# Attachment B: Separating Technical Change and Time-Varying Inefficiency Models

## 1 October 2025

Attachment to: Quantonomics (1 October 2025) *"Electricity Distribution Benchmarking Opex Model Development- Phase 2"*, Prepared for Australian Energy Regulator by Michael Cunningham, Valentin Zelenyuk, Alice Giovani and Joseph Hirschberg.

### Contents

# Chapter 1: SFA time-varying inefficiency models

# 1 Frontier Economics' Specification (Battese-Coelli 1995)

As part of the Evoenergy submission to Quantonomics (2024), Frontier Economics (2025) provided several comments on approaches to improve the AER's econometric benchmarking estimates. In particular, it considers the assumption of time-invariant inefficiencies as serious misspecification. Frontier also noted that the jurisdictional time-trend models explored in the Quantonomics (2024) suggest likely differences across jurisdictions in the effects of changes in OEFs over the sample period. These differences, it argues, should be captured through separate time trends. Frontier also conducted a residual analysis, suggesting that omitted variables may be captured in the residuals, indicating potential model misspecification.

Frontier recommended using the *sfpanel* Stata ado-program (Belotti et al. 2012), which supports estimating a wider range of SFA models than the standard Stata commands. It proposed using the Battese-Coelli 1995 (*bc95)* model, in which the 'pre-truncation mean' of the stochastic inefficiency terms is a linear function of *z*-variables, as a starting point for investigating time-varying inefficiency in SFA models. Using this method, Frontier presented an example of an SFATLG time-varying inefficiency model using the short period. Frontier states that this model is intended solely to demonstrate the use of the *sfpanel* command in Stata and is not a proposed or preferred specification. Frontier provided the Stata code and output files used in its analysis, enabling us to replicate its model. In doing so, we have also run the corresponding SFACD version.

In the Frontier model, the 'pre-truncation mean' of the inefficiency distribution is a function of DNSP dummy variables and jurisdiction-specific time trends. More specifically, the *z* variables are an intercept, dummy variables for 60 of the 61 DNSPs in the sample and jurisdiction-specific time trend variables.[1] There is no explanation for country-specific fixed effects in determining $u_{it}$ additional to the random effect in $W_i$. There are two firm-specific effects in the inefficiency term for each DNSP in Frontier's specification.

To produce starting values for the main TLG model, Frontier first estimated simplified models. Unlike the AER's approach, which first estimates the TLG model using ordinary least squares (OLS), Frontier has two steps using OLS and then SFA to estimate the Cobb-Douglas (CD) model. For estimating the final SFA model, initial values equal to zero were used for the second-order TLG terms, and the coefficients of the z-variables (the country-specific dummies and the jurisdiction-specific trends). The Davidon–Fletcher–Powell (DFP) algorithm was chosen for numerical optimisation.

Tables 1.1 and 1.2 present our replication of Frontier Economics Model in both the CD and TLG version for both the long and short sample periods. The short-period TLG results can be compared to Table 1.2.2 of Frontier Economics (2025). Frontier's CD short-period results are

[1] The time trend variables—aus_yr, nz_yr, and ont_yr—are each defined as yr – 2017.5 for their respective countries. The reference year, 2017.5, is the midpoint of the 2012–2023 period (or 2014.5 for long-period models), which Frontier suggests facilitates both interpretation of parameter estimates and optimisation of the model.

available in its supporting files. We are able to replicate Frontier Economics' results to a reasonable degree of precision, although we are unable to obtain the exact parameters reported by Frontier using the *sfpanel* command.[2] Most of these differences are under 1 per cent. Discrepancies of this kind are common when using complex MLE models.

Table 1.1 Frontier Economics model results (long period)*

| | *SFACD* | | | *SFATLG* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *Frontier* | | | | | | |
| ly1 | 0.475 | 0.047 | 10.13 | 0.639 | 0.061 | 10.54 |
| ly2 | 0.136 | 0.022 | 6.29 | 0.087 | 0.022 | 3.89 |
| ly3 | 0.365 | 0.047 | 7.78 | 0.226 | 0.061 | 3.730 |
| ly11 | | | | -0.196 | 0.646 | -0.300 |
| ly12 | | | | -0.023 | 0.221 | -0.100 |
| ly13 | | | | 0.266 | 0.455 | 0.580 |
| ly22 | | | | -0.010 | 0.094 | -0.100 |
| ly23 | | | | 0.083 | 0.143 | 0.580 |
| ly33 | | | | -0.425 | 0.356 | -1.200 |
| lz1 | -0.069 | 0.028 | -2.49 | -0.097 | 0.038 | -2.580 |
| yr | 0.009 | 0.001 | 8.11 | 0.007 | 0.001 | 6.300 |
| jur2 | 0.048 | 0.041 | 1.17 | 0.134 | 0.090 | 1.480 |
| jur3 | 0.216 | 0.036 | 5.94 | 0.227 | 0.101 | 2.240 |
| _cons | -7.654 | 2.177 | -3.52 | -3.675 | 2.124 | -1.730 |
| *Mu* | | | | | | |
| aus_yr | -0.019 | 0.003 | -7.15 | -0.016 | 0.003 | -5.440 |
| nz_yr | 0.022 | 0.002 | 10.44 | 0.022 | 0.002 | 10.700 |
| ont_yr | -0.009 | 0.002 | -3.77 | -0.004 | 0.002 | -2.320 |
| _cons | 0.361 | 0.035 | 10.18 | 0.312 | 0.033 | 9.340 |
| *Usigma* | | | | | | |
| _cons | -4.778 | 0.145 | -32.85 | -4.776 | 0.134 | -35.540 |
| *Vsigma* | | | | | | |
| _cons | -4.916 | 0.083 | -59.28 | -5.064 | 0.086 | -59.220 |
| sigma_u | 0.092 | 0.007 | 13.75 | 0.092 | 0.006 | 14.880 |
| sigma_v | 0.086 | 0.004 | 24.12 | 0.080 | 0.003 | 23.390 |
| lambda | 1.071 | 0.009 | 116.65 | 1.154 | 0.009 | 134.010 |
| LLH | 892.69 | | | 911.91 | | |
| Iterations | 752** | | | 784** | | |
| *N* | 1098 | | | 1098 | | |

* The coefficients on the DNSP dummies used as z-variables are omitted.

** Stata reports an error in MLE convergence.

[2] We ran Frontier's Stata programs using both Stata version 14—which appears to be the version used by Frontier—and Stata 19. In both cases, the results differed from Frontier's outputs, but only for the *sfpanel* command. All other estimation commands were replicated without discrepancies in values.

Table 1.2 Frontier Economics models results (short period)*

| | SFACD | | | SFATLG | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *Frontier* | | | | | | |
| ly1 | 0.280 | 0.068 | 4.12 | 0.474 | 0.053 | 8.93 |
| ly2 | 0.190 | 0.021 | 8.90 | 0.225 | 0.022 | 10.20 |
| ly3 | 0.516 | 0.072 | 7.14 | 0.204 | 0.060 | 3.41 |
| ly11 | | | | 0.540 | 0.373 | 1.45 |
| ly12 | | | | -0.114 | 0.074 | -1.54 |
| ly13 | | | | -0.384 | 0.351 | -1.09 |
| ly22 | | | | 0.199 | 0.027 | 7.50 |
| ly23 | | | | -0.045 | 0.075 | -0.61 |
| ly33 | | | | 0.243 | 0.337 | 0.72 |
| lz1 | -0.101 | 0.022 | -4.62 | 0.013 | 0.027 | 0.50 |
| yr | 0.004 | 0.002 | 1.59 | -0.001 | 0.002 | -0.33 |
| jur2 | 0.015 | 0.034 | 0.43 | -0.264 | 0.045 | -5.88 |
| jur3 | 0.158 | 0.036 | 4.42 | -0.045 | 0.037 | -1.21 |
| _cons | 2.749 | 4.490 | 0.61 | 11.379 | 3.574 | 3.18 |
| *Mu* | | | | | | |
| aus_yr | -0.039 | 0.004 | -11.05 | -0.040 | 0.003 | -11.85 |
| nz_yr | 0.033 | 0.003 | 11.61 | 0.033 | 0.002 | 13.89 |
| ont_yr | -0.006 | 0.003 | -2.37 | -0.005 | 0.002 | -2.05 |
| _cons | 0.318 | 0.031 | 10.39 | 0.229 | 0.030 | 7.59 |
| *Usigma* | | | | | | |
| _cons | -6.917 | 1.218 | -5.68 | -6.773 | 0.679 | -9.97 |
| *Vsigma* | | | | | | |
| _cons | -5.189 | 0.175 | -29.60 | -5.270 | 0.117 | -45.02 |
| sigma_u | 0.031 | 0.019 | 1.64 | 0.034 | 0.011 | 2.95 |
| sigma_v | 0.075 | 0.007 | 11.41 | 0.072 | 0.004 | 17.09 |
| lambda | 0.421 | 0.025 | 16.58 | 0.472 | 0.015 | 30.95 |
| LLH | 811.92 | | | 835.024 | | |
| Iterations # | 512** | | | 617** | | |
| *N* | 732 | | | 732 | | |

* The coefficients on the DNSP dummies used as z-variables are omitted.

** Stata reports an error in MLE convergence.

Frontier also included in its report a figure showing the efficiency scores produced by its SFA TLG short-period model (Frontier Economics 2025, p.11). However, these are not the direct results of its model. The directly estimated efficiency scores are shown in Table 1.3 and Figure 1.1. As Frontier Economics noted in its Stata program, its SFATLG model did not produce efficiency scores for all DNSPs because of extremely large negative values of the inefficiency intercept for two DNSPs,[3] which led to a division-by-zero error in the calculation of the conditional expectation of the inefficiency term. To work around this problem, Frontier

[3] More specifically, 2 Australians DNSPs, PCR and UED.

"rearrang[ed] the BC1988 formula to use the lognormal functionality in Stata".[4] This was done by manually reconstructing the efficiency scores for Australian DNSPs in the SFATLG model.

Table 1.3 Frontier Economics model average efficiency scores *

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *SFACD* | *SFATLG* | *SFACD* | *SFATLG* |
| EVO | 0.562 | 0.515 | 0.565 | 0.676 |
| AGD | 0.657 | 0.605 | 0.710 | 0.465 |
| CIT | 0.954 | 0.828 | 0.899 | 0.946 |
| END | 0.749 | 0.680 | 0.813 | 0.610 |
| ENX | 0.758 | 0.730 | 0.775 | 0.570 |
| ERG | 0.528 | 0.545 | 0.672 | 0.690 |
| ESS | 0.577 | 0.637 | 0.712 | 0.874 |
| JEN | 0.789 | 0.770 | 0.717 | 0.845 |
| PCR | 0.968 | . | . | . |
| SAP | 0.967 | 0.970 | 0.980 | 0.983 |
| AND | 0.797 | 0.824 | 0.784 | 0.880 |
| TND | 0.863 | 0.813 | 0.974 | 0.981 |
| UED | . | . | . | . |
| Australia | 0.764 | 0.720 | 0.782 | 0.774 |

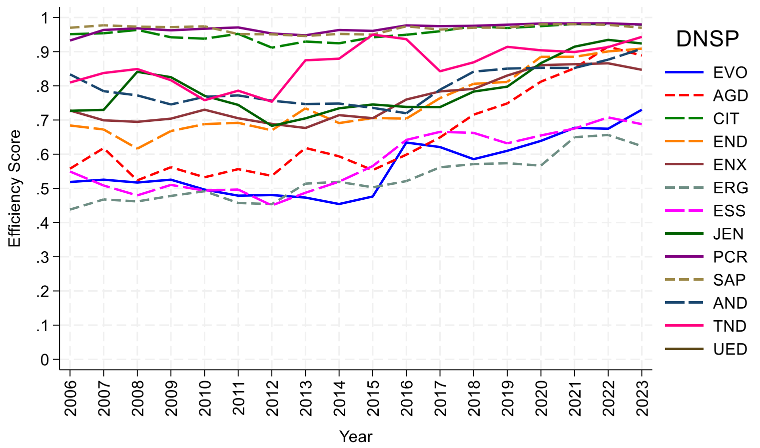
* These efficiency scores are raw outputs from the model, without applying the lognormal transformation used by Frontier Economics.

Table 1.4 Monotonicity violations in Frontier Economics models

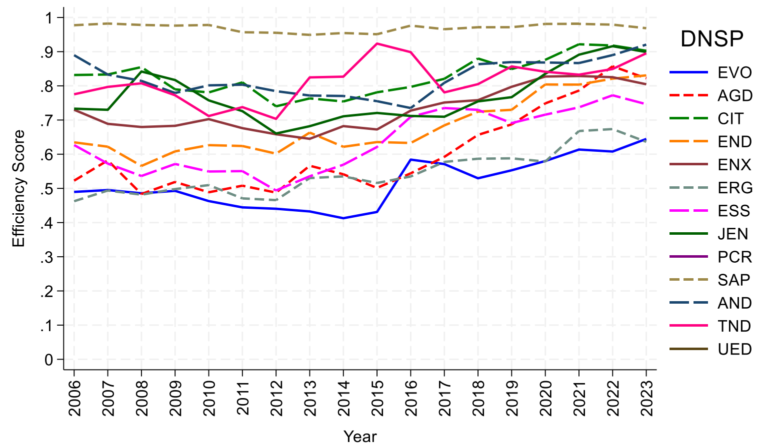
| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| <u>*By DNSP*</u> | | | | | | | | |
| EVO | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| AGD | 0.00 | 0.00 | 72.20 | 72.20 | 0.00 | 0.00 | 100.00 | 100.00 |
| CIT | 0.00 | 0.00 | 22.20 | 22.20 | 0.00 | 0.00 | 0.00 | 0.00 |
| END | 0.00 | 0.00 | 5.60 | 5.60 | 0.00 | 0.00 | 100.00 | 100.00 |
| ENX | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 100.00 |
| ERG | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 100.00 |
| ESS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 100.00 |
| JEN | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 100.00 |
| PCR | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 100.00 |
| SAP | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 100.00 |
| AND | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 100.00 |
| TND | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 100.00 |
| UED | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 100.00 |
| <u>*By jurisdiction*</u> | | | | | | | | |
| Australia | 0.00 | 0.00 | 7.70 | 7.70 | 0.00 | 0.00 | 84.60 | 84.60 |
| New Zealand | 0.00 | 36.80 | 0.00 | 36.80 | 0.00 | 0.00 | 10.50 | 10.50 |
| Ontario | 0.00 | 0.00 | 12.10 | 12.10 | 0.00 | 16.70 | 9.20 | 25.90 |
| Full sample | 0.00 | 11.50 | 7.40 | 18.90 | 0.00 | 7.90 | 25.70 | 33.60 |

[4] Coding comment in *2025-04-14 SF models.do*.

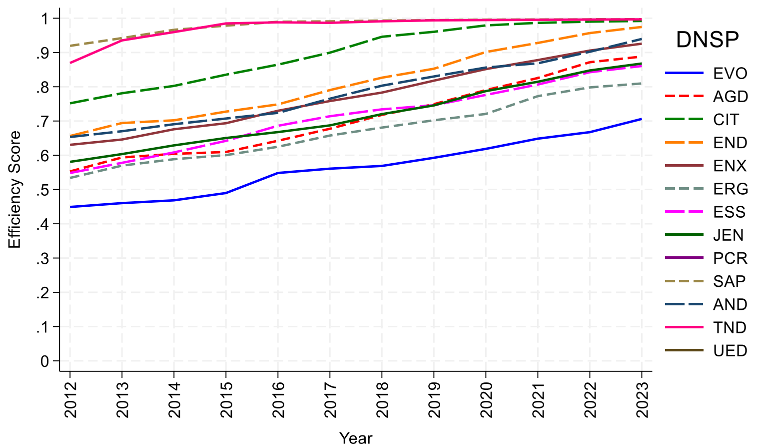
## Figure 1.1 Efficiency Trends by DNSP- Frontier Economics



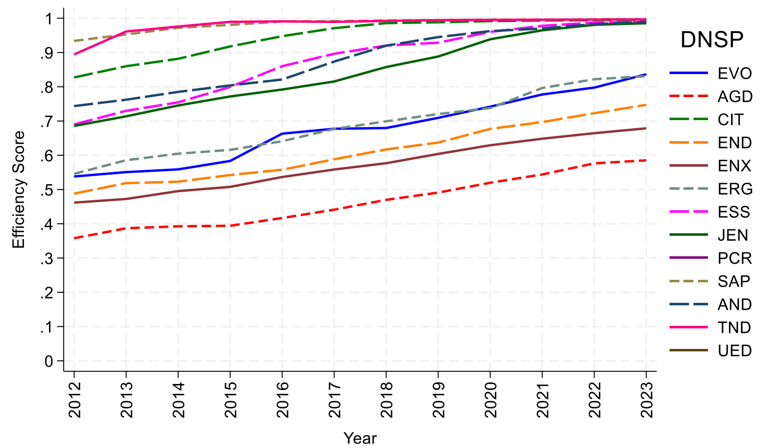

*SFACD Long Period*




*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

We understand that Frontier used this approach merely as an example to demonstrate the potential application of the *sfpanel bc95* package model. However, in practice, it highlighted the challenges associated with implementing this method. In our view, such workarounds are not suitable in a regulatory context.

The foregoing problem is sufficient grounds for rejecting Frontier's presented model specification. However, there are at least two other major problems with it:

- For all four models (the CD and TLG models in short and long periods), Stata returned an error message in relation to MLE convergence, indicating failure to converge correctly at the specified convergence criteria.
- The frequency of monotonicity violations (MVs) remains high (see Table 1.4), especially in the short-period model. In Table 1.5, these MV frequencies are compared to those of the JTT model presented in Quantonomics (2024), which can be used here as a benchmark for comparing time-varying inefficiency models presented by Frontier Economics. The Frontier Economic model has much poorer MV performance in the short period, and in the long sample period it performs better for Australian DNSPs but worse for the full sample of all DNSPs.

We reiterate that Frontier Economics presented this model discussed in this section as a basis for further discussion and not as a proposed or preferred specification. Based on the foregoing information, some improvements can be made to the model specification presented by Frontier Economics to enhance its outcomes. These are outlined in the following sections.

# 2 Alternative Battese-Coelli 1995 Specifications

In this section, we present the empirical results from the Battese-Coelli 1995 (*bc95)* method, as implemented in Stata using **sfpanel y xlist, model(bc95)**. Recall that in this model:

$$u_{it} \sim N^{+}(\mu_{it}, \sigma_u^2), \quad \text{where: } \mu_{it} = \delta_0 + \boldsymbol{z_{it}\delta} \tag{B2.1}$$

We tested 8 different specifications; however, only one successfully produced results consistently for both the CD and TLG forms in both the long and short sample periods. The successful specification, presented in Section 2.1, is referred to as BC95-JTT-HN. In this model the z-variables are jurisdiction time trends and there is no constant term ($\delta_0 = 0$). Technical efficiency is measured by a simple time-trend. Section 2.2 briefly outlines several other tested specifications, explaining how they failed. The reason for suppressing the constant term in the bc95 model relates to computational identification of its value given the constant term in the frontier, as discussed in section 2.2 of the main report.

In the bc95 method, the time-varying inefficiencies can be equivalently expressed as (Battese and Coelli 1995, 327):

$$u_{it} = \delta_0 + \boldsymbol{z'_{it}\delta} + \varpi_{it} \tag{B2.2}$$

where $\varpi_{it}$ is a random variable distributed as a truncation of a normal distribution with zero mean and constant variance, the truncation point being: $-\delta_0 - \boldsymbol{z'_{it}\delta}$. Substituting (B2.2) into the generic cost model (see equations (2.1) and (2.2) of the main report):

$$\begin{aligned} c_{it} &= \alpha_0 + \boldsymbol{x'_{it}\beta} + u_{it} + v_{it} \qquad \text{(B2.3)} \\ &= \alpha_0 + \boldsymbol{x'_{it}\beta} + \delta_0 + \boldsymbol{z_{it}\delta} + \varpi_{it} + v_{it} \end{aligned}$$

The inclusion of the two constants $\alpha_0$ and $\delta_0$ does not imply a lack of formal identification because $\delta_0$ also appears in the truncation point of the distribution of $\varpi_{it}$. Nevertheless, the use of the constant term $\delta_0$ can make it more difficult to successfully compute a solution to the model (referred to above as 'computational identification').

The bc95 does appear to allow for flexibility in the time patterns of inefficiency, for instance compared to the smooth efficiency trends imposed by some methods that rely on the scaling property, when the same *z*-variables are used. This may be due to the variation of $\varpi_{it}$ between both firms and periods. The methodological characteristics of the bc95 model are further detailed in Section 3.1.5 of the draft report *"Electricity Distribution Benchmarking Opex Model Development- Phase 2"*.

## 2.1 BC95-JTT-HN: Jurisdiction time trends as determinants of mu

In this specification, we use the same variables as the standard model. The estimation follows three steps.

a) First, an ordinary least squares (OLS) regression is estimated using the corresponding functional form (Translog or Cobb-Douglas as applicable).

b) Second, using the parameter estimates from this initial step as starting values, a half-normal SFA model (using the *xtfrontier* command) is estimated.

c) Third, the *sfpanel bc95* model is estimated, this time including the $\boldsymbol{z}'_{it}$ variables (jurisdiction-specific time trends) using the coefficients from the previous step as starting values. Very small positive values were used as starting values of the jurisdiction time trends.

### 2.1.1 Estimation results

Tables 2.1.1 and 2.1.2 show the both the SFACD and SFATLG models for the long and short sample periods.

