NER by relying in part on the MPFP model. The AER could better satisfy the opex criteria by placing no consideration on the MPFP model.

While the AER has previously turned to the MPFP model as a flexible, granular tool to fit a variety of purposes, the cost functions can be adapted for all of these same purposes, but with a more robust and reliable methodology underpinning them.

Appendix A. MPFP Modelling Approach Description

A.1. Calculating output weights

A.1.1. Leontief regression models

EI uses regressions to estimate the contribution of each of four outputs to demand for each of four inputs. It uses unique regressions for each of the four inputs and each of the 13 providers, giving a total of 52 regressions. The four inputs are: operational expenditure in 2006 AUD; overhead lines (OHL) in MVAkms; underground cables (UG) in MVAkms; and transformers in MVA. The four outputs are: Energy; Customers; RM Demand; and Length.

The regression model used is

$$x_{ift} \sim \left(1 + b_{if}t\right)\left[a_{if1}^2 y_{1ft} + a_{if2}^2 y_{2ft} + a_{if3}^2 y_{3ft} + a_{if4}^2 y_{4ft}\right]$$

where i indexes the input (one per regression); f indexes the firm (one per regression); and t indexes time (13 years). The level of the input at time t is x_{ift} and the level of output 1 at time t is y_{1ft} (outputs 2-4 are analogous). The output coefficients are a_{if1}^2 through a_{if4}^2, which capture the contribution of the relevant output to input demand (the model forces the coefficient to be positive by requiring it to be a square). The time coefficient b_{if} captures how the relationship between the input and output changes over time.

EI estimates these coefficients using a maximum likelihood function in Shazam. We have replicated this analysis in Stata, an industry-standard statistical software. We have replicated the coefficients of the model to a high degree (out of 260 coefficients, including time, the largest discrepancy is 0.09 – our estimate of the coefficient of RM Demand on ACT's opex is 2.21, while EI's is 2.12), though our replicated t statistics are somewhat different. There is no clear directional bias, so we assume that the differences are caused by differences in the maximization algorithm.

A.1.2. Converting coefficients into output weights

The coefficients estimated from the Leontief regressions are used to calculate output weights according to the following procedure.

First, the predicted total cost of each input, for a given DNSP f at a given time t, is calculated, based on the regression. The formula is:

$$\hat{C}_{ift} = p_{it} \times \hat{x}_{ift} = p_{it} \times \left(1 + \hat{b}_{if}t\right)\left[\hat{a}_{if1}^2 y_{1ft} + \hat{a}_{if2}^2 y_{2ft} + \hat{a}_{if3}^2 y_{3ft} + \hat{a}_{if4}^2 y_{4ft}\right]$$

Here $\{\hat{b}_{ift}, \hat{a}_{if1}^2, \ldots, \hat{a}_{if4}^2\}$ are the coefficients estimated from the regression; $\hat{x}_{ift}$ is the predicted demand for input i by DNSP f at time t, and p_{it} is the price of input i at time t. Thus $\hat{C}_{ift}$ is the predicted cost of input i to DNSP f at time t.

Second, the predicted total cost for all four inputs is calculated. That is:

$$\hat{C}_{ft} = \sum_{i=1}^{4} \hat{C}_{ift}$$

Third, the predicted contribution of each output to total cost is calculated. This calculation relies on the assumption of a Leontief cost function. The assumption that the demand for the input due to a given output does not at all depend on the levels of other outputs is what allows us to allocate costs to each output. The calculation is:

$$\hat{C}_{jft} = \sum_{i=1}^{4} \{p_{it} \times (1 + \hat{b}_{if}t)[\hat{a}_{ifj}^{2} y_{jft}]\}$$

Here j indexes the output, of which there are four (Energy, RM Demand, Customers, and Length). The contribution of output j to total costs for DNSP f at time t is $\hat{C}_{jft}$.

Fourth, a ratio is taken to calculate the contribution of each output to total cost as a share of total cost. That is,

$$\hat{S}_{jft} = \frac{\hat{C}_{jft}}{\hat{C}_{ft}}$$

Here $\hat{S}_{jft}$ is the share of the total costs of DNSP f at time t that are attributed to output j . At this point, all constructions are still DNSP- and time-specific.