**Table 2.1.1 BC95-JTT-HN SFACD Parameter Estimates**

| | *Long Period* | | | *Short Period*[1] | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *Frontier* | | | | | | |
| ly1 | 0.496 | 0.036 | 13.62 | 0.399 | 0.043 | 9.24 |
| ly2 | 0.113 | 0.016 | 7.17 | 0.134 | 0.018 | 7.41 |
| ly3 | 0.381 | 0.034 | 11.18 | 0.461 | 0.041 | 11.19 |
| lz1 | -0.181 | 0.014 | -13.17 | -0.171 | 0.016 | -10.83 |
| yr | 0.010 | 0.001 | 10.09 | 0.000 | 0.002 | -0.02 |
| jur2 | 0.128 | 0.034 | 3.72 | 0.054 | 0.041 | 1.31 |
| jur3 | 0.394 | 0.033 | 11.87 | 0.380 | 0.041 | 9.18 |
| _cons | -9.849 | 1.925 | -5.12 | 9.791 | 3.579 | 2.74 |
| *Mu* | | | | | | |
| aus_yr | 0.000 | 0.000 | 0.26 | 0.000 | 0.000 | -0.48 |
| nz_yr | 0.000 | 0.000 | 0.07 | 0.000 | 0.000 | 1.36 |
| ont_yr | -0.001 | 0.000 | -2.89 | -0.002 | 0.002 | -0.85 |
| *Usigma* | | | | | | |
| _cons | -1.768 | 0.239 | -7.41 | -1.919 | 0.280 | -6.86 |
| *Vsigma* | | | | | | |
| _cons | -4.521 | 0.132 | -34.15 | -4.426 | 0.228 | -19.44 |
| sigma_u | 0.413 | 0.049 | 8.38 | 0.383 | 0.054 | 7.15 |
| sigma_v | 0.104 | 0.007 | 15.11 | 0.109 | 0.012 | 8.78 |
| lambda | 3.960 | 0.048 | 82.23 | 3.503 | 0.051 | 68.51 |
| LLH | 261.76 | | | 236.35 | | |
| Iterations # | 125 | | | 170 | | |
| Pseudo Adj $R^2$ | 0.997 | | | 0.996 | | |
| BIC | -432.50 | | | -386.96 | | |
| *N* | 1,098 | | | 732 | | |

[1] The model could not compute an improvement during estimation as it encountered a flat region in the likelihood surface.

Table 2.1.2 BC95-JTT-HN SFATLG Parameter Estimates

| | Long Period | | | Short Period[1] | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *Frontier* | | | | | | |
| ly1 | 0.448 | 0.038 | 11.75 | 0.405 | 0.044 | 9.21 |
| ly2 | 0.103 | 0.016 | 6.54 | 0.155 | 0.017 | 9.04 |
| ly3 | 0.415 | 0.034 | 12.07 | 0.384 | 0.040 | 9.71 |
| ly11 | 0.334 | 0.289 | 1.16 | 0.394 | 0.329 | 1.20 |
| ly12 | 0.026 | 0.065 | 0.40 | -0.022 | 0.074 | -0.29 |
| ly13 | -0.538 | 0.237 | -2.27 | -0.588 | 0.270 | -2.18 |
| ly22 | -0.005 | 0.023 | -0.23 | 0.041 | 0.027 | 1.54 |
| ly23 | 0.016 | 0.054 | 0.29 | 0.002 | 0.061 | 0.04 |
| ly33 | 0.680 | 0.194 | 3.51 | 0.801 | 0.221 | 3.63 |
| lz1 | -0.178 | 0.015 | -12.25 | -0.135 | 0.016 | -8.57 |
| yr | 0.011 | 0.001 | 11.05 | 0.000 | 0.002 | 0.01 |
| jur2 | 0.070 | 0.040 | 1.76 | -17.006 | 11.440 | -1.49 |
| jur3 | 0.298 | 0.038 | 7.78 | 0.281 | 0.051 | 5.46 |
| _cons | -12.368 | 1.992 | -6.21 | 9.735 | 3.492 | 2.79 |
| *Mu* | | | | | | |
| aus_yr | 0.000 | 0.000 | 0.57 | 0.000 | 0.000 | 4.01 |
| nz_yr | 0.000 | 0.000 | 0.28 | 0.009 | 0.006 | 1.51 |
| ont_yr | -0.001 | 0.000 | -2.53 | 0.000 | 0.000 | -1.90 |
| *Usigma* | | | | | | |
| _cons | -2.044 | 0.262 | -7.79 | -3.101 | 0.128 | -24.19 |
| *Vsigma* | | | | | | |
| _cons | -4.457 | 0.135 | -32.95 | -4.651 | 0.209 | -22.28 |
| sigma_u | 0.360 | 0.047 | 7.63 | 0.212 | 0.014 | 15.60 |
| sigma_v | 0.108 | 0.007 | 14.78 | 0.098 | 0.010 | 9.58 |
| lambda | 3.342 | 0.046 | 72.39 | 2.171 | 0.019 | 112.92 |
| LLH | 318.69 | | | 304.92 | | |
| Iterations # | 164 | | | 212 | | |
| Pseudo Adj $R^2$ | 0.997 | | | 0.997 | | |
| BIC | -504.35 | | | -484.52 | | |
| *N* | 1,098 | | | 732 | | |

[1] The model could not compute an improvement during estimation as it encountered a flat region in the likelihood surface.

### 2.1.2 Consistency with economic theory or industry knowledge

As shown in Tables 2.1.1 and 2.1.2, the estimation results for the SFACD and SFATLG models across both the long and short periods indicate that the coefficients on the primary log output variables have the expected signs and are statistically significant. The coefficient on the log share of undergrounding is negative and statistically significant in all models.

Table 2.1.3 presents the output elasticities for the SFA models in the long and short period. The sum of output elasticities across all four models is close to 1, suggesting near constant returns to scale. The output elasticities are broadly consistent across both the long and short periods and between the SFACD and SFATLG models. Customer numbers and RMD account for the largest share of the weights, while circuit length consistently receives a lower weight in all models.

Table 2.1.3 BC95-JTT-HN Output elasticities

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| _SFACD_ | | | | | | | | |
| Full Sample | 0.496 | 0.113 | 0.381 | 0.990 | 0.399 | 0.134 | 0.461 | 0.994 |
| _SFATLG_ | | | | | | | | |
| Australia | 0.189 | 0.167 | 0.630 | 0.985 | 0.077 | 0.201 | 0.684 | 0.962 |
| New Zealand | 0.712 | 0.073 | 0.161 | 0.946 | 0.655 | 0.174 | 0.069 | 0.898 |
| Ontario | 0.391 | 0.095 | 0.485 | 0.971 | 0.389 | 0.121 | 0.455 | 0.965 |
| Full sample | 0.448 | 0.103 | 0.415 | 0.967 | 0.405 | 0.155 | 0.383 | 0.944 |

Table 2.1.4 reports the monotonicity violations (MVs) in the SFATLG model for both the long and short periods.

Table 2.1.4 BC95-JTT-HN Monotonicity violations in SFATLG models (%)

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| _By DNSP_ | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 100.0 | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| CIT | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| END | 22.2 | 0.0 | 0.0 | 22.2 | 100.0 | 0.0 | 0.0 | 100.0 |
| ENX | 5.6 | 0.0 | 0.0 | 5.6 | 100.0 | 0.0 | 0.0 | 100.0 |
| ERG | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| ESS | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| JEN | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| PCR | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 50.0 | 0.0 | 0.0 | 50.0 |
| AND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| _By jurisdiction_ | | | | | | | | |
| Australia | 9.8 | 0.0 | 0.0 | 9.8 | 34.6 | 0.0 | 0.0 | 34.6 |
| New Zealand | 0.0 | 0.0 | 26.9 | 26.9 | 0.0 | 0.0 | 36.4 | 36.4 |
| Ontario | 9.0 | 0.0 | 0.0 | 9.0 | 10.3 | 0.0 | 0.0 | 10.3 |
| Full sample | 6.4 | 0.0 | 8.4 | 14.8 | 12.3 | 0.0 | 11.3 | 23.6 |

In the long-period estimation, one DNSP (AGD) had 50 per cent or more of its observations affected by monotonicity violations, and 9.8 per cent of all Australian observations show violations. In the short period, five DNSPs (AGD, END, ENX, ERG, and SAP) had at least 50 per cent of their observations affected, with a total of 34.6 per cent of Australian observations exhibiting violations. These results shows that the present model performs better than the standard SFATLG models in terms of MVs. However, it does not solve the problem of excessive MVs in the short period.

### 2.1.3 Convergence & Specification Tests

Tables 2.1.1 and 2.1.2 show the BIC and Pseudo Adjusted $R^2$ goodness-of-fit statistic for each model, as well the number of iterations. Other diagnostic statistics are shown in Table 2.1.5.

Table 2.1.5 BC95-JTT-HN Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value** | *Stat.* | *p-value** |
| ***SFACD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers)[(1)] | 0.64 | | 0.27 | |
| Shapiro–Wilk W test[(2)] | 0.936 | 0.000 | 0.964 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF[(3)] | 24.98 | | 25.89 | |
| Condition number[(3)] | 1084.23 | | 1619.52 | |
| *Specification* | | | | |
| Link test[(4)] | 2.32 | 0.020 | 1.21 | 0.225 |
| ***SFATLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.09 | | 0.27 | |
| Shapiro–Wilk W test | 0.957 | 0.000 | 0.986 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 714.08 | | 717.50 | |
| Condition number | 1641.03 | | 2427.54 | |
| Specification | | | | |
| Link test | 0.64 | 0.520 | 40.16 | 0.000 |
| Joint parameter tests | | | | |
| Higher-order output terms | 118.90 | 0.000 | 170.44 | 0.000 |

Note: * Null hypothesis is rejected in these tests, if the p-value is less than 0.05. Equivalently, the reported statistic exceeds the critical value for that statistic; (1) Severe outliers comprise about .0002% of the normal population; (2) The null hypothesis is that residuals are normally distributed; (3) Collinearity is potentially a problem if VIF>10 or the Condition number > 30; (4) Absolute value of t-statistic on hatsq. The null hypothesis is that the model is correctly specified.

Both the SFACD and SFATLG models were estimated for both the long period and short period, converging after between 125 and 212 iterations. However, in both short-period estimations, the models returned the message "*cannot compute an improvement — flat region encountered*", indicating that the optimisation reached an area of the likelihood surface where further improvement was not possible. Further, the anomalous parameter value for the NZ dummy (*jur2*) in the SFATLG short period model may indicate a computational issue.

Residual tests show that severe outliers are rare (<0.7%) in both SFACD and SFATLG models, though normality of the residuals is rejected by the Shapiro–Wilk test.

Multicollinearity is moderate in SFACD but very high in SFATLG due to the inclusion of interaction and squared terms. The link test suggests potential misspecification for SFACD in the long period (p = 0.02) and for SFATLG in the short period (p = 0.00), but not for the for the SFACD short period and SFATLG in long period. The SFATLG model is well-supported by functional form tests, with higher-order terms significant in both periods, validating the Translog specification.

### 2.1.4 Efficiency Scores

Table 2.1.6 present the average SFACD and SFATLG efficiency scores for each Australian DNSP in both the long and short period analyses. The ranking of the average efficiency scores is largely consistent across the SFACD and SFATLG models in both periods and aligns well with the rankings from the standard ABR24 models.

Table 2.1.6 BC95-JTT-HN Average Efficiency Scores by Australian DNSP

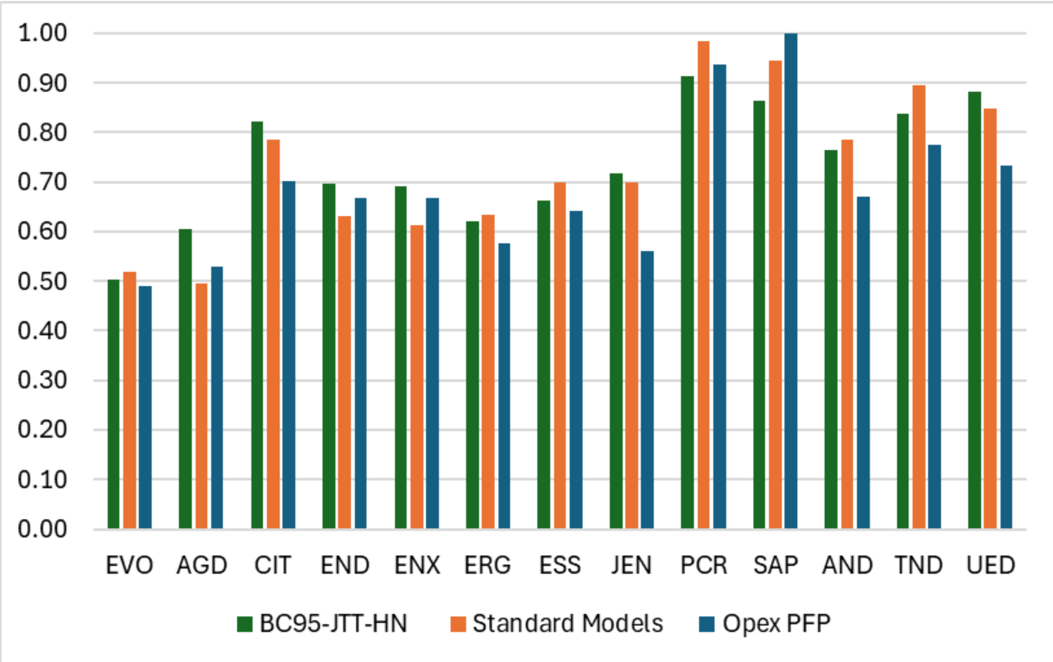
| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *SFACD* | *Rank* | *SFATLG* | *Rank* | *SFACD* | *Rank* | *SFATLG* | *Rank* |
| EVO | 0.490 | 13 | 0.514 | 13 | 0.549 | 13 | 0.566 | 13 |
| AGD | 0.609 | 11 | 0.603 | 12 | 0.704 | 11 | 0.660 | 12 |
| CIT | 0.816 | 5 | 0.827 | 5 | 0.846 | 5 | 0.831 | 5 |
| END | 0.677 | 9 | 0.717 | 7 | 0.767 | 7 | 0.754 | 6 |
| ENX | 0.689 | 8 | 0.692 | 9 | 0.749 | 8 | 0.694 | 10 |
| ERG | 0.575 | 12 | 0.669 | 11 | 0.670 | 12 | 0.719 | 8 |
| ESS | 0.640 | 10 | 0.683 | 10 | 0.730 | 9 | 0.725 | 7 |
| JEN | 0.722 | 7 | 0.711 | 8 | 0.727 | 10 | 0.690 | 11 |
| PCR | 0.913 | 1 | 0.916 | 1 | 0.927 | 1 | 0.894 | 1 |
| SAP | 0.851 | 3 | 0.879 | 2 | 0.876 | 3 | 0.860 | 3 |
| AND | 0.770 | 6 | 0.757 | 6 | 0.784 | 6 | 0.712 | 9 |
| TND | 0.825 | 4 | 0.852 | 4 | 0.875 | 4 | 0.858 | 4 |
| UED | 0.898 | 2 | 0.867 | 3 | 0.923 | 2 | 0.867 | 2 |
| Australia | 0.729 | | 0.745 | | 0.779 | | 0.756 | |

In the long period, the SFACD model yields an average efficiency score 4.5 per cent lower than the standard SFACD model, while the SFATLG model produces an average score 7.5 per cent higher than its standard counterpart. For the short period, the SFACD model reports a 4.1 per cent increase over the standard, whereas the SFATLG model shows an average of efficiency 85.1 per cent higher than the average from the standard short-period SFATLG model, which did not converge.

Looking at the correlation of average efficiency scores, the alignment between the BC95-JTT-HN and standard models varies across specifications and periods. For the SFACD models, the correlation are very high (0.975 in the long period and 0.937 in the short), indicating strong consistency in average levels. In contrast, the SFATLG model shows weaker alignment (correlation of 0.705 for the long period and just 0.202 in the short period), pointing to limited agreement, particularly where the standard short-period model faced convergence issues. In terms of efficiency rankings, correlations with the standard rankings are 0.967 in the long and short periods for SFACD, indicating a high degree of consistency in the relative ordering of DNSPs. For the SFATLG specification, the ranking correlation is more moderate at 0.588 in the long period and drops further to 0.330 in the short period.

Figure 2.1.1 shows the averages of efficiency scores across the models standard LSECD, LSETLG, SFACD and SFATLG models, in the long period sample, and compares them to the average efficiency scores of the BC95-JTT-HN and the average opex partial factor productivity (OPFP) measures for each DNSP also in the long sample.

Figure 2.1.1 Average Efficiency Scores by DNSP (2006–2023)




The correlation coefficients between the efficiency scores for Australian DNSPs from the BC95-JTT-HN long period SFACD and SFATLG models and the OPFP measures are 0.840 for SFACD and 0.876 for SFATLG, above to the standard models (in which each DNSP's efficiency is constant), for which the correlation coefficients are 0.686 for SFACD and 0.734 for SFATLG.[5]

Figure 2.1.2 illustrates the trends in efficiency scores over time for each model. A general pattern of increasing efficiency over time is observed for most DNSPs, particularly from around 2015 onwards, which is aligned with the findings from the MTFP indexes analysis in ABR24. Figure 2.1.3 shows scatter charts of the residuals of these models plotted against fitted

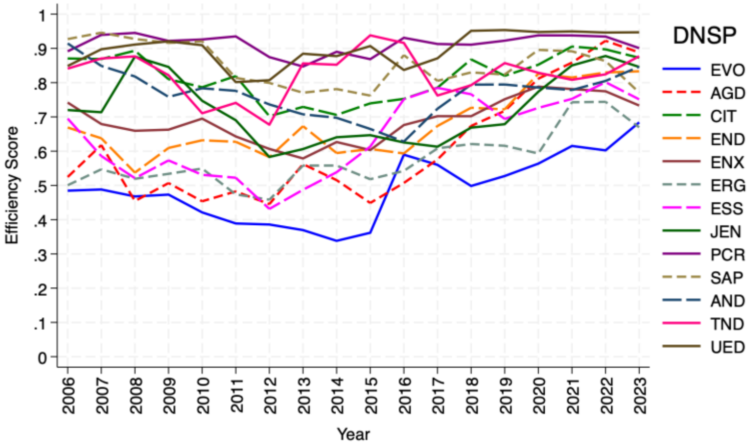
[5] The correlation was calculated using all efficiency scores across each year and DNSP. In the standard models, efficiency scores are time-invariant; therefore, each DNSP's score remains constant over the years.

values of the dependent variable. A right-bending pattern can be observed in the residuals of the Australian and New Zealand DNSPs, which may indicate heteroskedasticity.

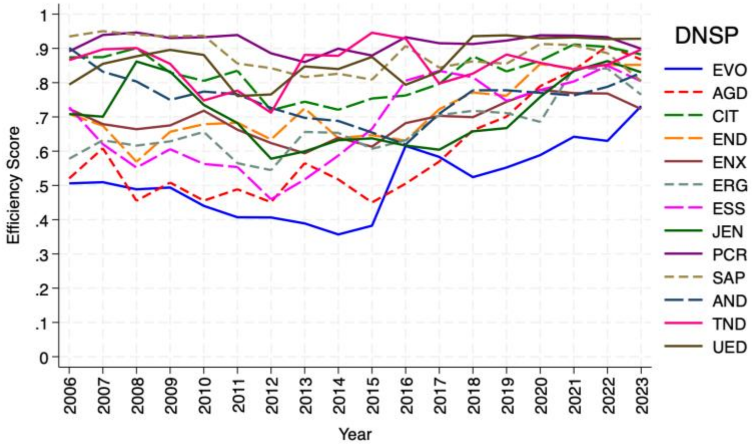
### 2.1.5 Concluding Comments

The BC95-JTT-HN models produced consistent output coefficients with near-constant returns to scale and meaningful efficiency scores. They showed slight improvements over the standard specifications in reducing monotonicity violations. The SFATLG short-period model appeared to have a computational issue, due to the anomalous coefficient reported for the NZ dummy variable and the message indicating a flat region encountered after the optimisation. The trends in efficiency scores have almost no correlation with the OPFP-based measure of efficiency. The residuals plot suggests heteroskedasticity.

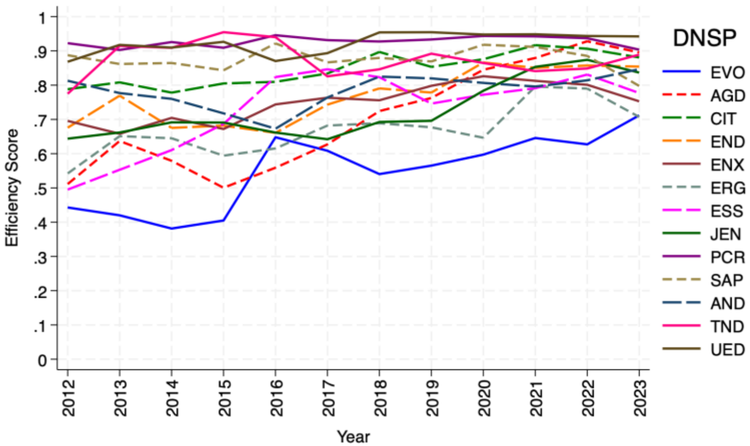
Figure 2.1.2 BC95-JTT-HN Efficiency Trends by DNSP



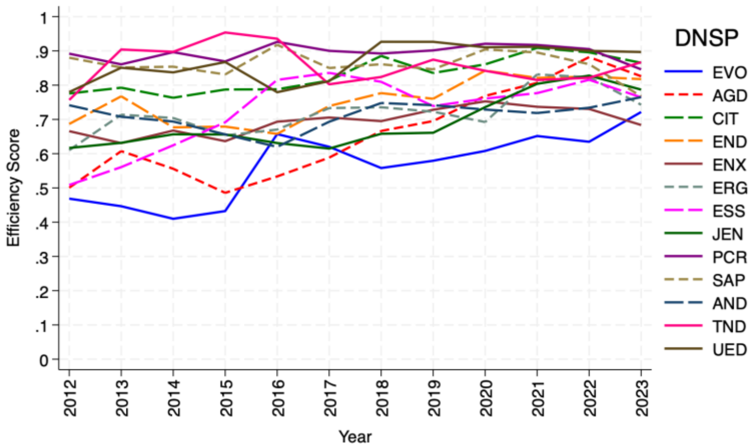

*SFACD Long Period*




*SFATLG Long Period*

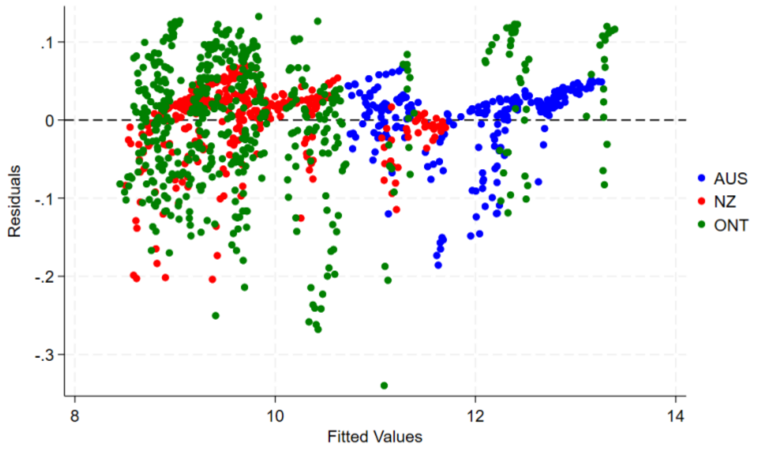



*SFACD Short Period*



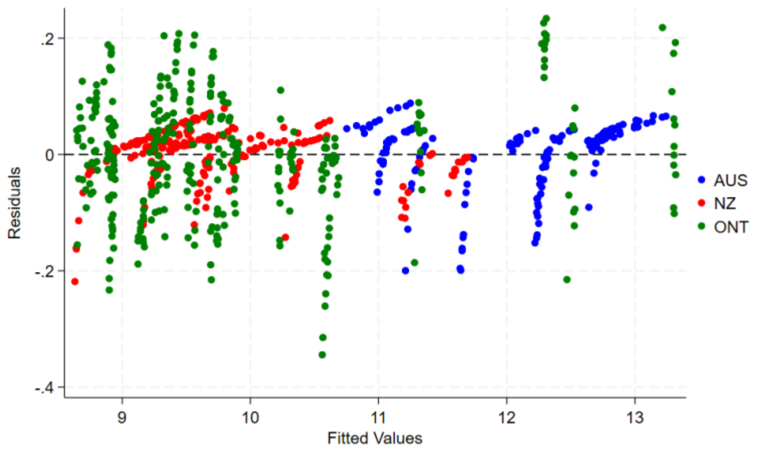

*SFATLG Short Period*

Figure 2.1.3 BC95-JTT-HN: Residual plots

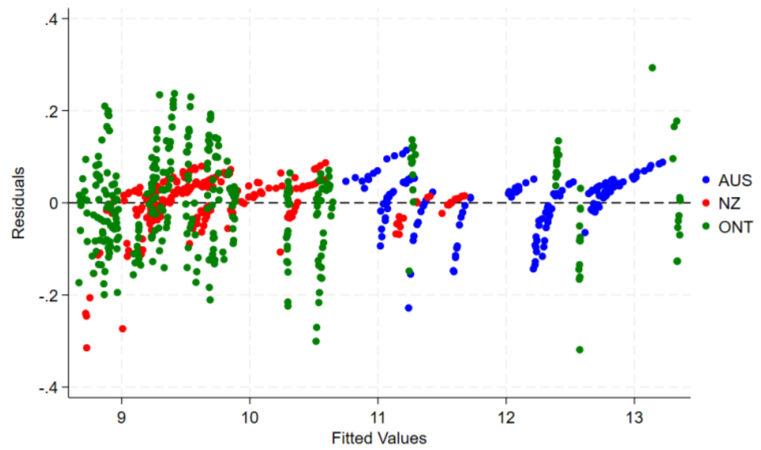



*SFACD Long Period*


*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

## 2.2 Unsuccessful BC95 models summary

The nine BC95 specifications that were tested but found to be unsuccessful are as follows:

- *BC95-JTT-HN-GTC:* This model includes jurisdictional time trends as determinants of inefficiency (via mu) and uses the General Technical Change Index (ie, dummy variables for a set of periods). It failed to produce efficiency scores for the Australian DNSPs in the long sample period, although it was able to do so in the short sample period. In the long-period SFACD model, no standard errors were produced for any estimated coefficients, indicating computational issues. The long-period SFATLG specification also performed poorly, producing a negative and statistically significant coefficient for output CL, failing to generate meaningful standard errors for any coefficients, and producing excessive monotonicity violations (100% for Australian DNSPs). These issues were not present in the short-period results, where the model performed reasonably well: standard errors were available, monotonicity violations were low, and efficiency scores were reasonable.
- *BC95-AJTT-HN:* This model generalises the *BC95-JTT-HN* model by including, as determinants of mu, DNSP-specific time trends for Australian businesses in addition to jurisdictional trends for New Zealand and Ontario. Technical change is reflected by a standard time trend. This model failed to produce efficiency scores for the Australian DNSPs in the long sample period.[6] In both SFACD and SFATLG long-period specifications, no standard errors were produced, pointing again to computational issues. In the short-period models, although estimation was partially successful, some standard errors were still missing and not all DNSPs received efficiency scores.
- *BC95-AJTT-HN-GTC:* This model is similar to BC95-AJTT-HN but replaces the standard time trend with general technical change variables. It failed to estimate efficiency scores for the Australian DNSPs in both the long and short sample periods.[7] In both the CD and TLG models in long and short-periods, standard errors were either missing for all or some coefficients.

This sequence of results shows that the BC95 model becomes more difficult to estimate as the models become more complex, and with the ABR24 data, estimation was only feasible in the simplest of the model specifications tested.

We also tested variants of these models which allowed for the variance of the idiosyncratic error term to be a function of a measure of scale. The scales variables were a weighted average of the mean values, for each DNSP, of each log output. The weights were given by the estimated coefficients of the ordinary least squares CD model also used in producing starting values for the SFACD model. This line of inquiry was not promising since this scale variable

[6] Efficiency scores were either zero or not calculated at all.
[7] Efficiency scores were either zero or not calculated at all.

was not in general a statistically significant explanator of the squared residuals of the *BC95-JTT-HN* models.

Each of the above three specifications, along with the successful baseline model, was re-estimated with heterogeneity in the idiosyncratic error term. These models were denoted:

- BC95-JTT-HN-hY
- BC95-JTT-HN-GTC-hY
- BC95-AJTT-HN-hY
- BC95-AJTT-HN-GTC-hY

All exhibited similar computational problems as described above, including missing standard errors, implausible or missing efficiency scores. Hence, the *BC95-JTT-HN* models were the only feasible versions of the BC95 approach to be estimated.

# 3 Kumbhakar et al (1990)

In this section, we present the empirical results from the Kumbhakar 1990 (*Kumb90)* method, implemented in Stata using **sfpanel *y xlist*, model(kumb90)**. In this approach, the time-varying inefficiency is to define $u_{it}$ such that it has a cross-sectional element and a time varying element:

$$u_{it} = g(\boldsymbol{z}) \cdot u_i \qquad \text{where: } u_i \sim N^+(0, \sigma_u^2) \tag{3.1}$$

Here $g(\boldsymbol{z})$ is a scaling function, and $u_i$ is the one-sided random cross-sectional inefficiency term, which has a half-normal distribution. Although in Kumbhakar (1990) has a specific function for $g(\boldsymbol{z})$ quadratic in the time trend, whereas the sfpanel implementation is a generalisation of this approach with:

$$g(z) = [1 + \exp(\delta_0 + \boldsymbol{z}_{it}'\boldsymbol{\delta})]^{-1} \tag{3.2}$$

where $\boldsymbol{z}_{it}$ is a vector of exogenous variables. Note that in this model, the constant term $\delta_0$ only affects the scaling of the inefficiency term and does not affect the truncation point of the random inefficiency term, which remains at zero. Hence, it does not give rise to the same partial identification issue as with the bc95 model.[8]

The estimation of the models presented here followed three steps:

a) First, the frontier component of the model was first estimating using ordinary least squares (OLS). The parameter estimates obtained were used as starting values of the frontier parameters in the next step.

b) Second, using the parameter estimates from this initial step as starting values, a half-normal SFA model (using the *xtfrontier* command) is estimated.

c) Finally, the *sfpanel* command was run with the *kumb90* model option and specifying btvars (ie, the $\boldsymbol{z}_{it}'$ variables as in equation (3.2)). Starting values for the delta parameters were set at 0.001.

We tested ten different specifications; but only six are presented here as the other suffered with optimization issues or included control for heteroscedasticity.[9] Since time trends feature in the expression for $u_{it}$, we also test the general technical change index. This means subtracting the average year from each observation's year to create a time trend with a mean of zero. Centring the time variable helps reduce multicollinearity when it is used in interaction terms or nonlinear functions.

[8] Other methodological characteristics of this model are further detailed in Sections 2.2.2 and 2.2.5 of the draft report *"Electricity Distribution Benchmarking Opex Model Development- Phase 2"*.

[9] The kumb90 modelling option does not allow the variance of the idiosyncratic error term to be a function of a measure of scale, but it does allow for cluster-robust standard errors that allow for intragroup correlation. Although we tested this option, these variants were ultimately excluded, supported by the finding that the scale effect, the key rationale for expecting heteroscedasticity, is not statistically significant

### 3.1 Kumb90-JTT-HN: Jurisdiction Time Trends as *z*-variables

In this specification, the jurisdictional time trend variables are included as z-variables.

#### 3.1.1 Estimation Results

The results of estimating the Cobb-Douglas and Translog with both the long and short samples are presented in Table 3.1.1 and 3.1.2.

#### 3.1.2 Consistency with economic theory or industry knowledge

As shown in Tables 3.1.1 and 3.1.2, the estimation results for the SFACD and SFATLG models across both the long and short periods indicate that the coefficients on the primary log output variables have the expected signs and are statistically significant. The coefficient on the log share of underground cables is negative and statistically significant only in the SFACD long-period model. In the SFACD short period the coefficient is positive and statistically insignificant. In both Translog models it is negative but not statistically significant.

Table 3.1.1 Kumb90-JTT-HN: SFACD Parameter Estimates

| | *Long Period* | | | *Short Period*[1] | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| **Frontier** | | | | | | |
| ly1 | 0.469 | 0.065 | 7.25 | 0.380 | 0.067 | 5.63 |
| ly2 | 0.213 | 0.029 | 7.39 | 0.315 | 0.033 | 9.49 |
| ly3 | 0.292 | 0.057 | 5.12 | 0.240 | 0.062 | 3.89 |
| lz1 | -0.063 | 0.028 | -2.21 | 0.010 | 0.035 | 0.30 |
| yr | 0.021 | 0.001 | 16.11 | 0.010 | 0.001 | 8.65 |
| jur2 | 0.074 | 0.071 | 1.04 | -0.151 | 0.076 | -2.00 |
| jur3 | 0.234 | 0.055 | 4.28 | 0.206 | 0.062 | 3.31 |
| _cons | -31.699 | 2.598 | -12.20 | -11.156 | 2.466 | -4.52 |
| **Bt** | | | | | | |
| t_aus | 0.454 | 0.048 | 9.40 | 0.300 | 0.052 | 5.80 |
| t_nz | -0.071 | 0.040 | -1.78 | -0.120 | 0.024 | -4.97 |
| t_ont | 0.383 | 0.041 | 9.33 | 0.146 | 0.041 | 3.60 |
| _cons | -2.262 | 0.212 | -10.66 | -0.490 | 0.286 | -1.71 |
| /sigmau_2 | 0.194 | 0.040 | 4.84 | 0.343 | 0.099 | 3.45 |
| /sigmav_2 | 0.011 | 0.000 | 22.65 | 0.007 | 0.000 | 18.07 |
| sigma_u | 0.440 | 0.045 | 9.68 | 0.586 | 0.085 | 6.89 |
| sigma_v | 0.104 | 0.002 | 45.31 | 0.082 | 0.002 | 36.14 |
| lambda | 4.222 | 0.045 | 93.04 | 7.144 | 0.085 | 84.18 |
| LLH | 800.56 | | | 668.52 | | |
| Iterations # | 100 | | | 148 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.996 | | |
| BIC | -1503.1 | | | -1244.7 | | |
| N | 1098 | | | 732 | | |

[1] The model could not compute an improvement during estimation as it encountered a flat region in the likelihood surface.

Table 3.1.2 Kumb90-JTT-HN: SFATLG Parameter Estimates

| | Long Period | | | Short Period[1] | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.487 | 0.066 | 7.38 | 0.500 | 0.085 | 5.90 |
| ly2 | 0.223 | 0.033 | 6.84 | 0.262 | 0.038 | 6.83 |
| ly3 | 0.276 | 0.060 | 4.60 | 0.201 | 0.066 | 3.05 |
| ly11 | 0.593 | 0.371 | 1.60 | -0.462 | 0.514 | -0.90 |
| ly12 | -0.197 | 0.081 | -2.43 | 0.165 | 0.117 | 1.40 |
| ly13 | -0.421 | 0.322 | -1.31 | 0.153 | 0.421 | 0.36 |
| ly22 | 0.121 | 0.037 | 3.22 | 0.052 | 0.047 | 1.11 |
| ly23 | 0.093 | 0.067 | 1.38 | -0.204 | 0.087 | -2.33 |
| ly33 | 0.313 | 0.291 | 1.07 | 0.150 | 0.359 | 0.42 |
| lz1 | -0.017 | 0.032 | -0.55 | -0.018 | 0.038 | -0.48 |
| yr | 0.020 | 0.001 | 13.92 | 0.018 | 0.002 | 8.79 |
| jur2 | 0.064 | 0.060 | 1.06 | -0.044 | 0.084 | -0.53 |
| jur3 | 0.217 | 0.054 | 3.99 | 0.220 | 0.062 | 3.54 |
| _cons | -29.814 | 2.867 | -10.40 | -26.233 | 4.147 | -6.33 |
| ***Bt*** | | | | | | |
| t_aus | 0.473 | 0.049 | 9.73 | 0.354 | 0.049 | 7.25 |
| t_nz | -0.066 | 0.040 | -1.67 | -0.106 | 0.025 | -4.24 |
| t_ont | 0.366 | 0.041 | 9.01 | 0.275 | 0.052 | 5.28 |
| _cons | -2.277 | 0.215 | -10.60 | -0.775 | 0.176 | -4.40 |
| /sigmau_2 | 0.201 | 0.043 | 4.66 | 0.275 | 0.068 | 4.06 |
| /sigmav_2 | 0.011 | 0.000 | 22.58 | 0.006 | 0.000 | 18.07 |
| sigma_u | 0.449 | 0.048 | 9.32 | 0.524 | 0.065 | 8.12 |
| sigma_v | 0.103 | 0.002 | 45.16 | 0.080 | 0.002 | 36.14 |
| lambda | 4.345 | 0.048 | 90.46 | 6.567 | 0.064 | 101.94 |
| LLH | 808.48 | | | 684.93 | | |
| Iterations # | 183 | | | 225 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.996 | | |
| BIC | -1476.93 | | | -1239.22 | | |
| *N* | 1098 | | | 732 | | |

[1] The model could not compute an improvement during estimation as it encountered a flat region in the likelihood surface.

Table 3.1.3 presents the output elasticities for both the long- and short-period models. Across all four specifications, the sum of output elasticities is close to one, indicating near-constant returns to scale. Customer numbers consistently receive the greatest weight, followed by RMD in the long-period models and CL in the short-period models. In the short period, CL and RMD have similar weights, while in the long period, Customer numbers and CL carry comparable weight.

Table 3.1.4 reports the monotonicity violations in the SFATLG model for both the long and short periods. In the long-period model, there is no MVs. In contrast, in the short-period model, one DNSP shows excessive violations, with only 3.8 per cent of the Australian sample and 21.3 per cent of the total sample affected. These results indicate that the Kumb90-JTT-HN model performs better than the standard SFATLG specifications in terms of reducing monotonicity violations. These results indicate that the Kumb90-JTT-HN model performs better than the standard SFATLG specifications in terms of reducing monotonicity violations.

Table 3.1.3 Kumb90-JTT-HN: Output elasticities

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| <u>*SFACD*</u> | | | | | | | | |
| Full Sample | 0.469 | 0.213 | 0.292 | 0.974 | 0.380 | 0.315 | 0.240 | 0.935 |
| <u>*SFATLG*</u> | | | | | | | | |
| Australia | 0.454 | 0.266 | 0.230 | 0.950 | 0.247 | 0.320 | 0.327 | 0.893 |
| New Zealand | 0.449 | 0.287 | 0.283 | 1.019 | 0.688 | 0.342 | -0.059 | 0.971 |
| Ontario | 0.528 | 0.162 | 0.293 | 0.983 | 0.491 | 0.183 | 0.314 | 0.988 |
| Full sample | 0.487 | 0.223 | 0.276 | 0.987 | 0.500 | 0.262 | 0.201 | 0.962 |

Table 3.1.4 Kumb90-JTT-HN: Monotonicity violations in SFATLG models (%)

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| <u>*By DNSP*</u> | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 0.0 | 0.0 | 0.0 | 0.0 | 50.0 | 0.0 | 0.0 | 50.0 |
| CIT | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| END | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ENX | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ERG | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ESS | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| JEN | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| PCR | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| <u>*By jurisdiction*</u> | | | | | | | | |
| Australia | 0.0 | 0.0 | 0.0 | 0.0 | 3.8 | 0.0 | 0.0 | 3.8 |
| New Zealand | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 68.4 | 68.4 |
| Ontario | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Full sample | 0.0 | 0.0 | 0.0 | 0.0 | 0.8 | 0.0 | 21.3 | 22.1 |

### 3.1.3 Convergence & Specification Tests

Both the SFACD and SFATLG models were estimated for the long and short periods, with converging within 100 to 225 iterations. However, in the short-period models, estimation returned the message "*cannot compute an improvement — flat region encountered*", suggesting the optimisation reached a flat likelihood region and that the results may be unreliable.

Tables 3.1.1 and 3.1.2 report the BIC, pseudo-adjusted $R^2$, and the number of iterations for each model. Additional diagnostic statistics are presented in Table 3.1.5.

Table 3.1.5 Kumb90-JTT-HN: Statistics Results

| | Long Period | | Short Period | |
|---|---|---|---|---|
| | *Stat.* | *p-value** | *Stat.* | *p-value** |
| ***SFACD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers)(1) | 0.27 | | 0.14 | |
| Shapiro–Wilk W test(2) | 0.982 | 0.000 | 0.983 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF(3) | 24.98 | | 25.89 | |
| Condition number(3) | 1084.2 | | 1619.5 | |
| *Specification* | | | | |
| Link test(4) | 2.26 | 0.024 | -6.62 | 0.000 |
| ***SFATLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.27 | | 0.28 | |
| Shapiro–Wilk W test | 0.984 | 0.000 | 0.982 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 714.08 | | 717.50 | |
| Condition number | 1641.0 | | 2427.5 | |
| Specification | | | | |
| Link test | 3.36 | 0.001 | -5.44 | 0.000 |
| Joint parameter tests | | | | |
| Higher-order output terms | 17.77 | 0.015 | 38.57 | 0.000 |

Note: * Null hypothesis is rejected in these tests, if the p-value is less than 0.05. Equivalently, the reported statistic exceeds the critical value for that statistic; (1) Severe outliers comprise about .0002% of the normal population; (2) The null hypothesis is that residuals are normally distributed; (3) Collinearity is potentially a problem if VIF>10 or the Condition number > 30; (4) Absolute value of t-statistic on hatsq. The null hypothesis is that the model is correctly specified.

Residual diagnostics indicate that severe outliers are rare (fewer than 0.3%) across both models. However, the Shapiro–Wilk test rejects the normality of residuals. Multicollinearity is moderate in the SFACD model but very high in the SFATLG model, due to the inclusion of interaction and squared terms. The link test suggests potential misspecification in all models and the functional form tests support the SFATLG specification, with higher-order terms statistically significant in both periods.

### 3.1.4 Efficiency Scores

Table 3.1.6 present the average SFACD and SFATLG efficiency scores for each Australian DNSP in both the long and short period analyses. Compared to the standard models, in the long period, the SFACD model produces an average efficiency score 6.3 per cent lower than its standard counterpart, while the SFATLG model shows an average that is 4.8 per cent higher. In the short period, the SFACD model returns 1.6 per cent lower average efficiency score than the standard model. In contrast, the SFATLG model displays a great difference of 74.3 per cent above the standard short-period SFATLG model, which did not converge.