Fifth and finally, a weighted average of the shares is taken over both DNSPs and time. The weight on a given DNSP-time observation equals the share of the total cost incurred by that DNSP f at that time t as a proportion of the total cost incurred by all DNSPs across all time periods. Thus the final calculated share of costs attributed to an output j is

$$\hat{S}_{j} = \sum_{t=1}^{13} \sum_{f=1}^{13} \hat{S}_{jft} \times \left(\frac{\hat{C}_{ft}}{\sum_{t} \sum_{f} \hat{C}_{ft}} \right)$$

Here $\hat{S}_{j}$ is the share of costs attributed to output j. This is then taken forward as the output weight.

A.2. Measuring MPFP based on outputs and inputs

Using the weights derived above, EI calculates an output index over the 2006-18 period. To do so, it follows the multilateral Törnqvist TFP technique proposed by Caves, Christensen and Diewert (1982).[80]

The steps that EI adopts in defining the output index are as follows:

- After a small adjustment for the value of customer minutes lost (a negative value that varies by DNSP and year), EI calculates adjusted output shares which are somewhat larger than the original output shares. For example, the original output share for Energy is 8.32 per cent; the adjusted output share ranges from 8.49 per cent to 12.04 per cent.

[80] Economic Insights (25 August 2020), Economic Benchmarking Results for the Australian Energy Regulator's 2020 DNSP Annual Benchmarking Report, p.116

- For each output (including customer minutes lost), EI calculates the average weight across all DNSPs and all years, and adds this average to the DNSP- and year-specific output weight.
- For each output, EI calculates the natural logarithm of each DNSP's level in each year. It then calculates the average of the natural logarithm across the set and subtracts this from the DNSP- and year-specific level.
- For each output, EI then multiplies the mean-adjusted (i.e. added) weight by the mean-adjusted (i.e. subtracted) logged output level.
- EI sums the resulting product across the five outputs (including customer minutes lost) and divides by two.
- This yields the natural logarithm of the output index, which EI normalises by subtracting the level of the first row (ACT in 2006) from all terms. It then converts into level terms by taking the natural exponential of it, so the first row is equal to 1 (because $e^0 = 1$).

The output index is divided by various measures of input costs to yield various measures of productivity, but the output index itself does not vary between these productivity measures.

In the case of the opex MPFP model, the output index is divided by the opex index, which is itself equal to opex divided by the opex price index. The opex price index is equal to 1 in 2006 and inflates each year based on a composite labour, materials and services price index. We have not investigated the opex price index further.

We list each DNSP's annual opex MPFP score in Table A.1 below, where a higher score indicates greater opex productivity.

Table A.1: Opex MPFP Scores

DNSP	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
ACT	1.00	0.99	0.98	0.96	0.86	0.75	0.76	0.71	0.63	0.68	1.25	1.10	0.96	1.00
AGD	0.77	0.91	0.64	0.70	0.65	0.69	0.63	0.81	0.72	0.62	0.69	0.78	0.92	0.98
AND	1.52	1.30	1.32	1.11	1.23	1.20	1.17	1.05	1.00	0.98	0.85	1.04	1.07	1.05
CIT	1.85	1.68	1.82	1.51	1.39	1.56	1.22	1.28	1.24	1.31	1.32	1.40	1.62	1.46
END	1.20	1.13	0.92	1.04	1.12	1.09	1.05	1.16	1.06	1.03	0.98	1.11	1.24	1.31
ENX	1.21	1.17	1.13	1.14	1.16	1.08	1.03	0.96	1.05	1.01	1.16	1.19	1.18	1.26
ERG	0.91	1.17	1.08	1.08	1.14	0.96	0.98	1.26	1.29	1.09	1.07	1.25	1.20	1.15
ESS	1.41	1.27	1.08	1.11	1.11	1.10	0.88	0.99	1.13	1.13	1.42	1.39	1.36	1.18
JEN	0.91	0.90	1.16	1.07	0.94	0.97	0.86	0.89	0.90	0.90	0.86	0.83	0.92	0.88
PCR	1.70	1.93	2.00	1.76	1.89	1.88	1.58	1.47	1.59	1.55	1.84	1.78	1.68	1.76
SAP	2.02	2.12	2.09	1.94	1.86	1.53	1.55	1.44	1.37	1.38	1.62	1.39	1.45	1.40
TND	1.51	1.48	1.48	1.28	1.10	1.24	1.11	1.41	1.32	1.64	1.52	1.17	1.26	1.43
UED	1.11	1.18	1.21	1.23	1.20	0.97	0.94	1.06	1.03	1.11	0.99	1.09	1.36	1.37

Source: EI

The other input indices in the MTFP models are the input series used to calibrate the output weights, described in Section A.1 (overhead lines measured in MVAkm, underground cables measured in MVAkm, and transformers measured in MVA).