Table 3.1.6 Kumb90-JTT-HN: Average Efficiency Scores by Australian DNSP

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *SFACD* | *Rank* | *SFATLG* | *Rank* | *SFACD* | *Rank* | *SFATLG* | *Rank* |
| EVO | 0.517 | 13 | 0.531 | 13 | 0.563 | 13 | 0.545 | 12 |
| AGD | 0.557 | 11 | 0.535 | 12 | 0.583 | 12 | 0.534 | 13 |
| CIT | 0.782 | 5 | 0.813 | 4 | 0.750 | 6 | 0.778 | 5 |
| END | 0.658 | 9 | 0.642 | 10 | 0.704 | 7 | 0.667 | 8 |
| ENX | 0.684 | 8 | 0.662 | 8 | 0.695 | 8 | 0.632 | 9 |
| ERG | 0.550 | 12 | 0.618 | 11 | 0.616 | 11 | 0.614 | 11 |
| ESS | 0.596 | 10 | 0.652 | 9 | 0.661 | 9 | 0.694 | 7 |
| JEN | 0.694 | 7 | 0.720 | 7 | 0.661 | 10 | 0.630 | 10 |
| PCR | 0.912 | 2 | 0.904 | 2 | 0.924 | 2 | 0.904 | 1 |
| SAP | 0.916 | 1 | 0.948 | 1 | 0.934 | 1 | 0.889 | 2 |
| AND | 0.764 | 6 | 0.760 | 6 | 0.761 | 5 | 0.724 | 6 |
| TND | 0.803 | 4 | 0.799 | 5 | 0.872 | 3 | 0.850 | 3 |
| UED | 0.860 | 3 | 0.862 | 3 | 0.850 | 4 | 0.792 | 4 |
| Australia | 0.715 | | 0.726 | | 0.736 | | 0.712 | |

When comparing average efficiency scores, the correlation between the Kumb90-JTT-HN and standard models varies across specifications. For SFACD, correlations are very high, 0.962 for the long period and 0.991 for the short period, indicating strong alignment. For SFATLG, the correlation is lower, 0.745 for the long period and only 0.335 in the short period.

The efficiency rankings tell a similar story. For SFACD, the correlation with the standard rankings is 0.940 in the long period and 0.995 in the short, suggesting a high degree of agreement in the relative performance of DNSPs. The SFATLG rankings are less consistent, with a correlation of 0.588 in the long period and falling to 0.390 in the short period.

Figure 3.1.1 compares average efficiency scores across the standard LSECD, LSETLG, SFACD and SFATLG models, in the long period sample, and compares them to the average efficiency scores of the Kumb90-JTT-HN and the average opex partial factor productivity (OPFP) measures. The results are reasonably similar across all approaches.

The efficiency scores for Australian DNSPs from the long-period SFACD and SFATLG models show strong correlations with the OPFP measures, at 0.722 and 0.724, respectively. These correlations are higher than those observed in the standard SFACD models (0.686) and comparable to the standard SFATLG model (0.734).

Figure 3.1.1 Average Efficiency Scores by DNSP (2006–2023)

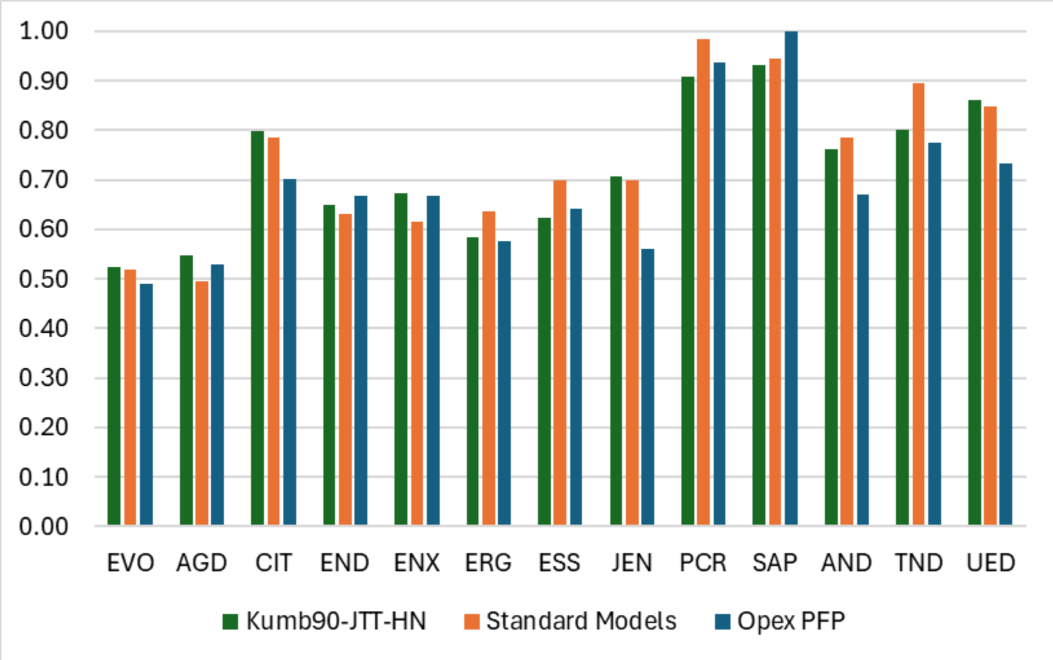
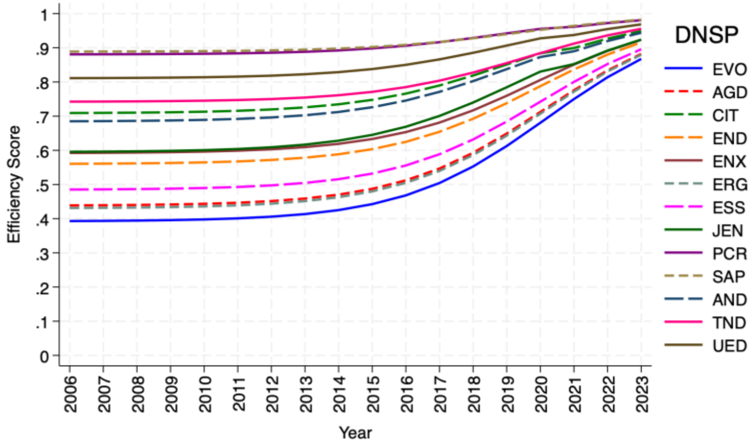



Figure 3.1.2 illustrate the trends in efficiency scores over time for all models. A consistent pattern emerges: most DNSPs show a gradual but steady increase in efficiency over time. This upward trend is particularly evident from around 2014 onwards, with nearly all DNSPs converging toward higher efficiency scores by the end of the sample period. Figure 3.1.3 shows scatter charts of the residuals of these models plotted against fitted values of the dependent variable.

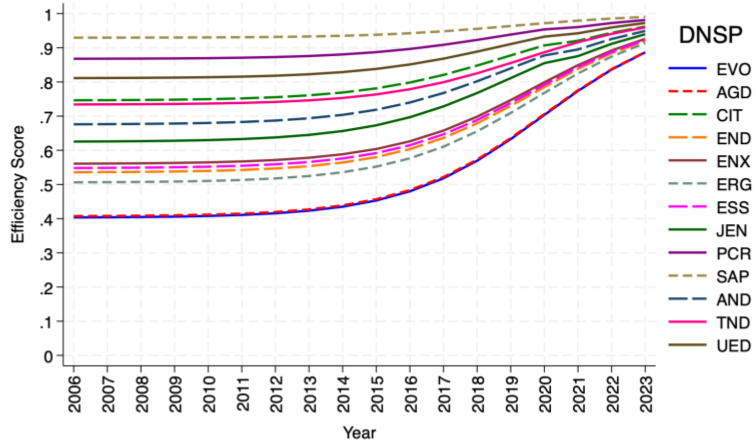
### 3.1.5 Concluding Comments

The Kumb90-JTT-HN models produced consistent output elasticities, indicating near-constant returns to scale, and generated meaningful efficiency scores. They performed better than the standard specifications in reducing monotonicity violations, and the efficiency scores showed a strong correlation with opex partial factor productivity index. However, the short sample period models presented issues with convergence.

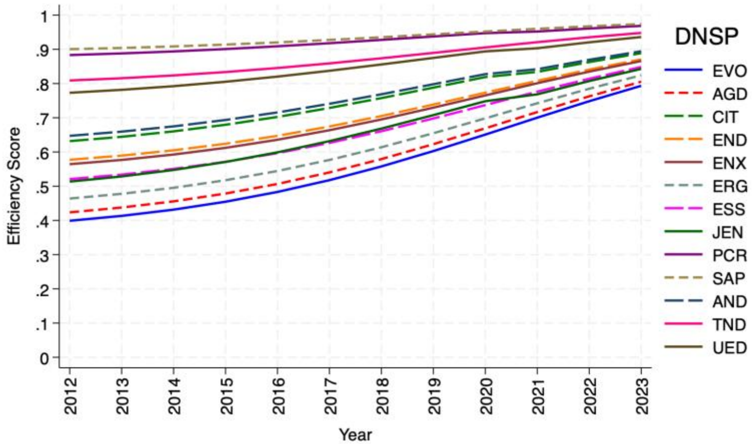
Figure 3.1.2 Kumb90-JTT-HN Efficiency Trends by DNSP



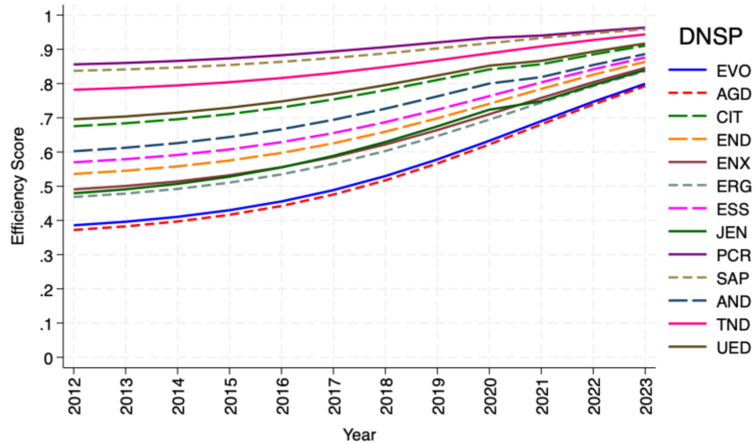

*SFACD Long Period*




*SFATLG Long Period*

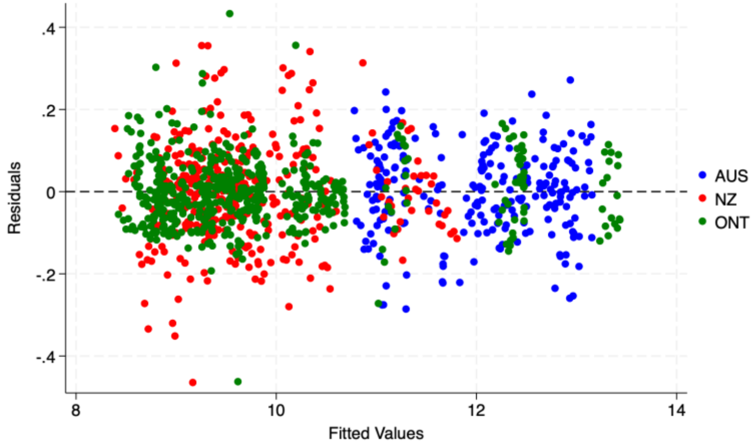



*SFACD Short Period*

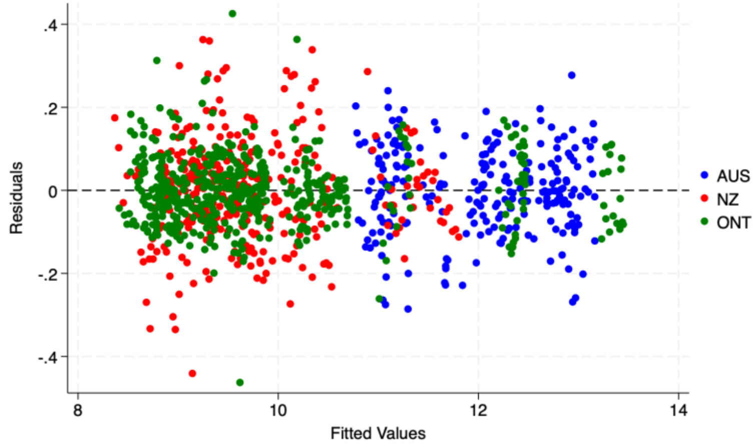



*SFATLG Short Period*

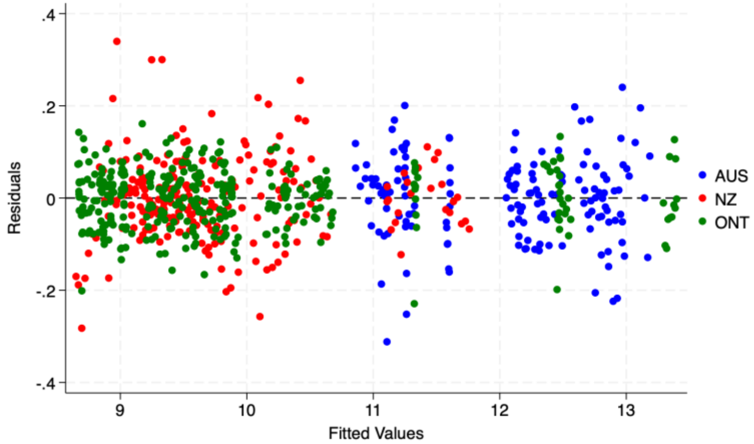
Figure 3.1.3 Kumb90-JTT-HN: Residual plots



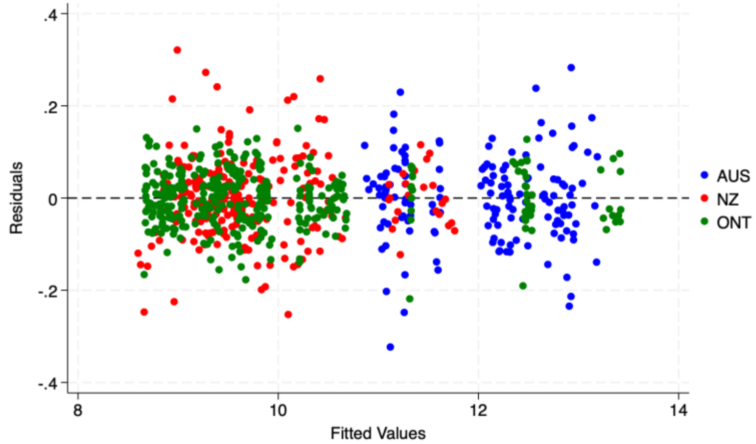

*SFACD Long Period*




*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

## 3.2 Kumb90-JTT-HN-GTC: Jurisdiction Time Trends as z-variables & General Technical Change

In this specification, the jurisdictional time trend variables are included as z-variables. Furthermore, instead of using the 'yr' variable, GTC dummy variables are included.

### 3.2.1 Estimation Results

The results of estimating the Cobb-Douglas and Translog with both the long and short samples are presented in Table 3.2.1 and 3.2.2.

Table 3.2.1 Kumb90-JTT-HN-GTC: SFACD Parameter Estimates

| | *Long Period* | | | *Short Period* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.461 | 0.066 | 6.98 | 0.434 | 0.072 | 6.05 |
| ly2 | 0.225 | 0.029 | 7.86 | 0.327 | 0.034 | 9.56 |
| ly3 | 0.287 | 0.059 | 4.84 | 0.168 | 0.068 | 2.48 |
| lz1 | -0.038 | 0.029 | -1.28 | 0.029 | 0.036 | 0.81 |
| gtc2 | 0.042 | 0.012 | 3.62 | | | |
| gtc3 | 0.112 | 0.013 | 8.72 | | | |
| gtc4 | 0.164 | 0.015 | 11.00 | 0.040 | 0.010 | 3.82 |
| gtc5 | 0.230 | 0.017 | 13.40 | 0.054 | 0.015 | 3.68 |
| gtc6 | 0.266 | 0.020 | 13.06 | 0.021 | 0.019 | 1.08 |
| jur2 | 0.018 | 0.069 | 0.26 | -0.270 | 0.079 | -3.40 |
| jur3 | 0.200 | 0.052 | 3.88 | 0.193 | 0.060 | 3.21 |
| _cons | 9.683 | 0.071 | 136.22 | 10.002 | 0.074 | 135.66 |
| ***Bt*** | | | | | | |
| t_aus | 0.443 | 0.056 | 7.95 | 0.110 | 0.023 | 4.76 |
| t_nz | -0.101 | 0.037 | -2.76 | -0.063 | 0.012 | -5.31 |
| t_ont | 0.343 | 0.051 | 6.73 | 0.030 | 0.009 | 3.22 |
| _cons | -2.133 | 0.267 | -8.00 | 2.377 | 1.790 | 1.33 |
| /sigmau_2 | 0.184 | 0.038 | 4.88 | 18.659 | 61.207 | 0.30 |
| /sigmav_2 | 0.011 | 0.000 | 22.67 | 0.007 | 0.000 | 18.04 |
| sigma_u | 0.429 | 0.044 | 9.76 | 4.320 | 7.085 | 0.61 |
| sigma_v | 0.106 | 0.002 | 45.35 | 0.081 | 0.002 | 36.07 |
| lambda | 4.046 | 0.044 | 92.08 | 53.485 | 7.085 | 7.55 |
| LLH | 783.65 | | | 673.75 | | |
| Iterations # | 57 | | | 157 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.996 | | |
| BIC | -1441.29 | | | -1241.96 | | |
| *N* | 1098 | | | 732 | | |

Table 3.2.2 Kumb90-JTT-HN-GTC: SFATLG Parameter Estimates

| | Long Period | | | Short Period | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.503 | 0.073 | 6.91 | 0.394 | 0.081 | 4.84 |
| ly2 | 0.222 | 0.034 | 6.52 | 0.327 | 0.039 | 8.47 |
| ly3 | 0.262 | 0.064 | 4.07 | 0.218 | 0.078 | 2.79 |
| ly11 | 0.555 | 0.405 | 1.37 | 0.259 | 0.459 | 0.56 |
| ly12 | -0.224 | 0.095 | -2.35 | -0.059 | 0.107 | -0.54 |
| ly13 | -0.351 | 0.339 | -1.03 | -0.217 | 0.393 | -0.55 |
| ly22 | 0.135 | 0.044 | 3.03 | 0.184 | 0.051 | 3.63 |
| ly23 | 0.112 | 0.071 | 1.58 | -0.122 | 0.090 | -1.36 |
| ly33 | 0.214 | 0.303 | 0.71 | 0.329 | 0.347 | 0.95 |
| lz1 | 0.009 | 0.032 | 0.27 | 0.095 | 0.037 | 2.55 |
| gtc2 | 0.039 | 0.012 | 3.37 | | | |
| gtc3 | 0.107 | 0.013 | 8.13 | | | |
| gtc4 | 0.155 | 0.016 | 9.94 | 0.036 | 0.010 | 3.48 |
| gtc5 | 0.217 | 0.018 | 11.96 | 0.047 | 0.015 | 3.21 |
| gtc6 | 0.249 | 0.021 | 11.73 | 0.011 | 0.020 | 0.57 |
| jur2 | 0.037 | 0.054 | 0.69 | -0.273 | 0.079 | -3.48 |
| jur3 | 0.192 | 0.051 | 3.74 | 0.168 | 0.058 | 2.87 |
| _cons | 9.719 | 0.064 | 152.01 | 10.065 | 0.070 | 143.49 |
| ***Bt*** | | | | | | |
| t_aus | 0.458 | 0.054 | 8.43 | 0.114 | 0.036 | 3.16 |
| t_nz | -0.094 | 0.035 | -2.67 | -0.075 | 0.020 | -3.72 |
| t_ont | 0.322 | 0.048 | 6.74 | 0.031 | 0.012 | 2.50 |
| _cons | -2.146 | 0.262 | -8.19 | 2.003 | 2.018 | 0.99 |
| /sigmau_2 | 0.199 | 0.043 | 4.65 | 8.195 | 29.262 | 0.28 |
| /sigmav_2 | 0.011 | 0.000 | 22.57 | 0.006 | 0.000 | 17.92 |
| sigma_u | 0.446 | 0.048 | 9.30 | 2.863 | 5.111 | 0.56 |
| sigma_v | 0.105 | 0.002 | 45.14 | 0.080 | 0.002 | 35.85 |
| lambda | 4.255 | 0.048 | 88.88 | 35.931 | 5.111 | 7.03 |
| LLH | 793.03 | | | 687.25 | | |
| Iterations # | 334 | | | 185 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.997 | | |
| BIC | -1418.03 | | | -1229.39 | | |
| *N* | 1098 | | | 732 | | |

### 3.2.2 Consistency with economic theory or industry knowledge

As shown in Tables 3.2.1 and 3.2.2, the SFACD and SFATLG models for both long and short periods generally produce output coefficients with the expected signs and are statistically significant. The coefficient on the log share of underground cables has the expected negative sign only in the SFACD long period model but is not statistically significant. It has a small positive and statistically insignificant value in the long period SFATLG model. It is positive and statistically significant only in the SFATLG short-period model, which goes against expectations and suggests a possible issue with this specification.

Table 3.2.3 shows the output elasticities for both the long- and short-period models. In all four specifications, the sum of elasticities is close to one, suggesting near-constant returns to scale. Customer numbers consistently carry the greatest weight across all models. In the long-period model, this is followed by RMD, although CL has a very similar weight to RMD. In the short period, CL ranks second, with a larger gap between CL and RMD.