These calculations are performed in Shazam, but we have replicated them in Microsoft Excel.

A.3. MPFP benchmarking results

To calculate relative efficiency between firms under the opex TFP model, EI calculates each company's average opex MPFP productivity over the selected window. In the case of the 2020 EI report, it uses productivity estimates from 2006 to 2019. The firm with the highest average score is Powercor (PCR), with a score of 1.743 over the period, while Ausgrid (AGD) has the lowest average score of 0.749.

To calculate the MPFP benchmarking scores, EI divides each DNSP's average score by that of the best performing firm. Thus, PCR has a score of 1 by construction, AGD has a score of 0.43, and all other firms fall somewhere in between. We show this calculation in Table A.2 below.

Table A.2: MPFP Multiyear Benchmarking Results

DNSP	2006-19 MPFP Score	MPFP Benchmark Score
ACT	0.90	0.52
AGD	0.75	0.43
AND	1.14	0.65
CIT	1.48	0.85
END	1.10	0.63
ENX	1.12	0.64
ERG	1.12	0.64
ESS	1.18	0.68
JEN	0.93	0.53
PCR	1.74	1.00
SAP	1.65	0.95
TND	1.35	0.78
UED	1.13	0.65

Source: EI

These scores can be presented on an annual basis as well, by dividing the annual figures in Table A.1 by PCR's 2006-19 average as shown in Table A.2.

Appendix B. Results from Leontief regressions

These are estimates from our replication of EI's analysis, as well as the alternative models describes in Section 3.1.5. All tables show the estimated coefficients on Energy, RM Demand (Dem.), Customer numbers (Cust.), Circuit Length (Length), and Time. The raw coefficients, before squaring, are reported along with t-statistics. Blank cells indicate regressions where the maximum likelihood procedure did not converge after 16,000 iterations (the default maximum iterations in Stata).

B.1. Replication of EI model

Table B.1: ACT Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.475	3.123
Dem.	2.211	0.101	9.356	10.552	2.226	2.883	0.000	0.000
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Length	2.719	1.153	1.630	2.426	1.078	5.133	0.722	11.794
Time	0.002	0.148	-0.006	-6.896	0.021	10.366	0.007	4.079

Source: NERA analysis

Table B.2: AGD Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.015	0.002	0.001	0.000	0.000	0.000	0.000	0.000
Dem.	-7.928	-30.51	0.007	0.001	0.000	0.000	-2.028	-120.1
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Length	0.000	0.000	-3.036	-223.8	-2.026	-201.3	0.000	0.000
Time	-0.001	-0.173	-0.003	-2.633	0.007	4.740	0.022	8.473

Source: NERA analysis

Table B.3: CIT Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	2.193	31.757	0.000	0.000	0.438	1.129	0.721	3.369
Dem.	0.000	0.000	0.000	0.000	0.000	0.000	0.394	0.356
Cust.	0.000	0.000	0.082	1.573	0.000	-0.001	0.000	0.000
Length	0.000	0.000	1.355	5.790	1.358	6.986	0.810	5.378
Time	0.038	3.390	-0.010	-12.736	0.020	4.086	0.013	2.608

Source: NERA analysis

Table B.4: END Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	T-Stat	Coef.	T-Stat	Coef.	T-Stat	Coef.	T-Stat
Energy	3.013	2.668	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	5.274	3.037	0.000	0.000	0.606	0.863
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.001
Length	-0.719	-0.275	2.842	7.499	0.945	84.969	0.642	8.223
Time	0.018	0.941	-0.010	-10.919	0.073	15.307	0.019	12.579

Source: NERA analysis

Table B.5: ENX Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	T-Stat	Coef.	T-Stat	Coef.	T-Stat	Coef.	T-Stat
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Dem.	6.921	50.829	1.556	1.139	3.242	157.774	1.283	12.384
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Length	0.000	0.000	-2.351	-26.116	0.000	0.000	0.520	20.399
Time	0.006	1.063	0.000	-0.034	0.040	18.443	0.018	26.185

Source: NERA analysis

Table B.6: ERG Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	T-Stat	Coef.	T-Stat	Coef.	T-Stat	Coef.	T-Stat
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001
Dem.	-2.784	-0.231	6.503	1.749	1.913	98.210	0.000	0.000
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.130	153.975
Length	1.225	2.265	1.624	5.525	0.000	0.000	0.000	0.001
Time	0.001	0.128	-0.004	-1.398	0.055	14.421	0.020	10.691

Source: NERA analysis

Table B.7: ESS Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.003	0.000	3.171	0.973	0.000	0.000	0.010	0.007
Dem.	0.001	0.000	0.000	0.000	1.578	1.845	0.000	0.000
Cust.	-0.577	-26.267	0.000	0.000	0.000	0.000	0.141	66.676
Length	0.000	0.000	1.423	3.149	0.150	1.324	0.000	0.000
Time	-0.007	-0.714	0.048	11.224	0.072	2.982	0.010	3.235

Source: NERA analysis

Table B.8: JEN Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	-0.001	0.000	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	-1.212	-0.558	0.000	0.000	0.844	3.306
Cust.	0.383	56.098	0.209	0.708	0.000	0.002	0.000	0.000
Length	0.001	0.000	-2.352	-1.728	1.140	160.373	0.680	13.089
Time	0.017	3.131	-0.005	-3.599	0.041	20.933	0.021	13.100

Source: NERA analysis

Table B.9: PCR Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	2.220	0.320	0.000	0.000	1.841	5.212	0.517	3.072
Cust.	0.000	0.001	-0.622	-6.664	0.040	0.722	0.000	0.000
Length	1.153	2.744	1.561	4.521	0.000	0.000	0.321	37.485
Time	0.015	1.339	-0.011	-4.968	0.050	7.123	0.025	28.420

Source: NERA analysis

Table B.10: SAP Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	-0.001	0.000	1.457	3.354	0.000	0.000	0.535	1.600
Dem.	6.193	36.542	0.000	0.000	1.495	7.660	0.602	0.797
Cust.	0.000	0.000	-0.207	-2.493	0.000	0.000	0.000	0.000
Length	0.000	0.000	1.298	10.785	-0.439	-19.189	0.281	5.289
Time	0.043	4.453	-0.003	-1.763	0.017	19.113	0.029	3.389

Source: NERA analysis

Table B.11: AND Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	7.378	37.241	1.176	0.374	0.000	0.000	1.525	9.352
Cust.	0.000	0.000	0.000	0.000	0.152	228.446	0.059	1.259
Length	0.000	0.000	2.151	29.533	0.000	0.000	0.138	0.407
Time	0.035	3.897	-0.001	-1.447	0.044	28.832	0.014	2.286

Source: NERA analysis

Table B.12: TND Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	3.398	31.473	2.069	6.132	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cust.	0.000	0.000	0.000	0.000	0.109	1.748	0.115	207.716
Length	0.000	0.000	1.908	24.356	0.558	3.797	0.000	0.000
Time	0.022	2.077	0.002	2.157	0.014	7.016	0.016	10.785

Source: NERA analysis

Table B.13: UED Leontief regression results: EI replication

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	3.080	2.946	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	1.563	0.179	2.353	2.191	0.877	5.421	0.965	7.742
Cust.	0.000	0.000	0.355	15.900	0.077	2.340	0.086	19.650
Length	0.000	0.000	0.000	0.000	0.581	2.790	0.000	0.000
Time	0.015	0.966	0.003	2.124	0.025	14.422	0.018	16.041

Source: NERA analysis

B.2. Model in logs

Table B.14: ACT Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.001				
Dem.	0.349	0.144	0.885	14.782				
Cust.	0.000	0.000	0.000	0.000				
Length	1.073	1.781	0.848	17.832				
Time	0.000	-0.081	-0.001	-15.100				

Source: NERA analysis

Table B.15: AGD Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.001	0.002						
Dem.	1.214	386.784						
Cust.	0.000	0.000						
Length	0.000	0.000						
Time	0.000	-0.432						

Source: NERA analysis

Table B.16: CIT Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	1.077	9.874	0.000	0.000	0.445	1.917	0.612	2.689
Dem.	0.000	0.000	0.000	0.000	0.001	0.002	0.399	1.637
Cust.	0.000	0.000	0.439	2.305	0.000	0.000	0.000	0.000
Length	0.140	0.159	0.900	6.363	0.940	8.127	0.719	6.322
Time	0.003	3.783	-0.001	-7.529	0.002	4.862	0.001	2.344