Table 3.2.3 Kumb90-JTT-HN-GTC: Output elasticities

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| <u>*SFACD*</u> | | | | | | | | |
| Full Sample | 0.461 | 0.225 | 0.287 | 0.973 | 0.434 | 0.327 | 0.168 | 0.929 |
| <u>*SFATLG*</u> | | | | | | | | |
| Australia | 0.465 | 0.277 | 0.213 | 0.955 | 0.380 | 0.380 | 0.138 | 0.898 |
| New Zealand | 0.422 | 0.289 | 0.314 | 1.025 | 0.406 | 0.500 | 0.051 | 0.958 |
| Ontario | 0.572 | 0.154 | 0.250 | 0.976 | 0.392 | 0.189 | 0.364 | 0.945 |
| Full sample | 0.503 | 0.222 | 0.262 | 0.987 | 0.394 | 0.327 | 0.218 | 0.939 |

Table 3.2.4 reports the monotonicity violations in the SFATLG model for both the long and short periods.

Table 3.2.4 Kumb90-JTT-HN-GTC: Monotonicity violations in SFATLG models (%)

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| <u>*By DNSP*</u> | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| CIT | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| END | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ENX | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ERG | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ESS | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| JEN | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| PCR | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 8.3 | 8.3 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| <u>*By jurisdiction*</u> | | | | | | | | |
| Australia | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 8.3 | 8.3 |
| New Zealand | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 20.2 | 18.0 |
| Ontario | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Full sample | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 8.1 | 8.1 |

In the long-period model, there is no monotonicity violations. In the short-period model, one DNSP (ESS) displays violations in 100 per cent of observations and other (PCR) in 8.3 per cent of its observations, resulting in 8.3 per cent of the Australian sample and 8.1 per cent of the total sample being affected by monotonicity violations. These results indicate that the Kumb90-JTT-HN-GTC model performs better than the standard SFATLG specifications in terms of reducing monotonicity violations.

### 3.2.3 Convergence & Specification Tests

Both the SFACD and SFATLG models were estimated for the long and short periods, with convergence achieved after 57 to 334 iterations. Tables 3.2.1 and 3.2.2 report the BIC, pseudo-adjusted $R^2$, and the number of iterations for each model. Additional diagnostic statistics are presented in Table 3.2.5.

**Table 3.2.5 Kumb90-JTT-HN-GTC: Statistics Results**

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value** | *Stat.* | *p-value** |
| ***SFACD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers)[(1)] | 0.27 | | 0.41 | |
| Shapiro–Wilk W test[(2)] | 0.982 | 0.000 | 0.979 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF[(3)] | 16.61 | | 20.50 | |
| Condition number[(3)] | 22.20 | | 22.56 | |
| *Specification* | | | | |
| Link test[(4)] | 2.37 | 0.018 | -2.96 | 0.003 |
| ***SFATLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.18 | | 0.27 | |
| Shapiro–Wilk W test | 0.984 | 0.000 | 0.980 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 547.46 | | 621.85 | |
| Condition number | 367.04 | | 366.68 | |
| Specification | | | | |
| Link test | 3.17 | 0.002 | -2.47 | 0.013 |
| Joint parameter tests | | | | |
| Higher-order output terms | 18.36 | 0.005 | 24.37 | 0.000 |

Note: * Null hypothesis is rejected in these tests, if the p-value is less than 0.05. Equivalently, the reported statistic exceeds the critical value for that statistic; (1) Severe outliers comprise about .0002% of the normal population; (2) The null hypothesis is that residuals are normally distributed; (3) Collinearity is potentially a problem if VIF>10 or the Condition number > 30; (4) Absolute value of t-statistic on hatsq. The null hypothesis is that the model is correctly specified.

Residual diagnostics indicate that severe outliers are rare (fewer than 0.5%) across both models. However, the Shapiro–Wilk test rejects the normality of residuals. Multicollinearity is moderate in the SFACD model but high in the SFATLG model, due to the inclusion of interaction and squared terms.

The link test suggests potential misspecification in all models and the functional form tests support the SFATLG specification, with higher-order terms statistically significant in both periods.

### 3.2.4 Efficiency Scores

Table 3.2.6 present the average SFACD and SFATLG efficiency scores for each Australian DNSP in both the long and short period analyses. The average efficiency rankings are broadly consistent across the SFACD and SFATLG models in both periods and align closely with those from the standard ABR24 models.

**Table 3.2.6 Kumb90-JTT-HN-GTC: Average Efficiency Scores by Australian DNSP**

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *SFACD* | *Rank* | *SFATLG* | *Rank* | *SFACD* | *Rank* | *SFATLG* | *Rank* |
| EVO | 0.544 | 13 | 0.551 | 12 | 0.572 | 13 | 0.588 | 12 |
| AGD | 0.579 | 11 | 0.551 | 12 | 0.589 | 12 | 0.563 | 13 |
| CIT | 0.808 | 5 | 0.835 | 4 | 0.752 | 6 | 0.846 | 3 |
| END | 0.686 | 9 | 0.659 | 10 | 0.713 | 7 | 0.689 | 8 |
| ENX | 0.713 | 7 | 0.684 | 8 | 0.704 | 8 | 0.665 | 10 |
| ERG | 0.560 | 12 | 0.629 | 11 | 0.611 | 11 | 0.657 | 11 |
| ESS | 0.604 | 10 | 0.662 | 9 | 0.664 | 10 | 0.746 | 7 |
| JEN | 0.711 | 8 | 0.737 | 7 | 0.675 | 9 | 0.677 | 9 |
| PCR | 0.920 | 2 | 0.906 | 2 | 0.940 | 2 | 0.906 | 2 |
| SAP | 0.953 | 1 | 0.974 | 1 | 0.958 | 1 | 0.967 | 1 |
| AND | 0.779 | 6 | 0.766 | 6 | 0.782 | 5 | 0.754 | 6 |
| TND | 0.823 | 4 | 0.806 | 5 | 0.879 | 3 | 0.845 | 4 |
| UED | 0.876 | 3 | 0.875 | 3 | 0.865 | 4 | 0.840 | 5 |
| Australia | 0.735 | | 0.741 | | 0.747 | | 0.750 | |

Over the long period, the SFACD model reports an average efficiency score 3.7 per cent lower than its standard equivalent, while the SFATLG model comes in 6.9 per cent higher. In the short period, the SFACD model produces a nearly identical average to the standard version, only 0.1 per cent lower. The SFATLG model, however, has an average efficiency score 83.6 per cent above that of the standard short-period model, which did not converge.

In terms of how closely the average scores align, the correlation between the Kumb90-JTT-HN-GTC and standard models varies across specifications. For SFACD, the correlations are very strong (0.961 in the long period and 0.986 in the short) indicating close agreement. For SFATLG, the match is less convincing, with a correlation of 0.725 in the long period and just 0.304 in the short.

The efficiency rankings reflect similar patterns. For SFACD, the rank of DNSPs remains highly consistent with the standard models, with ranking correlations of 0.929 in the long period and 0.989 in the short. In contrast, the SFATLG rankings show weaker alignment: 0.590 in the long period and 0.368 in the short.

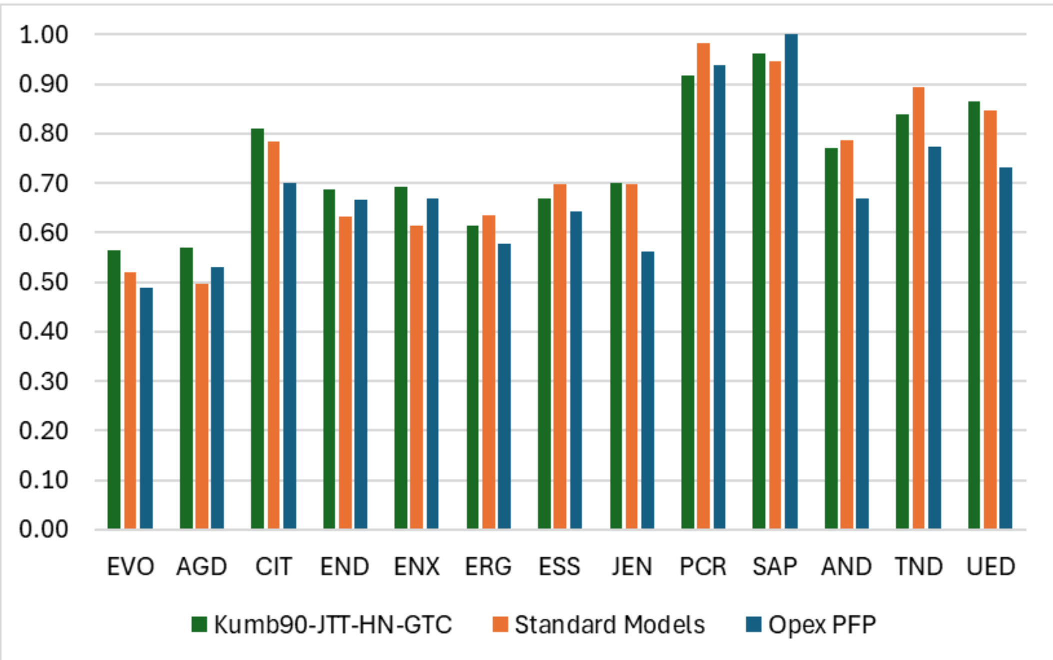
Figure 3.2.1 average efficiency scores across the standard LSECD, LSETLG, SFACD and SFATLG models, in the long period sample, and compares them to the average efficiency scores of the Kumb90-JTT-HN-GTC and the average opex partial factor productivity (OPFP) measures. The results are reasonably similar across all approaches.

The efficiency scores for Australian DNSPs from the long-period SFACD and SFATLG models show strong correlations with the OPFP measures, at 0.732 and 0.727, respectively. These correlations are higher than those observed in the standard SFACD models (0.686) and comparable to the standard SFATLG model (0.734).

Figure 3.2.2 illustrate the trends in efficiency scores over time for all models. Across all models and period, the efficiency scores display a smooth and consistent upward trajectory. Most DNSPs show gradual improvements year-on-year. A noticeable feature is the distinct pattern observed in the long period models, where efficiency scores remain relatively flat for most DNSPs until around 2015, after which there is a marked and consistent increase. In contrast, the short period models display a more gradual and steady increase in efficiency across the entire period.

Figure 3.2.3 shows the scatter of residuals plotted against fitted values of the dependent variable. Some vertical line patterns can be observed, particularly for the Australian DNSPs in the short period, which could indicate potential heteroskedasticity.

Figure 3.2.1 Average Efficiency Scores by DNSP (2006–2023)

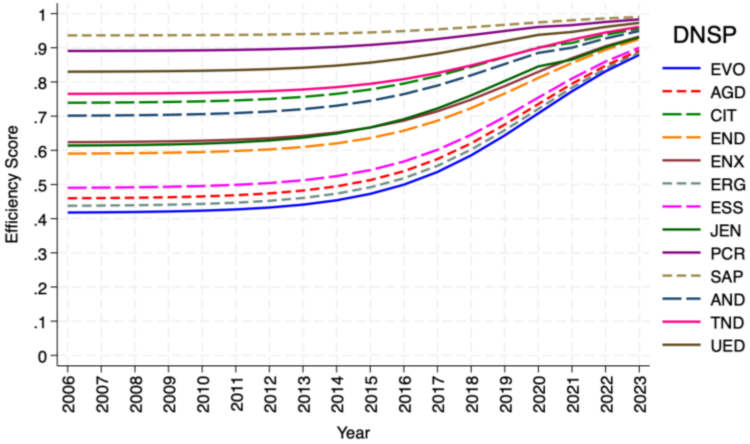


### 3.2.5 Concluding Comments

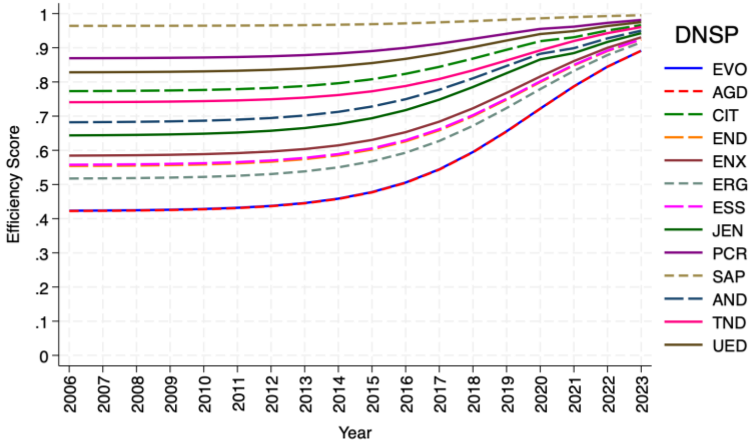
The Kumb90-JTT-HN-GTC models produced consistent output elasticities, indicating near-constant returns to scale, and generated meaningful efficiency scores. The efficiency scores showed a strong correlation with opex partial factor productivity index. The TLG form of these models performed better than the standard specifications in reducing monotonicity violations, and over the sample as a whole, there were fewer MVs than the Kumb90-JTT-HN models. There is no MVs in the long-period and 8.1 per cent in the short period. The corresponding Kumb90-JTT-HN models had MVs accounted for 5.3 per cent of all observations in the long-period and 11.6 per cent in the short period. The Kumb90-JTT-HN-GTC models had no MVs from Australian DNSPs in the long-period, but 8.3 per cent in the short-period, which is higher than for the Kumb90-JTT-HN model.

One shortcoming is the sign and significance of the undergrounding cables variable.

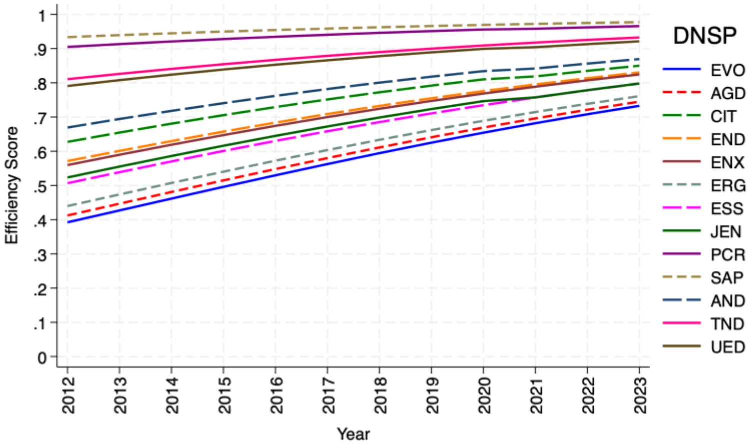
Figure 3.2.2 Kumb90-JTT-HN-GTC Efficiency Trends by DNSP



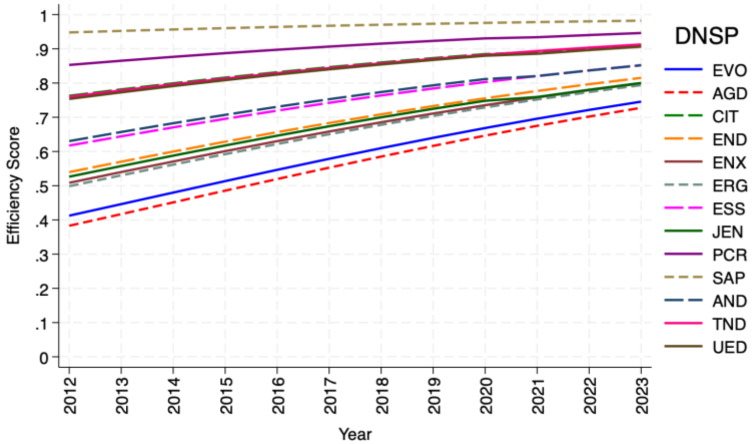

*SFACD Long Period*




*SFATLG Long Period*

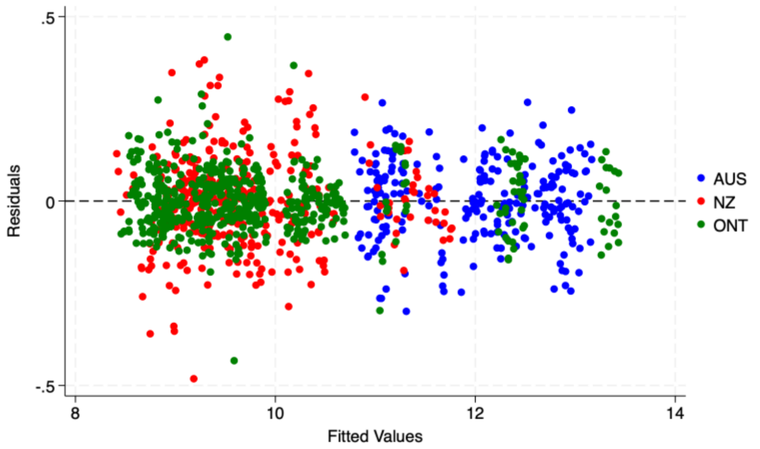



*SFACD Short Period*

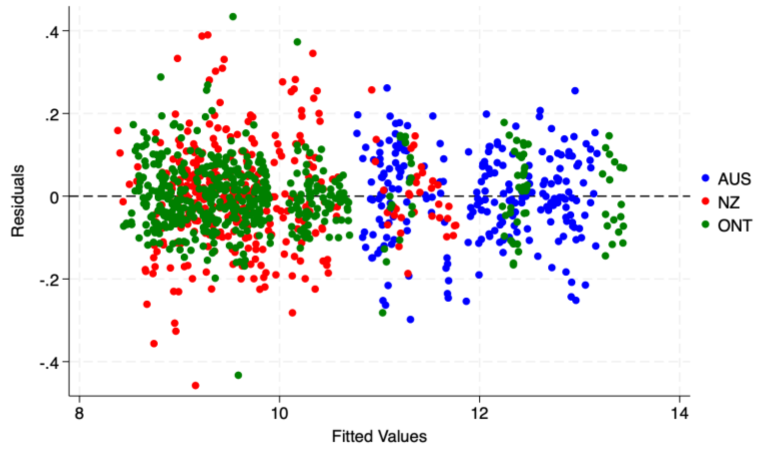



*SFATLG Short Period*

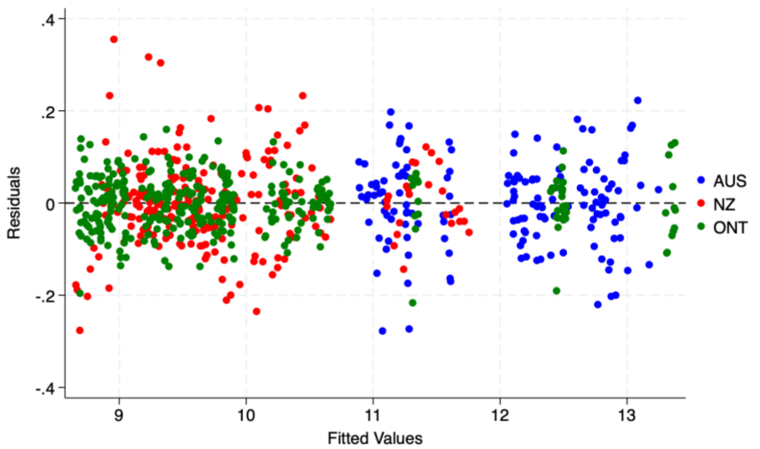
## Figure 3.2.3 Kumb90-JTT-HN-GTC: Residual plots



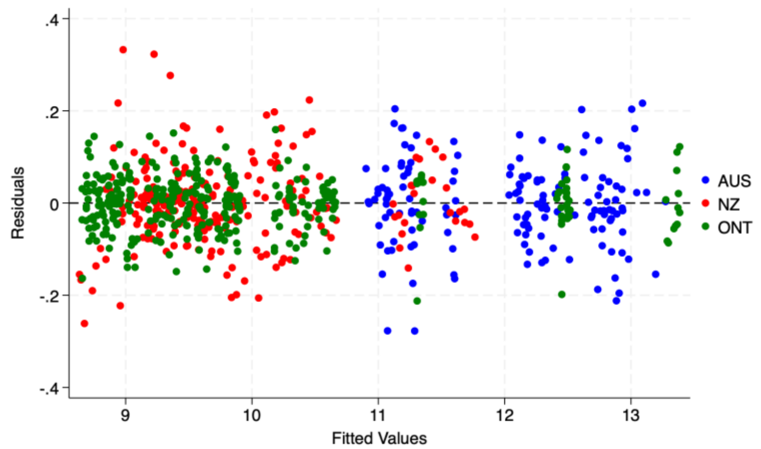

*SFACD Long Period*




*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

### 3.3 Kumb90-AJTT-HN: Australian DNSP Specific & Jurisdiction Time Trends as *z*-variables

In this specification, the Australian DNSP-specific time trends and the New Zealand and Ontario jurisdictional time trend variables are included as z variables.

#### 3.3.1 Estimation Results

The results of estimating the Cobb-Douglas and Translog with both the long and short samples are presented in Table 3.3.1 and 3.3.2.

#### 3.3.2 Consistency with economic theory or industry knowledge

Tables 3.3.1 and 3.3.2 show that, for both the SFACD and SFATLG models over the long- and short-period samples, the main log-output coefficients have the expected signs and are statistically significant. The log share of underground cables is negative and significant only in the SFACD long period. It is negative but not statistically significant in the SFACD short period and SFATLG long period but in the SFATLG short-period its coefficient is unexpectedly positive (although insignificant), raising doubts about that specification.

Table 3.3.3 presents the output elasticities for both the long- and short-period models. Across all four specifications, the sum of output elasticities is close to one, indicating near-constant returns to scale. Notably, the total elasticity in the SFATLG in the long period model slightly exceeds one. Customer numbers consistently receive the greatest weight, followed by RMD in the SFACD long-period model and CL in the other models.