Source: NERA analysis

Table B.17: END Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy								
Dem.								
Cust.								
Length								
Time								

Source: NERA analysis

Table B.18: ENX Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000						
Dem.	1.207	792.427						
Cust.	0.000	0.000						
Length	0.000	0.000						
Time	0.000	0.047						

Source: NERA analysis

Table B.19: ERG Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Dem.	0.338	0.638	0.513	2.111	1.079	1092.695	0.000	0.000
Cust.	0.002	0.003	0.000	0.000	0.000	0.000	0.833	371.429
Length	0.982	8.036	0.963	11.127	0.000	0.000	0.006	0.016
Time	0.000	0.143	0.000	-1.569	0.004	16.689	0.002	16.299

Source: NERA analysis

Table B.20: ESS Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.002	0.003	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	0.000	0.000	0.536	0.660	0.000	0.000
Cust.	0.958	320.270	0.914	6.766	0.000	0.000	0.843	922.469
Length	0.000	0.000	0.385	1.072	0.761	2.068	0.000	0.000
Time	0.000	-0.438	0.002	8.650	0.006	3.206	0.001	4.628

Source: NERA analysis

Table B.21: JEN Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.001				
Dem.	0.000	0.000	0.212	1.041				
Cust.	0.920	593.458	0.001	0.004				
Length	0.001	0.001	1.098	35.489				
Time	0.002	3.517	-0.001	-7.105				

Source: NERA analysis

Table B.22: PCR Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy								
Dem.								
Cust.								
Length								

Time								

Source: NERA analysis

Table B.23: SAP Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000						
Dem.	1.070	3.563						
Cust.	0.430	0.977						
Length	0.000	0.000						
Time	0.003	4.951						

Source: NERA analysis

Table B.24: AND Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000						
Dem.	1.239	612.363						
Cust.	0.000	0.000						
Length	0.000	0.000						
Time	0.002	4.476						

Source: NERA analysis

Table B.25: TND Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	1.120	3.736	0.468	6.505	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	0.000	0.000	0.000	0.000	0.461	1.977
Cust.	0.156	0.108	0.000	0.001	0.425	1.805	0.729	8.760
Length	0.000	0.000	0.984	34.011	0.834	5.549	0.000	0.000
Time	0.002	1.628	0.000	1.155	0.002	12.373	0.002	11.023

Source: NERA analysis

Table B.26: UED Leontief regression results: log model

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	1.051	4.888	0.000	0.001	0.000	0.000	0.000	0.002
Dem.	0.426	0.674	0.328	2.060	0.452	8.204	0.541	8.546
Cust.	0.000	0.000	0.891	26.726	0.581	16.311	0.701	25.280
Length	0.000	0.000	0.000	0.001	0.574	10.647	0.000	0.000
Time	0.001	1.106	0.000	2.548	0.002	24.719	0.002	16.368

Source: NERA analysis

B.3. Model with a constant

Table B.27: ACT Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.427	2.303
Dem.	-2.175	-0.055	9.356	10.644	2.289	3.055	0.000	0.000
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Length	2.723	0.649	1.630	2.447	0.857	1.029	0.661	5.178
Time	0.002	0.140	-0.006	-6.904	0.024	2.187	0.009	2.378
Const.	0.000	0.000	0.000	0.000	42.579	0.626	22.601	0.034

Source: NERA analysis

Table B.28: AGD Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	-7.928	-31.914	0.001	0.000	0.001	0.001	-2.028	-120.091
Cust.	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
Length	0.000	0.000	-3.036	-168.839	2.026	199.380	0.000	0.000
Time	-0.001	-0.173	-0.003	-2.631	0.007	4.740	0.022	8.472
Const.	0.003	0.000	-2.772	-0.005	-0.339	-0.001	0.000	0.000

Source: NERA analysis

Table B.29: CIT Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	2.193	31.757	0.000	0.000	0.438	1.122	0.721	3.322
Dem.	0.000	0.000	0.000	0.000	0.000	0.000	0.393	0.350
Cust.	0.000	0.000	0.000	-0.001	0.000	0.000	0.000	0.000
Length	0.000	0.000	1.274	5.868	1.358	6.938	0.810	5.344
Time	0.038	3.390	-0.007	-2.498	0.020	4.060	0.013	2.576
Const.	-0.003	0.000	53.285	2.581	0.000	0.000	0.037	0.020