Table 3.3.4 reports the monotonicity violations in the SFATLG model for both the long and short periods. In the long-period model, seven DNSPs exhibit monotonicity violations in more than 50 per cent of observations. Overall, 55.1 per cent of the Australian sample and 27.0 per cent of the total sample is affected. In contrast, in the short-period model, two DNSP shows excessive violations, with 15.4 per cent of the Australian sample and 20.1 per cent of the total sample affected. These results indicate that, Although the Kumb90–AJTT–HN models reduce monotonicity violations compared to the standard SFATLG specifications, they still exhibit a high number of violations, particularly in the long-period model

## Table 3.3.1 Kumb90-AJTT-HN: SFACD Parameter Estimates

| | *Long Period* | | | *Short Period*[1] | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.582 | 0.073 | 7.95 | 0.575 | 0.086 | 6.69 |
| ly2 | 0.154 | 0.033 | 4.63 | 0.211 | 0.037 | 5.74 |
| ly3 | 0.256 | 0.063 | 4.10 | 0.183 | 0.074 | 2.46 |
| lz1 | -0.066 | 0.031 | -2.16 | -0.034 | 0.037 | -0.92 |
| yr | 0.019 | 0.001 | 14.70 | 0.017 | 0.002 | 6.86 |
| jur2 | 0.206 | 0.065 | 3.15 | 0.096 | 0.076 | 1.25 |
| jur3 | 0.298 | 0.055 | 5.39 | 0.296 | 0.061 | 4.85 |
| _cons | -29.497 | 2.689 | -10.97 | -24.521 | 5.040 | -4.87 |
| **Bt** | | | | | | |
| t_dnsp1 | 0.355 | 0.043 | 8.32 | 0.293 | 0.042 | 6.91 |
| t_dnsp2 | 0.611 | 0.072 | 8.52 | 0.642 | 0.107 | 5.99 |
| t_dnsp3 | 0.475 | 0.116 | 4.09 | 0.411 | 0.112 | 3.68 |
| t_dnsp4 | 0.509 | 0.083 | 6.17 | 0.437 | 0.098 | 4.47 |
| t_dnsp5 | 0.395 | 0.074 | 5.32 | 0.301 | 0.066 | 4.57 |
| t_dnsp6 | 0.320 | 0.044 | 7.26 | 0.213 | 0.040 | 5.32 |
| t_dnsp7 | 0.392 | 0.060 | 6.57 | 0.301 | 0.052 | 5.84 |
| t_dnsp8 | 0.395 | 0.064 | 6.20 | 0.415 | 0.072 | 5.73 |
| t_dnsp9 | 0.698 | 0.305 | 2.29 | 0.926 | 0.580 | 1.60 |
| t_dnsp10 | -0.303 | 0.181 | -1.67 | 0.334 | 0.180 | 1.86 |
| t_dnsp11 | 0.327 | 0.074 | 4.44 | 0.317 | 0.079 | 4.00 |
| t_dnsp12 | 0.291 | 0.078 | 3.75 | 0.128 | 0.073 | 1.76 |
| t_dnsp13 | 1.009 | 0.265 | 3.81 | 2.780 | 1.572 | 1.77 |
| t_nz | -0.110 | 0.039 | -2.80 | -0.105 | 0.025 | -4.26 |
| t_ont | 0.384 | 0.040 | 9.54 | 0.268 | 0.045 | 6.02 |
| _cons | -2.346 | 0.207 | -11.32 | -0.854 | 0.160 | -5.33 |
| /sigmau_2 | 0.215 | 0.045 | 4.79 | 0.304 | 0.067 | 4.55 |
| /sigmav_2 | 0.010 | 0.000 | 22.61 | 0.006 | 0.000 | 18.09 |
| sigma_u | 0.463 | 0.048 | 9.58 | 0.551 | 0.061 | 9.09 |
| sigma_v | 0.101 | 0.002 | 45.22 | 0.077 | 0.002 | 36.18 |
| lambda | 4.573 | 0.048 | 94.70 | 7.134 | 0.061 | 117.78 |
| LLH | 825.95 | | | 703.07 | | |
| Iterations # | 172 | | | 224 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.997 | | |
| BIC | -1469.86 | | | -1234.65 | | |
| *N* | 1098 | | | 732 | | |

[1] The model could not compute an improvement during estimation as it encountered a flat region in the likelihood surface.

Table 3.3.2 Kumb90-AJTT-HN: SFATLG Parameter Estimates

| | Long Period | | | Short Period[1] | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.616 | 0.077 | 7.99 | 0.553 | 0.089 | 6.21 |
| ly2 | 0.221 | 0.033 | 6.76 | 0.241 | 0.045 | 5.37 |
| ly3 | 0.172 | 0.072 | 2.39 | 0.164 | 0.071 | 2.31 |
| ly11 | 1.000 | 0.466 | 2.15 | -0.127 | 0.683 | -0.19 |
| ly12 | -0.376 | 0.109 | -3.46 | 0.055 | 0.156 | 0.35 |
| ly13 | -0.539 | 0.374 | -1.44 | 0.077 | 0.532 | 0.14 |
| ly22 | 0.246 | 0.046 | 5.33 | 0.114 | 0.075 | 1.52 |
| ly23 | 0.163 | 0.084 | 1.93 | -0.175 | 0.101 | -1.72 |
| ly33 | 0.275 | 0.313 | 0.88 | 0.111 | 0.434 | 0.26 |
| lz1 | -0.012 | 0.032 | -0.38 | 0.016 | 0.056 | 0.28 |
| yr | 0.018 | 0.001 | 13.99 | 0.015 | 0.005 | 3.24 |
| jur2 | 0.176 | 0.063 | 2.81 | -0.002 | 0.097 | -0.02 |
| jur3 | 0.417 | 0.080 | 5.18 | 0.254 | 0.075 | 3.38 |
| _cons | -27.384 | 2.640 | -10.37 | -20.341 | 9.390 | -2.17 |
| ***Bt*** | | | | | | |
| t_dnsp1 | 0.336 | 0.041 | 8.23 | 0.303 | 0.053 | 5.69 |
| t_dnsp2 | 0.626 | 0.076 | 8.21 | 0.712 | 0.155 | 4.61 |
| t_dnsp3 | 0.397 | 0.087 | 4.58 | 0.629 | 0.329 | 1.91 |
| t_dnsp4 | 0.488 | 0.068 | 7.22 | 0.481 | 0.125 | 3.85 |
| t_dnsp5 | 0.441 | 0.081 | 5.46 | 0.317 | 0.080 | 3.95 |
| t_dnsp6 | 0.496 | 0.078 | 6.38 | 0.244 | 0.054 | 4.54 |
| t_dnsp7 | 2.365 | 0.802 | 2.95 | 0.418 | 0.104 | 4.04 |
| t_dnsp8 | 0.458 | 0.067 | 6.87 | 0.392 | 0.081 | 4.86 |
| t_dnsp9 | 1.187 | 0.678 | 1.75 | 1.139 | 0.557 | 2.04 |
| t_dnsp10 | -0.669 | 0.336 | -1.99 | 0.876 | 0.659 | 1.33 |
| t_dnsp11 | 0.418 | 0.084 | 4.95 | 0.348 | 0.099 | 3.50 |
| t_dnsp12 | 0.271 | 0.068 | 3.97 | 0.115 | 0.087 | 1.33 |
| t_dnsp13 | 0.989 | 0.212 | 4.68 | 2.652 | 1.514 | 1.75 |
| t_nz | -0.090 | 0.038 | -2.37 | -0.140 | 0.036 | -3.92 |
| t_ont | 0.383 | 0.045 | 8.56 | 0.263 | 0.072 | 3.65 |
| _cons | -2.570 | 0.219 | -11.74 | -0.836 | 0.178 | -4.70 |
| /sigmau_2 | 0.250 | 0.060 | 4.18 | 0.244 | 0.055 | 4.44 |
| /sigmav_2 | 0.010 | 0.000 | 22.29 | 0.006 | 0.000 | 17.88 |
| sigma_u | 0.500 | 0.060 | 8.37 | 0.494 | 0.056 | 8.88 |
| sigma_v | 0.099 | 0.002 | 44.58 | 0.077 | 0.002 | 35.76 |
| lambda | 5.030 | 0.060 | 84.51 | 6.412 | 0.056 | 115.52 |
| LLH | 840.18 | | | 712.52 | | |
| Iterations # | 220 | | | 341 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.997 | | |
| BIC | -1456.32 | | | -1213.97 | | |
| *N* | 1098 | | | 732 | | |

[1] The model could not compute an improvement during estimation as it encountered a flat region in the likelihood surface.

### Table 3.3.3 Kumb90-AJTT-HN: Output elasticities

| | Long Period | | | | Short Period | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *SFACD* | | | | | | | | |
| Full Sample | 0.582 | 0.154 | 0.256 | 0.992 | 0.575 | 0.211 | 0.183 | 0.969 |
| *SFATLG* | | | | | | | | |
| Australia | 0.764 | 0.31 | -0.012 | 1.062 | 0.563 | 0.273 | 0.144 | 0.979 |
| New Zealand | 0.395 | 0.357 | 0.297 | 1.049 | 0.577 | 0.376 | -0.010 | 0.943 |
| Ontario | 0.695 | 0.092 | 0.172 | 0.959 | 0.533 | 0.138 | 0.288 | 0.959 |
| Full sample | 0.616 | 0.221 | 0.172 | 1.009 | 0.553 | 0.241 | 0.164 | 0.958 |

### Table 3.1.4 Kumb90-AJTT-HN: Monotonicity violations in SFATLG models (%)

| | Long Period | | | | Short Period | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *By DNSP* | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| CIT | 0.0 | 50.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| END | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ENX | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ERG | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| ESS | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| JEN | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| PCR | 0.0 | 0.0 | 16.7 | 16.7 | 0.0 | 0.0 | 0.0 | 0.0 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AND | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| *By jurisdiction* | | | | | | | | |
| Australia | 0.0 | 3.8 | 55.1 | 55.1 | 0.0 | 0.0 | 15.4 | 15.4 |
| New Zealand | 8.5 | 0.0 | 5.3 | 13.7 | 0.0 | 0.0 | 53.9 | 53.9 |
| Ontario | 0.0 | 13.2 | 9.8 | 23.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Full sample | 2.6 | 7.1 | 18.0 | 27.0 | 0.0 | 0.0 | 20.1 | 20.1 |

### 3.3.3 Convergence & Specification Tests

Both the SFACD and SFATLG models were estimated for the long and short periods, with convergence achieved between 172 and 341 iterations. However, the short-period models presented the message "*cannot compute an improvement – flat region encountered*", indicating convergence issues.

Tables 3.3.1 and 3.3.2 report the BIC, pseudo-adjusted R2, and the number of iterations for each model. Additional diagnostic statistics are presented in Table 3.3.5. Residual diagnostics indicate that severe outliers are rare (fewer than 0.5%) across both models. However, the Shapiro–Wilk test rejects the normality of residuals. Multicollinearity is moderate in the SFACD model but very high in the SFATLG model, due to the inclusion of interaction and squared terms. The link test suggests potential misspecification in all models, except for the SFATLG in the long period, and the functional form tests support the SFATLG specification, with higher-order terms statistically significant in both periods.

Table 3.3.5 Kumb90-AJTT-HN: Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value** | *Stat.* | *p-value** |
| ***SFACD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers)(1) | 0.27 | | 0.41 | |
| Shapiro–Wilk W test(2) | 0.976 | 0.000 | 0.977 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF(3) | 24.98 | | 25.89 | |
| Condition number(3) | 1084.23 | | 1619.52 | |
| *Specification* | | | | |
| Link test(4) | 2.78 | 0.006 | -7.32 | 0.000 |
| ***SFATLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.36 | | 0.41 | |
| Shapiro–Wilk W test | 0.981 | 0.000 | 0.983 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 714.08 | | 717.50 | |
| Condition number | 1641.03 | | 2427.54 | |
| Specification | | | | |
| Link test | 1.26 | 0.208 | -6.94 | 0.000 |
| Joint parameter tests | | | | |
| Higher-order output terms | 33.58 | 0.000 | 39.09 | 0.000 |

Note: * Null hypothesis is rejected in these tests, if the p-value is less than 0.05. Equivalently, the reported statistic exceeds the critical value for that statistic; (1) Severe outliers comprise about .0002% of the normal population; (2) The null hypothesis is that residuals are normally distributed; (3) Collinearity is potentially a problem if VIF>10 or the Condition number > 30; (4) Absolute value of t-statistic on hatsq. The null hypothesis is that the model is correctly specified.

### 3.3.4 Efficiency Scores

Table 3.3.6 present the average SFACD and SFATLG efficiency scores for each Australian DNSP in both the long and short period analyses. The average efficiency rankings are broadly consistent across the SFACD and SFATLG models in both periods and align closely with those from the standard ABR24 models. For the long period, the SFACD model shows an average efficiency score that is 11.9 per cent lower than its standard counterpart, while the SFATLG model is only 0.2 per cent lower. For the short period, the SFACD is 7.6 per cent lower and the SFATLG model shows has average score 78.0 per cent higher than the standard short-period model, which did not converge.

Table 3.3.6 Kumb90-AJTT-HN: Average Efficiency Scores by Australian DNSP

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *SFACD* | *Rank* | *SFATLG* | *Rank* | *SFACD* | *Rank* | *SFATLG* | *Rank* |
| EVO | 0.469 | 12 | 0.407 | 13 | 0.501 | 13 | 0.521 | 13 |
| AGD | 0.577 | 10 | 0.545 | 12 | 0.618 | 10 | 0.646 | 11 |
| CIT | 0.778 | 4 | 0.693 | 6 | 0.744 | 5 | 0.819 | 4 |
| END | 0.640 | 9 | 0.575 | 11 | 0.670 | 7 | 0.695 | 7 |
| ENX | 0.656 | 8 | 0.633 | 10 | 0.659 | 9 | 0.682 | 9 |
| ERG | 0.458 | 13 | 0.646 | 9 | 0.504 | 12 | 0.558 | 12 |
| ESS | 0.521 | 11 | 0.783 | 4 | 0.576 | 11 | 0.687 | 8 |
| JEN | 0.676 | 7 | 0.651 | 8 | 0.664 | 8 | 0.659 | 10 |
| PCR | 0.855 | 2 | 0.901 | 2 | 0.875 | 2 | 0.902 | 1 |
| SAP | 0.829 | 3 | 0.936 | 1 | 0.823 | 3 | 0.899 | 2 |
| AND | 0.706 | 6 | 0.728 | 5 | 0.714 | 6 | 0.740 | 6 |
| TND | 0.716 | 5 | 0.657 | 7 | 0.754 | 4 | 0.758 | 5 |
| UED | 0.867 | 1 | 0.838 | 3 | 0.884 | 1 | 0.882 | 3 |
| Australia | 0.673 | | 0.692 | | 0.691 | | 0.727 | |

When it comes to the alignment of average efficiency scores, the correlation between the Kumb90-AJTT-HN model and the standard models varies notably by specification. For SFACD, the correlations are strong (0.967 in the long period and 0.909 in the short) indicating solid agreement. For SFATLG, however, the relationship is much weaker (0.674 in the long period, and a near-zero (and negative) correlation of -0.043 in the short period) highlighting poor alignment. Efficiency rankings follow a similar trend. The SFACD model continues to show strong consistency, with ranking correlations of 0.984 in the long period and 0.923 in the short. The SFATLG model shows limited agreement with the standard rankings, with correlations of 0.703 in the long period and just 0.154 in the short period. This suggests that while the SFACD specification under this model retains alignment with established results, the SFATLG version, particularly in the short period, diverges considerably.

Figure 3.3.1 average efficiency scores across the standard LSECD, LSETLG, SFACD and SFATLG models, in the long period sample, and compares them to the average efficiency scores of the Kumb90-AJTT-HN and the average opex partial factor productivity (OPFP) measures. The results are reasonably similar across all approaches. The efficiency scores for Australian DNSPs from the long-period SFACD and SFATLG models show strong correlations with the OPFP measures, at 0.688 and 0.733, respectively. These correlations are comparable to those observed in the standard SFACD (0.686) and SFATLG model (0.734).

Figure 3.3.1 Average Efficiency Scores by DNSP (2006–2023)

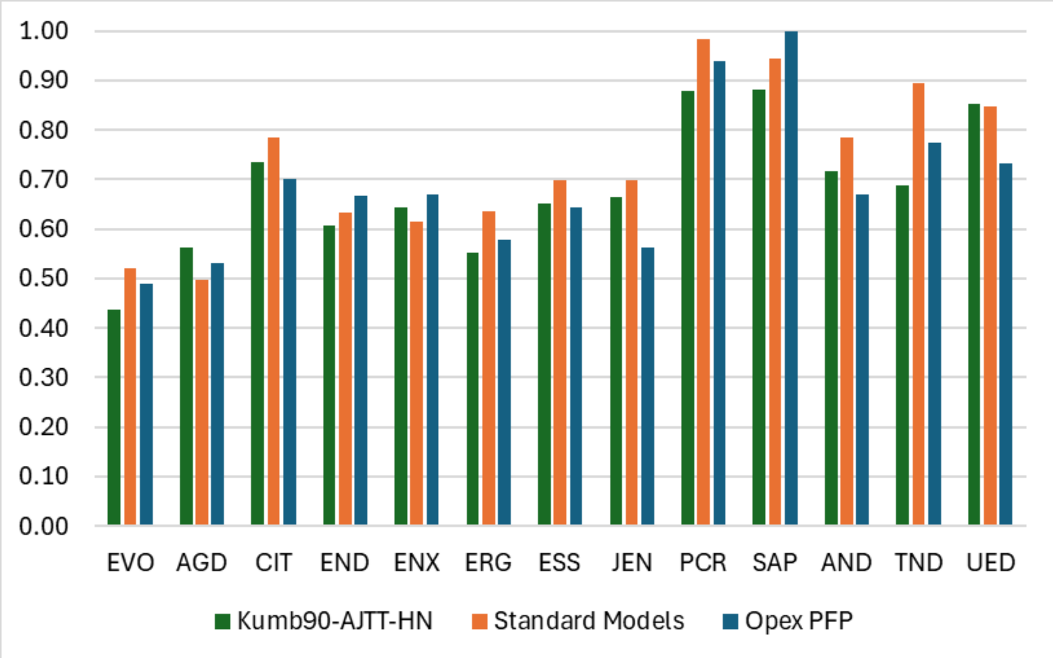
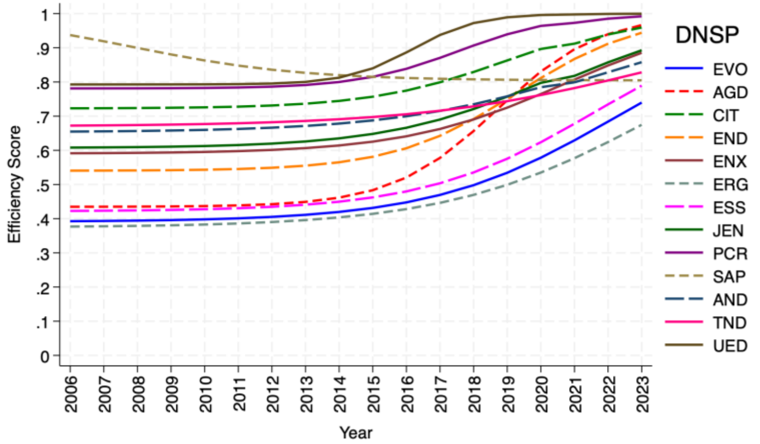



Figure 3.3.2 illustrates the trends in efficiency scores over time for all models. Overall, the figure highlights that under the Kumb90-AJTT-HN specification, efficiency scores tend to increase steadily over time for most DNSPs, particularly from 2015 onwards. While the general trend is constant, some sharper movements can be observed—especially in the SFACD short-period panel, where a few DNSPs exhibit more abrupt changes in efficiency year-to-year. Notably, SAP appears to diverge from the broader trend in the long-period figures, showing a gradual decline in efficiency over the period. Figure 3.3.3 shows scatter charts of residuals plotted against fitted values of the dependent variable.

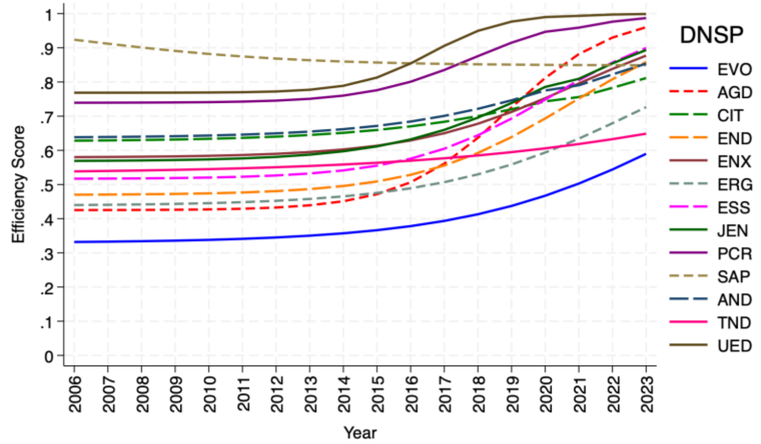
### 3.3.5 Concluding Comments

The Kumb90-AJTT-HN models produced consistent output elasticities, indicating near-constant returns to scale, and generated meaningful efficiency scores. However, this model produced excessive monotonicity violations.