Source: NERA analysis

Table B.30: END Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	2.706	2.435	0.000	0.000				
Dem.	0.000	0.000	-3.287	-1.076				
Cust.	0.000	0.000	0.000	0.000				
Length	0.000	0.000	0.000	0.000				
Time	0.018	2.210	0.000	0.045				
Const.	217.846	0.895	571.161	8.557				

Source: NERA analysis

Table B.31: ENX Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Dem.	6.921	50.829	3.252	5.872	3.242	157.777	1.374	16.691
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Length	0.000	0.000	-0.004	-0.002	0.000	0.000	0.000	0.000
Time	0.006	1.063	0.010	7.931	0.040	18.443	0.026	23.253
Const.	-0.001	0.000	472.678	26.374	0.000	0.000	107.820	0.000

Source: NERA analysis

Table B.32: ERG Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	-2.785	-0.233	6.503	1.744	1.913	98.210	0.000	0.000
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.063	0.801
Length	1.225	2.284	1.624	5.511	0.000	0.000	0.000	0.000
Time	0.001	0.128	-0.004	-1.396	0.055	14.421	0.036	2.507
Const.	-0.001	0.000	0.007	0.000	0.000	0.000	89.707	0.000

Source: NERA analysis

Table B.33: ESS Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.002	0.000	0.001	0.001	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	0.002	0.000	1.578	1.836	0.000	0.000
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Length	0.000	0.000	0.001	0.001	0.150	1.318	0.000	0.000
Time	0.004	0.341	0.050	16.590	0.072	2.973	0.023	7.359
Const.	512.566	26.113	710.016	122.840	0.004	0.000	125.242	0.000

Source: NERA analysis

Table B.34: JEN Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	1.212	0.569	0.000	0.000	0.627	1.929
Cust.	-0.229	-0.408	0.208	0.791	0.000	0.002	0.000	0.000
Length	0.002	0.001	-2.354	-1.937	1.140	164.708	0.000	-0.001
Time	0.026	0.931	-0.005	-3.771	0.041	20.933	0.033	14.256
Const.	165.832	0.729	0.000	0.000	0.000	0.000	54.108	0.000

Source: NERA analysis

Table B.35: PCR Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.002	0.000	0.001	0.001	0.001	0.001	0.000	0.000
Dem.	2.195	0.312	0.000	0.000	1.841	5.392	0.540	3.961
Cust.	0.000	0.001	0.475	5.779	0.040	0.747	0.000	0.000
Length	0.002	0.001	0.000	0.001	0.000	0.000	0.000	0.001
Time	0.019	1.319	-0.006	-2.564	0.050	7.181	0.030	30.069
Const.	309.055	2.748	531.580	10.877	0.001	0.000	85.466	0.000

Source: NERA analysis

Table B.36: SAP Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	-0.001	0.000	1.666	3.793	0.000	0.000	0.559	2.159
Dem.	6.193	36.541	0.000	0.000	-1.495	-7.678	0.584	0.853
Cust.	0.000	0.000	-0.223	-2.964	0.000	0.000	0.000	0.001
Length	0.000	0.000	-0.913	-1.461	0.439	19.232	0.000	0.000
Time	0.043	4.453	-0.001	-0.493	0.017	19.126	0.033	4.706
Const.	0.018	0.000	243.972	1.494	0.142	0.001	80.281	0.000

Source: NERA analysis

Table B.37: AND Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	7.378	37.241	1.176	0.374	0.000	0.000	1.526	11.579
Cust.	0.000	0.000	0.000	0.000	0.152	228.446	0.059	2.056
Length	0.000	0.000	2.151	29.564	0.000	0.000	0.138	0.673
Time	0.035	3.897	-0.001	-1.447	0.044	28.832	0.014	3.682
Const.	-0.001	0.000	0.024	0.000	0.000	0.000	0.222	0.002

Source: NERA analysis

Table B.38: TND Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	3.398	31.022	1.087	1.184	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cust.	-0.001	-0.001	0.000	0.000	0.109	1.795	0.115	207.718
Length	0.000	0.000	1.175	2.310	0.558	3.903	0.000	0.000
Time	0.022	2.076	0.005	2.802	0.014	7.148	0.016	10.786
Const.	-0.005	0.000	248.244	3.885	-0.008	0.000	0.000	0.000

Source: NERA analysis

Table B.39: UED Leontief regression results: model with constant

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	3.080	2.973	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	1.563	0.181	2.055	1.665	0.803	4.008	0.965	7.758
Cust.	0.000	0.000	0.000	-0.001	0.000	0.003	0.086	19.663
Length	0.000	0.000	0.001	0.001	0.588	3.379	0.000	0.000
Time	0.015	0.973	0.012	5.354	0.030	10.296	0.018	16.031
Const.	0.000	0.000	282.081	16.410	61.370	2.671	0.192	0.000

Source: NERA analysis

B.4. Model with a time trend

Table B.40: ACT Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000						
Dem.	1.517	0.060						
Cust.	0.000	0.000						
Length	2.771	1.507						
Time	12.285	0.436						
Const.	0.000	0.000						

Source: NERA analysis

Table B.41: AGD Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.813	0.291	0.001	0.000	0.000	0.000	0.000	0.000
Dem.	7.706	5.949	1.649	0.323	0.000	0.000	2.027	118.911
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Length	0.000	0.000	2.153	3.246	2.025	195.718	0.000	0.000
Time	-0.010	0.000	0.003	0.000	34.139	9.735	24.658	19.330
Const.	-0.001	0.000	400.650	4.844	-0.105	0.000	0.001	0.000

Source: NERA analysis

Table B.42: CIT Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	1.922	0.929	0.000	0.000	0.068	0.054	0.631	2.544
Dem.	0.000	0.000	0.000	0.000	0.000	0.000	0.659	0.959
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Length	1.335	0.289	0.627	4.583	1.457	15.960	0.864	6.147
Time	30.342	2.078	0.000	0.000	13.245	16.426	8.532	5.281
Const.	0.000	0.000	87.690	20.851	0.000	0.000	-0.001	0.000

Source: NERA analysis

Table B.43: END Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	2.902	2.641	0.000	0.000	0.000	0.001	0.000	0.000
Dem.	0.002	0.000	3.205	1.086	0.000	0.000	0.000	0.001
Cust.	0.000	0.001	0.000	0.000	0.183	83.680	0.000	0.000
Length	-0.006	-0.002	0.000	0.000	0.001	0.001	0.000	0.001
Time	55.628	5.083	8.688	0.158	48.754	46.473	22.597	62.978
Const.	168.345	0.504	572.914	9.139	0.141	0.001	120.877	254.266

Source: NERA analysis

Table B.44: ENX Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Dem.	6.920	50.116	2.991	1.891	3.235	156.796	1.377	17.268
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Length	0.000	0.000	1.034	0.364	0.000	0.000	0.001	0.001
Time	38.865	2.185	47.180	1.511	47.757	47.239	23.908	58.349
Const.	0.000	0.000	424.745	1.517	0.000	0.000	107.497	22.361

Source: NERA analysis

Table B.45: ERG Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	3.112	0.281	0.000	0.000	1.908	95.332	0.000	0.000
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Length	1.210	2.154	1.852	255.201	0.000	0.000	0.000	0.000
Time	14.704	0.184	0.000	0.000	25.646	38.599	21.018	48.374
Const.	-0.059	0.000	0.003	0.000	0.000	0.000	102.359	162.253

Source: NERA analysis

Table B.46: ESS Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	0.000	0.000	1.518	1.097	0.000	0.000
Cust.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Length	0.000	0.000	0.001	0.000	0.155	0.890	0.000	0.000
Time	-31.505	-0.698	159.040	43.618	29.194	7.744	18.881	16.770
Const.	512.561	26.114	710.016	122.868	0.005	0.000	125.242	104.349

Source: NERA analysis

Table B.47: JEN Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy								
Dem.								
Cust.								
Length								
Time								
Const.								