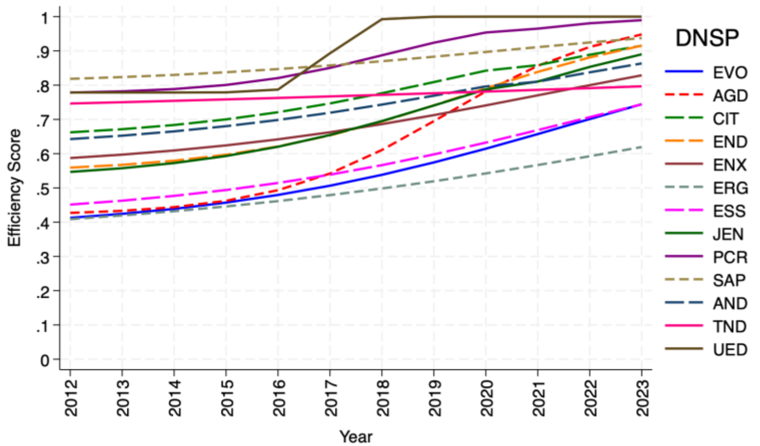
Figure 3.3.2 Kumb90-AJTT-HN Efficiency Trends by DNSP



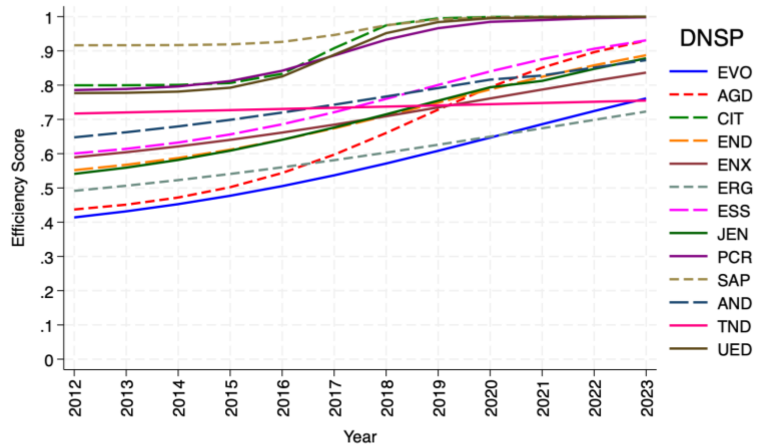

*SFACD Long Period*




*SFATLG Long Period*

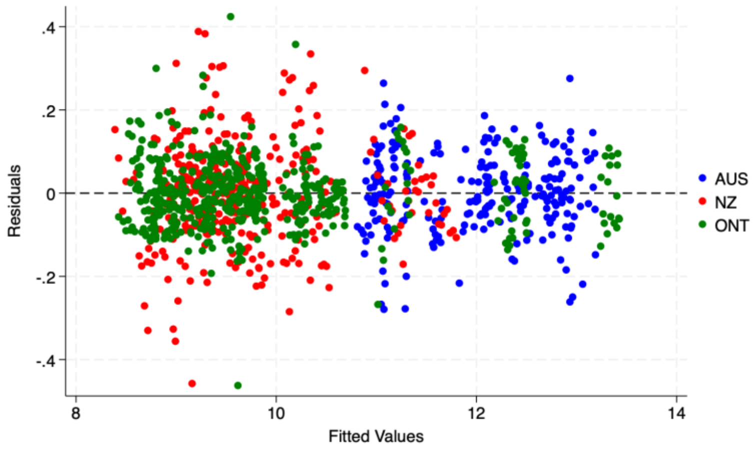



*SFACD Short Period*

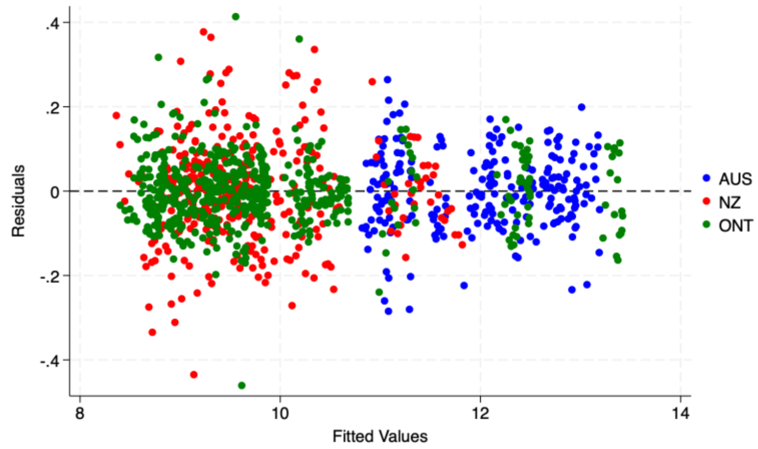



*SFATLG Short Period*

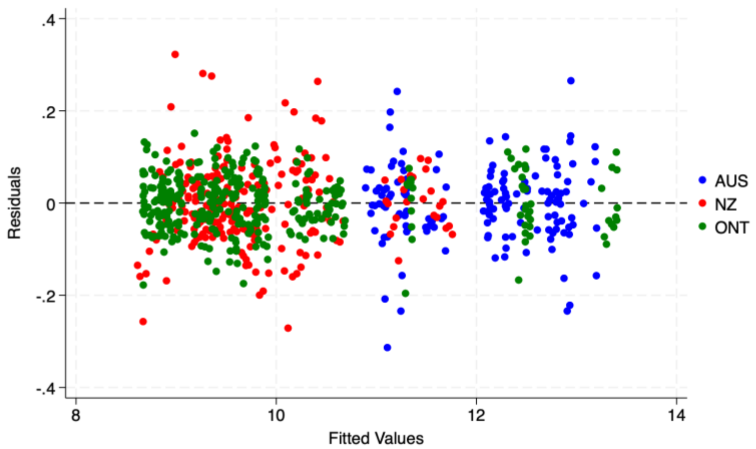
Figure 3.3.3 Kumb90-AJTT-HN: Residual plots



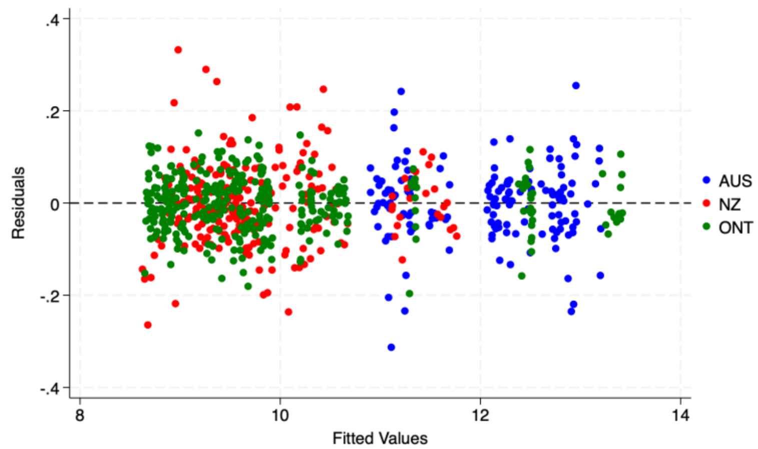

*SFACD Long Period*




*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

## 3.4 Kumb90-AJTT-HN-GTC: Australian DNSP Specific & Jurisdiction Time Trends as *z*-variables & General Technical Change

In this specification, the Australian DNSP-specific time trends and the New Zealand and Ontario jurisdictional time trend variables are included as z variables. Furthermore, instead of using the 'yr' variable, GTC dummy variables are included.

### 3.4.1 Estimation Results

The results of estimating the Cobb-Douglas and Translog with both the long and short samples are presented in Table 3.4.1 and 3.4.2. The SFATLG in the short period has computational issues and it is not detailed here.

### 3.4.2 Consistency with economic theory or industry knowledge

As shown Tables 3.4.1 and 3.4.2, in the long-period SFACD and SFATLG models, the output variables have the expected signs and are statistically significant. The undergrounding variable is negative but not statistically significant in the SFACD long period model, but it is positive although not statistically significant in the SFATLG long period and SFACD short period, suggesting a possible issue with this specification.

For the short-period models, the SFATLG specification encountered computational issues during estimation. After 59 iterations, the algorithm was unable to compute further improvements due to a flat region in the likelihood surface. As a result, standard errors were not produced, and the significance of the coefficients cannot be interpreted. In the SFACD short period specification, all output coefficients are positive, though RMD is not statistically significant. The undergrounding variable is positive and not significant.

Table 3.4.3 shows the output elasticities for all specifications. Across all models, the sum of elasticities is close to one, suggesting near-constant returns to scale. Overall, considering the total sample, customer numbers have the highest weight. The exception is the problematic SFATLG short period model, where RMD has the highest weight.

Table 3.4.4 reports the monotonicity violations (MVs) in the SFATLG model for both the long and short periods. Overall, 54.7 per cent of the Australian sample and 29.8 per cent of the total sample are affected by MVs in the SFATLG long period. In the short-period model, the SFATLG specification shows MVs in 50 per cent or more of observations for all Australian DNSPs.

Table 3.4.1 Kumb90-AJTT-HN-GTC: SFACD Parameter Estimates

| | Long Period | | | Short Period | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.584 | 0.078 | 7.47 | 0.506 | 0.085 | 5.95 |
| ly2 | 0.166 | 0.033 | 4.95 | 0.295 | 0.029 | 10.16 |
| ly3 | 0.242 | 0.067 | 3.61 | 0.139 | 0.083 | 1.68 |
| lz1 | -0.031 | 0.032 | -0.97 | 0.060 | 0.038 | 1.58 |
| gtc2 | 0.038 | 0.011 | 3.29 | | | |
| gtc3 | 0.104 | 0.013 | 7.97 | | | |
| gtc4 | 0.153 | 0.015 | 9.93 | 0.038 | 0.011 | 3.54 |
| gtc5 | 0.214 | 0.018 | 12.13 | 0.064 | 0.017 | 3.88 |
| gtc6 | 0.247 | 0.021 | 12.02 | 0.045 | 0.023 | 1.94 |
| jur2 | 0.146 | 0.064 | 2.29 | -0.226 | 0.091 | -2.48 |
| jur3 | 0.261 | 0.057 | 4.59 | 0.178 | 0.065 | 2.75 |
| _cons | 9.605 | 0.083 | 115.60 | 10.031 | 0.089 | 113.15 |
| **Bt** | | | | | | |
| t_dnsp1 | 0.344 | 0.050 | 6.91 | 0.417 | 0.132 | 3.17 |
| t_dnsp2 | 0.611 | 0.081 | 7.57 | 0.258 | 0.123 | 2.10 |
| t_dnsp3 | 0.485 | 0.142 | 3.41 | 0.329 | 0.129 | 2.56 |
| t_dnsp4 | 0.522 | 0.098 | 5.35 | 0.197 | 0.067 | 2.92 |
| t_dnsp5 | 0.392 | 0.088 | 4.44 | 0.119 | 0.032 | 3.78 |
| t_dnsp6 | 0.294 | 0.047 | 6.21 | 0.217 | 0.045 | 4.88 |
| t_dnsp7 | 0.362 | 0.060 | 6.05 | 0.269 | 0.077 | 3.48 |
| t_dnsp8 | 0.383 | 0.072 | 5.34 | 0.952 | 0.658 | 1.45 |
| t_dnsp9 | 0.670 | 0.299 | 2.24 | 0.874 | 1.032 | 0.85 |
| t_dnsp10 | -0.389 | 0.202 | -1.93 | 0.195 | 0.077 | 2.54 |
| t_dnsp11 | 0.309 | 0.081 | 3.82 | 0.020 | 0.074 | 0.27 |
| t_dnsp12 | 0.257 | 0.083 | 3.10 | 2.573 | 1.920 | 1.34 |
| t_dnsp13 | 1.016 | 0.290 | 3.51 | -0.100 | 0.018 | -5.63 |
| t_nz | -0.132 | 0.038 | -3.51 | 0.079 | 0.025 | 3.15 |
| t_ont | 0.339 | 0.049 | 6.90 | -0.028 | 0.318 | -0.09 |
| _cons | -2.221 | 0.262 | -8.47 | 0.547 | 0.205 | 2.67 |
| /sigmau_2 | 0.213 | 0.045 | 4.73 | 0.006 | 0.000 | 17.97 |
| /sigmav_2 | 0.011 | 0.000 | 22.58 | 0.740 | 0.138 | 5.34 |
| sigma_u | 0.461 | 0.049 | 9.45 | 0.078 | 0.002 | 35.95 |
| sigma_v | 0.103 | 0.002 | 45.16 | 9.469 | 0.138 | 68.46 |
| lambda | 4.479 | 0.049 | 91.99 | 0.417 | 0.132 | 3.17 |
| LLH | 809.89 | | | 695.56 | | |
| Iterations # | 80 | | | 144 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.997 | | |
| BIC | -1409.73 | | | -1206.43 | | |
| N | 1098 | | | 732 | | |

Table 3.4.2 Kumb90-AJTT-HN-GTC: SFATLG Parameter Estimates

| | Long Period | | | Short Period[1] | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.608 | 0.076 | 7.99 | 0.341 | . | . |
| ly2 | 0.230 | 0.033 | 6.97 | 0.168 | . | . |
| ly3 | 0.165 | 0.073 | 2.25 | 0.482 | . | . |
| ly11 | 0.962 | 0.481 | 2.00 | -0.065 | . | . |
| ly12 | -0.395 | 0.109 | -3.62 | 0.053 | . | . |
| ly13 | -0.462 | 0.388 | -1.19 | -0.503 | . | . |
| ly22 | 0.257 | 0.046 | 5.62 | -0.154 | . | . |
| ly23 | 0.173 | 0.086 | 2.01 | 0.055 | . | . |
| ly33 | 0.180 | 0.325 | 0.55 | 0.945 | . | . |
| lz1 | 0.024 | 0.032 | 0.75 | -0.160 | 0.000 | -3685725 |
| gtc2 | 0.038 | 0.011 | 3.36 | | | |
| gtc3 | 0.102 | 0.013 | 8.06 | | | |
| gtc4 | 0.150 | 0.015 | 9.93 | 0.221 | . | . |
| gtc5 | 0.206 | 0.018 | 11.72 | 0.258 | . | . |
| gtc6 | 0.232 | 0.021 | 10.98 | 0.201 | . | . |
| jur2 | 0.152 | 0.057 | 2.68 | -0.721 | 0.206 | -3.50 |
| jur3 | 0.400 | 0.078 | 5.15 | -0.146 | 0.008 | -19.11 |
| _cons | 9.487 | 0.079 | 119.45 | 10.104 | . | . |
| ***Bt*** | | | | | | |
| t_dnsp1 | 0.305 | 0.046 | 6.59 | -0.280 | . | . |
| t_dnsp2 | 0.624 | 0.086 | 7.23 | 0.103 | 0.627 | 0.16 |
| t_dnsp3 | 0.366 | 0.098 | 3.75 | 0.031 | 0.037 | 0.82 |
| t_dnsp4 | 0.480 | 0.077 | 6.24 | 0.055 | . | . |
| t_dnsp5 | 0.449 | 0.103 | 4.37 | -0.020 | 0.372 | -0.05 |
| t_dnsp6 | 0.458 | 0.083 | 5.49 | -0.320 | . | . |
| t_dnsp7 | 2.377 | 0.909 | 2.61 | -0.321 | . | . |
| t_dnsp8 | 0.425 | 0.072 | 5.89 | -0.086 | . | . |
| t_dnsp9 | 1.151 | 0.650 | 1.77 | -0.327 | . | . |
| t_dnsp10 | 24.896 | 351.596 | 0.07 | -0.047 | 1.482 | -0.03 |
| t_dnsp11 | 0.385 | 0.090 | 4.28 | -0.267 | . | . |
| t_dnsp12 | 0.221 | 0.071 | 3.11 | 0.012 | 0.000 | 5953 |
| t_dnsp13 | 0.979 | 0.229 | 4.27 | 0.031 | . | . |
| t_nz | -0.104 | 0.033 | -3.11 | -0.076 | 0.036 | -2.11 |
| t_ont | 0.335 | 0.048 | 7.02 | 0.202 | . | . |
| _cons | -2.335 | 0.260 | -8.99 | -0.403 | . | . |
| /sigmau_2 | 0.235 | 0.054 | 4.39 | 1.013 | . | . |
| /sigmav_2 | 0.010 | 0.000 | 22.45 | 0.032 | 0.000 | 1500323 |
| sigma_u | 0.485 | 0.055 | 8.79 | 1.006 | . | . |
| sigma_v | 0.101 | 0.002 | 44.90 | 0.178 | 0.000 | 3000000 |
| lambda | 4.790 | 0.055 | 87.09 | 5.664 | . | . |
| LLH | 823.88 | | | 137.18 | | |
| Iterations # | 342 | | | 59 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.985 | | |
| BIC | -1395.72 | | | -221.59 | | |
| *N* | 1098 | | | 732 | | |

[1] The model could not compute an improvement during estimation as it encountered a flat region in the likelihood surface.

Table 3.4.3 Kumb90-AJTT-HN-GTC: Output elasticities

| | Long Period | | | | Short Period | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *SFACD* | | | | | | | | |
| Full Sample | 0.584 | 0.166 | 0.242 | 0.992 | 0.506 | 0.295 | 0.139 | 0.940 |
| *SFATLG* | | | | | | | | |
| Australia | 0.778 | 0.323 | -0.022 | 1.080 | -0.534 | 0.048 | 1.293 | 0.807 |
| New Zealand | 0.340 | 0.372 | 0.327 | 1.038 | 0.818 | 0.060 | 0.002 | 0.880 |
| Ontario | 0.707 | 0.095 | 0.143 | 0.944 | 0.421 | 0.293 | 0.433 | 1.147 |
| Full sample | 0.608 | 0.230 | 0.165 | 1.002 | 0.341 | 0.168 | 0.482 | 0.991 |

Table 3.4.4 Kumb90-AJTT-HN-GTC: Monotonicity violations in SFATLG models (%)

| | Long Period | | | | Short Period | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *By DNSP* | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 50.0 | 0.0 | 0.0 | 50.0 |
| AGD | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| CIT | 0.0 | 61.1 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| END | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| ENX | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| ERG | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 100.0 |
| ESS | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 100.0 |
| JEN | 0.0 | 5.6 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| PCR | 0.0 | 0.0 | 11.1 | 11.1 | 100.0 | 100.0 | 0.0 | 100.0 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 100.0 |
| AND | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| UED | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| *By jurisdiction* | | | | | | | | |
| Australia | 0.0 | 5.1 | 54.7 | 54.7 | 96.2 | 38.5 | 0.0 | 96.2 |
| New Zealand | 14.6 | 0.0 | 5.3 | 19.9 | 10.5 | 19.7 | 52.2 | 68.0 |
| Ontario | 0.0 | 13.8 | 11.3 | 25.1 | 13.8 | 3.4 | 26.1 | 39.9 |
| Full sample | 4.6 | 7.7 | 18.7 | 29.8 | 30.3 | 16.0 | 28.7 | 60.7 |

### 3.4.3 Convergence & Specification Tests

The models converged between 59 to 342 iterations. The SFATLG short-period model completed 59 iterations but terminated with the message "*cannot compute an improvement – flat region encountered*", indicating convergence issues and failing to produce robust results, as shown in Table 3.4.2.

Tables 3.4.1 and 3.4.2 report the BIC, pseudo-adjusted $R^2$, and the number of iterations for each model. Additional diagnostic statistics are presented in Table 3.4.5. The Shapiro–Wilk test rejects the normality of residuals. Multicollinearity is moderate in the SFACD model but very high in the SFATLG model, due to the inclusion of interaction and squared terms.

The link test suggests potential misspecification in all models, except the SFATLG long period, and the functional form tests support the SFATLG long period specification.

Table 3.4.5 Kumb90-AJTT-HN-GTC: Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value** | *Stat.* | *p-value** |
| ***SFACD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers)(1) | 0.45 | | 0.55 | |
| Shapiro–Wilk W test(2) | 0.977 | 0.000 | 0.975 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF(3) | 24.98 | | 25.89 | |
| Condition number(3) | 1084.23 | | 1619.52 | |
| *Specification* | | | | |
| Link test(4) | 3.01 | 0.003 | -6.55 | 0.000 |
| ***SFATLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.36 | | 1.36 | |
| Shapiro–Wilk W test | 0.979 | 0.000 | 0.938 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 714.08 | | 717.50 | |
| Condition number | 1641.03 | | 2427.54 | |
| Specification | | | | |
| Link test | 1.35 | 0.176 | 4.11 | 0.000 |
| Joint parameter tests | | | | |
| Higher-order output terms | 38.39 | 0.000 | . | . |

Note: * Null hypothesis is rejected in these tests, if the p-value is less than 0.05. Equivalently, the reported statistic exceeds the critical value for that statistic; (1) Severe outliers comprise about .0002% of the normal population; (2) The null hypothesis is that residuals are normally distributed; (3) Collinearity is potentially a problem if VIF>10 or the Condition number > 30; (4) Absolute value of t-statistic on hatsq. The null hypothesis is that the model is correctly specified.

### 3.4.4 Efficiency Scores

Table 3.4.6 presents the average efficiency scores from the SFACD and SFATLG models for each Australian DNSP in both the long and short periods. The average efficiency rankings are broadly consistent between the models (except for the SFATLG model in the short period) and closely align with those from the standard ABR24 models.

Over the long period, the SFACD model shows an average efficiency score that is 9.8 per cent lower than its standard counterpart, while the SFATLG model is 2.3 per cent higher. For the short period, the SFACD model is 0.4 per cent higher than the standard model. In contrast, the SFATLG model shows a substantial difference, with an average score 124.1 per cent higher than the standard short-period model, which did not converge.

When it comes to the alignment of average efficiency scores, the correlation between the Kumb90-AJTT-HN-GTC model and the standard models varies notably by specification. For

SFACD, the correlations are strong (0.955 in the long period and 0.935 in the short) indicating solid agreement. For SFATLG, however, the relationship is much weaker (0.621 in the long period, and -0.317 in the short period).