Source: NERA analysis

Table B.48: PCR Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	0.335	0.158	-0.049	-0.012	0.000	0.000
Dem.	1.916	0.251	0.000	0.000	1.836	3.904	0.540	4.092
Cust.	0.000	0.000	0.198	10.947	0.039	0.397	0.000	0.000
Length	1.103	0.885	0.000	0.000	0.000	0.000	0.000	0.002
Time	41.757	2.661	0.000	0.000	22.544	11.564	15.572	78.777
Const.	103.499	0.117	636.555	61.520	0.002	0.000	85.449	45.434

Source: NERA analysis

Table B.49: SAP Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	1.828	8.009	0.000	0.000	0.376	0.823
Dem.	6.186	35.942	0.000	0.000	1.473	7.242	0.903	2.099
Cust.	0.000	0.001	0.224	2.497	0.000	0.000	0.000	0.000
Length	0.000	0.000	0.527	0.530	0.441	18.883	0.005	0.013
Time	72.760	11.311	0.000	0.000	20.627	42.556	18.016	11.200
Const.	0.020	0.000	316.471	3.264	-0.016	0.000	84.004	5.238

Source: NERA analysis

Table B.50: AND Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	-0.001	0.000	0.000	0.000	0.000	0.000
Dem.	7.365	36.792	1.367	0.473	0.000	0.000	1.502	9.904
Cust.	0.000	0.000	0.000	0.000	0.150	143.428	0.064	1.625
Length	0.000	0.000	1.989	10.669	0.000	0.000	0.108	0.276
Time	61.582	9.623	-0.001	0.000	27.333	49.866	10.294	5.595
Const.	0.002	0.000	164.124	2.446	-0.018	0.000	0.083	0.001

Source: NERA analysis

Table B.51: TND Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	2.929	1.074	1.008	1.002	0.000	0.000	0.000	0.000
Dem.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cust.	0.232	0.380	0.000	0.001	0.095	1.369	0.114	214.718
Length	0.000	0.000	1.123	2.136	0.586	4.261	0.000	0.000
Time	27.690	1.092	22.378	6.162	12.417	16.365	7.745	25.375
Const.	0.000	0.000	254.699	4.123	0.000	0.000	0.000	0.000

Source: NERA analysis

Table B.52: UED Leontief regression results: model with time trend

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	2.885	2.728	-0.001	0.000	0.000	0.000	0.000	0.000
Dem.	2.744	0.587	2.057	1.675	0.767	4.147	0.908	6.765
Cust.	0.000	0.000	0.002	0.006	0.065	1.428	0.088	20.241
Length	0.000	0.000	0.000	0.000	0.671	3.224	0.000	0.000
Time	30.900	1.920	33.171	11.760	16.191	34.107	11.219	36.719
Const.	-0.004	0.000	282.024	16.340	0.021	0.000	0.003	0.000

Source: NERA analysis

B.5. Fixed effects

Table B.53: Panel fixed effects Leontief regression: output coefficients

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
Energy	0.000	0.000	1.511	5.468	0.000	0.000	0.000	0.000
Dem.	-5.104	-12.804	0.000	0.000	-1.951	-7.367	0.994	6.488
Cust.	0.000	0.000	0.000	0.000	-0.055	-1.465	0.000	0.000
Length	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
Time	0.006	2.365	0.016	9.550	0.021	14.323	0.028	21.635

Source: NERA analysis

Table B.54: Panel fixed effects Leontief regression: fixed effect coefficients

	Opex		OHL		UG		Transformers	
	Coef.	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**	**Coef.**	**T-Stat**
ACT	92.718	0.097	154.689	0.971	-78.450	-4.222	7.172	0.003
AGD	0.000	0.000	-0.002	0.000	0.000	0.000	-6.975	-0.009
CIT	452.261	2.160	-485.894	-6.514	351.632	19.415	-108.056	-0.193
END	0.000	0.000	0.001	0.000	0.000	0.000	-25.148	-0.036
ENX	-241.038	-0.645	-366.172	-4.413	-91.320	-4.801	-49.866	-0.065
ERG	0.000	0.000	-0.002	0.000	0.000	0.000	-3.393	-0.004
ESS	-115.871	-0.151	-182.136	-1.322	51.210	2.614	-41.687	-0.055
JEN	115.871	0.152	182.136	1.435	0.000	0.000	-2.749	-0.003
PCR	-249.550	-0.689	515.750	7.300	-148.291	-8.073	81.081	0.120
SAP	0.000	0.000	-0.001	0.000	0.000	0.000	13.835	0.018
AND	312.236	1.065	-432.009	-5.569	-190.623	-10.450	97.705	0.161
TND	0.000	0.000	0.000	0.000	0.000	0.000	21.709	0.029
UED	385.749	1.606	639.444	9.844	0.000	0.000	-68.260	-0.096

Source: NERA analysis

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