Efficiency rankings follow a similar trend. The SFACD models continues to show strong consistency, with ranking correlations of 0.973 in the long period and 0.956 in the short. The SFATLG model, on the other hand, shows limited agreement with the standard rankings, with correlations of 0.538 in the long period and at -0.038 in the short period. This suggests that while the SFACD specification under this model retains alignment with established results, the SFATLG version, particularly in the short period, diverges considerably.

Table 3.4.6 Kumb90-AJTT-HN-GTC: Average Efficiency Scores by Australian DNSP

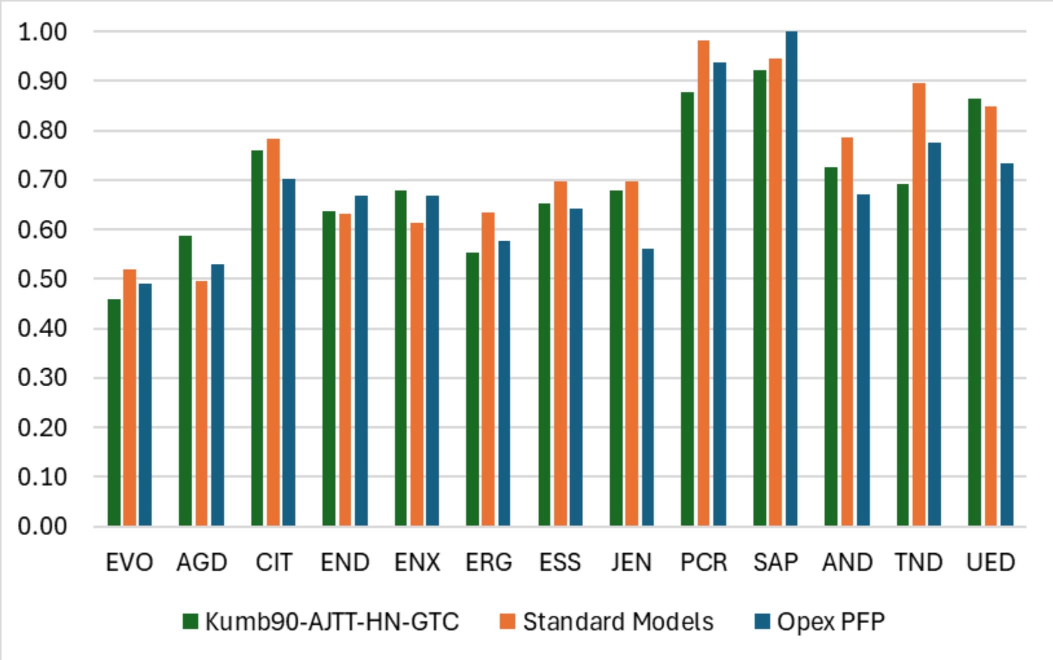
| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *SFACD* | *Rank* | *SFATLG* | *Rank* | *SFACD* | *Rank* | *SFATLG* | *Rank* |
| EVO | 0.496 | 12 | 0.424 | 13 | 0.591 | 12 | 0.939 | 8 |
| AGD | 0.599 | 10 | 0.576 | 12 | 0.650 | 10 | 0.837 | 11 |
| CIT | 0.805 | 4 | 0.714 | 6 | 0.796 | 5 | 0.992 | 2 |
| END | 0.668 | 9 | 0.603 | 11 | 0.744 | 7 | 0.985 | 4 |
| ENX | 0.685 | 8 | 0.673 | 7 | 0.724 | 8 | 0.888 | 9 |
| ERG | 0.456 | 13 | 0.653 | 10 | 0.547 | 13 | 0.835 | 12 |
| ESS | 0.517 | 11 | 0.789 | 4 | 0.621 | 11 | 0.686 | 13 |
| JEN | 0.693 | 7 | 0.662 | 8 | 0.709 | 9 | 0.961 | 7 |
| PCR | 0.854 | 3 | 0.902 | 2 | 0.919 | 2 | 0.981 | 5 |
| SAP | 0.861 | 2 | 0.981 | 1 | 0.951 | 1 | 0.971 | 6 |
| AND | 0.717 | 6 | 0.735 | 5 | 0.775 | 6 | 0.840 | 10 |
| TND | 0.724 | 5 | 0.657 | 9 | 0.832 | 4 | 0.993 | 1 |
| UED | 0.879 | 1 | 0.850 | 3 | 0.908 | 3 | 0.990 | 3 |
| Australia | 0.689 | | 0.709 | | 0.751 | | 0.915 | |

Figure 3.4.1 shows the average efficiency scores from the standard LSECD, LSETLG, SFACD, and SFATLG models for the long-period sample, and compares them with the average scores from the Kumb90-AJTT-HN-GTC model and the opex partial factor productivity (OPFP) measures. The results are reasonably consistent across all approaches.

The efficiency scores from the SFACD and SFATLG long-period models show strong correlations with the OPFP measures, at 0.683 and 0.727, respectively. These are in line with the correlations observed in the standard SFACD (0.686) and SFATLG (0.734) models.

Figure 3.4.2 illustrates the trends in efficiency scores over time across all models. Figure 3.4.3 shows scatter charts of the residuals of these models plotted against fitted values of the dependent variable.

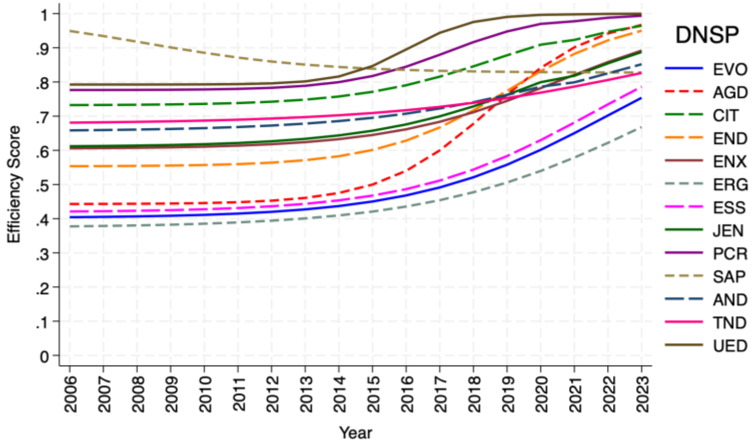
Figure 3.4.1 Average Efficiency Scores by DNSP (2006–2023)

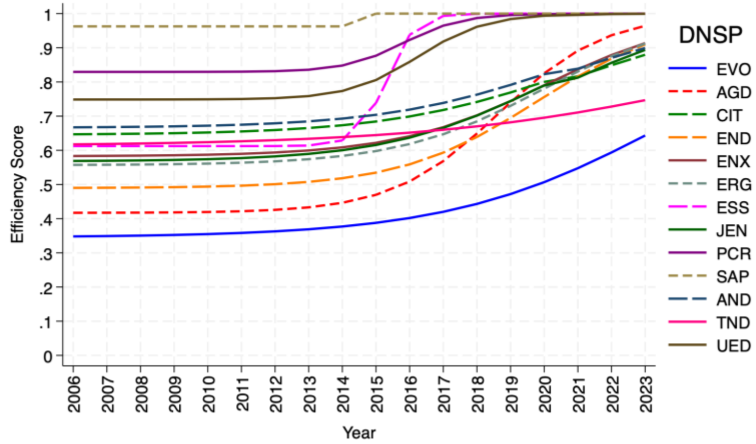



### 3.4.5 Concluding Comments

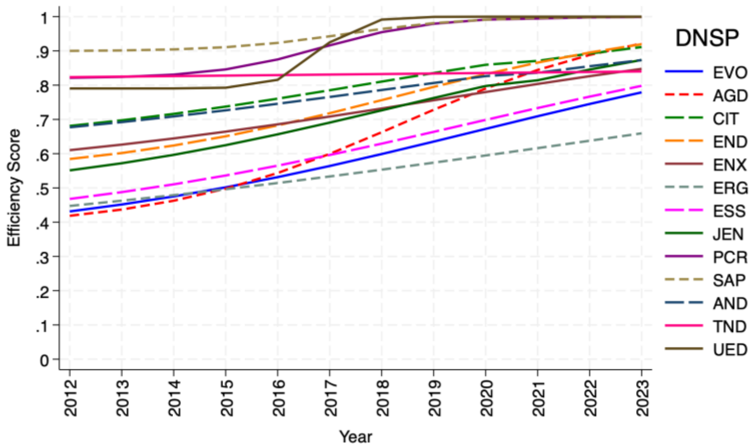
The Kumb90-AJTT-HN-GTC specification failed to run for the SFATLG model in the short period. Further, it generated high rates of monotonicity violations.

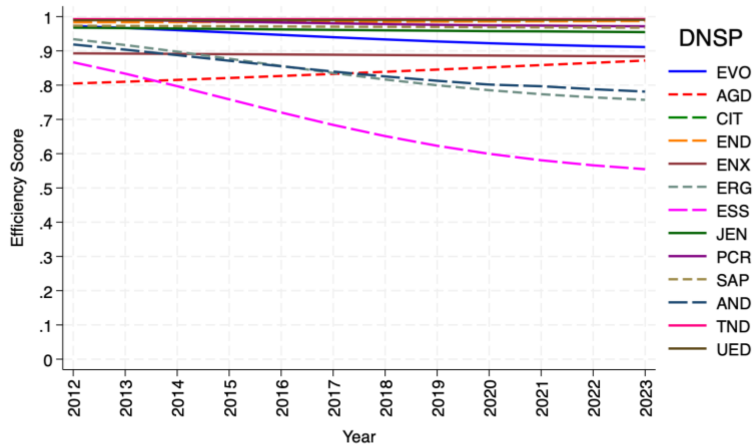
Figure 3.3.2 Kumb90-AJTT-HN-GTC Efficiency Trends by DNSP



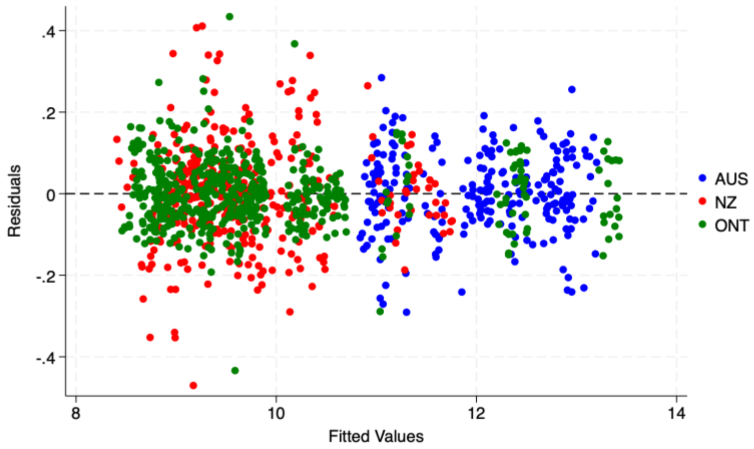

*SFACD Long Period* *SFATLG Long Period*



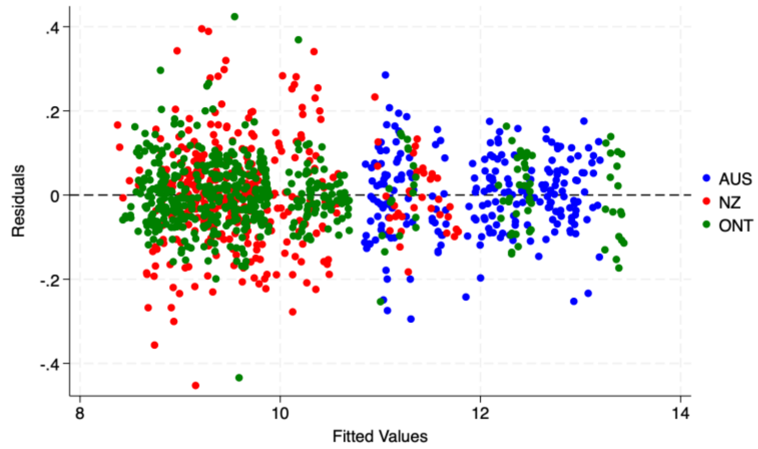




*SFACD Short Period* *SFATLG Short Period*

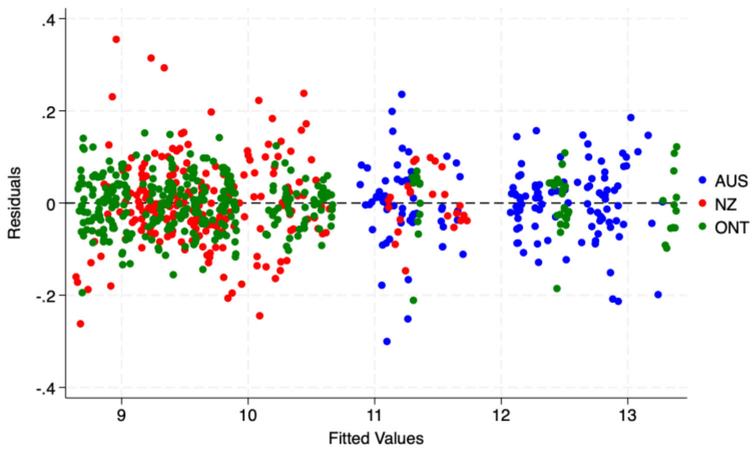
Figure 3.4.3 Kumb90-AJTT-HN-GTC: Residual plots



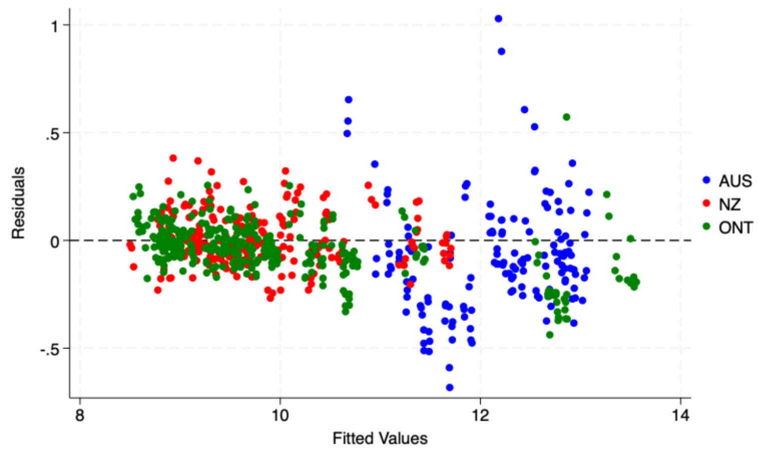

*SFACD Long Period*




*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

## 3.5 Kumb90-AJTTnz-HN: Australian DNSP Specific & New Zealand Jurisdiction Time Trend as *z*-variables

In this specification, the Australian DNSP-specific time trends and the New Zealand jurisdictional time trend variable are included as z variables.

### 3.5.1 Estimation Results

The results of estimating the Cobb-Douglas and Translog with both the long and short samples are presented in Table 3.5.1 and 3.5.2.

Table 3.5.1 Kumb90-AJTTnz-HN SFACD Parameter Estimates

| | *Long Period* | | | *Short Period* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| **Frontier** | | | | | | |
| ly1 | 0.657 | 0.097 | 6.75 | 0.597 | 0.108 | 5.51 |
| ly2 | 0.124 | 0.043 | 2.89 | 0.285 | 0.040 | 7.20 |
| ly3 | 0.273 | 0.084 | 3.25 | 0.079 | 0.088 | 0.89 |
| lz1 | -0.093 | 0.040 | -2.36 | 0.007 | 0.047 | 0.14 |
| yr | 0.007 | 0.001 | 5.54 | -0.004 | 0.002 | -2.58 |
| jur2 | 0.155 | 0.111 | 1.39 | -0.278 | 0.103 | -2.69 |
| jur3 | 0.345 | 0.084 | 4.11 | 0.253 | 0.084 | 3.01 |
| _cons | -5.363 | 2.697 | -1.99 | 17.960 | 3.106 | 5.78 |
| **Bt** | | | | | | |
| t_dnsp1 | 0.238 | 0.048 | 5.00 | 0.165 | 0.041 | 4.03 |
| t_dnsp2 | 0.539 | 0.086 | 6.29 | 0.377 | 0.100 | 3.79 |
| t_dnsp3 | 0.245 | 0.129 | 1.90 | 0.139 | 0.066 | 2.11 |
| t_dnsp4 | 0.380 | 0.084 | 4.55 | 0.234 | 0.082 | 2.86 |
| t_dnsp5 | 0.264 | 0.088 | 3.01 | 0.139 | 0.055 | 2.51 |
| t_dnsp6 | 0.221 | 0.050 | 4.40 | 0.105 | 0.032 | 3.24 |
| t_dnsp7 | 0.287 | 0.065 | 4.45 | 0.212 | 0.052 | 4.10 |
| t_dnsp8 | 0.236 | 0.080 | 2.96 | 0.222 | 0.065 | 3.42 |
| t_dnsp9 | 0.420 | 0.388 | 1.08 | 1.069 | 1.193 | 0.90 |
| t_dnsp10 | -0.597 | 0.247 | -2.42 | 0.020 | 0.254 | 0.08 |
| t_dnsp11 | -0.242 | 0.123 | -1.96 | 0.139 | 0.080 | 1.74 |
| t_dnsp12 | 0.082 | 0.110 | 0.74 | -0.089 | 0.097 | -0.93 |
| t_dnsp13 | 0.925 | 0.407 | 2.27 | 2.739 | 2.337 | 1.17 |
| t_nz | -0.181 | 0.030 | -5.97 | -0.132 | 0.023 | -5.69 |
| _cons | -1.982 | 0.261 | -7.60 | -0.215 | 0.270 | -0.80 |
| /sigmau_2 | 0.272 | 0.072 | 3.77 | 0.570 | 0.182 | 3.14 |
| /sigmav_2 | 0.012 | 0.001 | 22.12 | 0.007 | 0.000 | 17.75 |
| sigma_u | 0.521 | 0.069 | 7.54 | 0.755 | 0.120 | 6.28 |
| sigma_v | 0.109 | 0.002 | 44.23 | 0.081 | 0.002 | 35.49 |
| lambda | 4.762 | 0.069 | 69.23 | 9.350 | 0.120 | 77.84 |
| LLH | 738.17 | | | 667.70 | | |
| Iterations # | 71 | | | 173 | | |
| Pseudo Adj $R^2$ | 0.993 | | | 0.996 | | |
| BIC | -1301.32 | | | -1170.50 | | |
| N | 1098 | | | 732 | | |

Table 3.5.2 Kumb90-AJTTnz-HN: SFATLG Parameter Estimates

| | Long Period | | | Short Period | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.650 | 0.102 | 6.36 | 0.423 | 0.086 | 4.93 |
| ly2 | 0.101 | 0.040 | 2.48 | 0.283 | 0.040 | 7.05 |
| ly3 | 0.296 | 0.093 | 3.19 | 0.251 | 0.074 | 3.40 |
| ly11 | 1.307 | 0.535 | 2.44 | 0.674 | 0.486 | 1.39 |
| ly12 | -0.312 | 0.133 | -2.34 | -0.134 | 0.122 | -1.10 |
| ly13 | -0.913 | 0.430 | -2.12 | -0.570 | 0.400 | -1.43 |
| ly22 | 0.187 | 0.059 | 3.16 | 0.247 | 0.055 | 4.50 |
| ly23 | 0.206 | 0.113 | 1.82 | -0.111 | 0.096 | -1.16 |
| ly33 | 0.584 | 0.348 | 1.67 | 0.655 | 0.330 | 1.98 |
| lz1 | -0.105 | 0.037 | -2.88 | 0.056 | 0.036 | 1.54 |
| yr | 0.009 | 0.001 | 6.37 | -0.004 | 0.002 | -2.21 |
| jur2 | 0.284 | 0.067 | 4.24 | -0.361 | 0.081 | -4.48 |
| jur3 | 0.515 | 0.075 | 6.83 | 0.094 | 0.051 | 1.84 |
| _cons | -7.900 | 2.700 | -2.93 | 17.299 | 3.266 | 5.30 |
| ***Bt*** | | | | | | |
| t_dnsp1 | 0.249 | 0.047 | 5.35 | 0.213 | 0.049 | 4.39 |
| t_dnsp2 | 0.543 | 0.086 | 6.31 | 0.272 | 0.080 | 3.39 |
| t_dnsp3 | 0.217 | 0.089 | 2.45 | 2.137 | 3.715 | 0.58 |
| t_dnsp4 | 0.373 | 0.065 | 5.73 | 0.181 | 0.065 | 2.80 |
| t_dnsp5 | 0.326 | 0.084 | 3.88 | 0.092 | 0.040 | 2.29 |
| t_dnsp6 | 0.392 | 0.087 | 4.49 | 0.145 | 0.052 | 2.77 |
| t_dnsp7 | 2.475 | 1.057 | 2.34 | 0.452 | 0.198 | 2.28 |
| t_dnsp8 | 0.330 | 0.079 | 4.19 | 0.284 | 0.101 | 2.81 |
| t_dnsp9 | -0.652 | 2.292 | -0.28 | 0.997 | 1.143 | 0.87 |
| t_dnsp10 | -0.882 | 0.380 | -2.32 | -0.033 | 0.477 | -0.07 |
| t_dnsp11 | -0.279 | 0.141 | -1.98 | 0.124 | 0.076 | 1.64 |
| t_dnsp12 | 0.098 | 0.108 | 0.90 | -2.226 | 1.846 | -1.21 |
| t_dnsp13 | 0.844 | 0.248 | 3.40 | 2.846 | 2.444 | 1.16 |
| t_nz | -0.171 | 0.030 | -5.74 | -0.148 | 0.028 | -5.26 |
| _cons | -2.387 | 0.296 | -8.07 | -0.144 | 0.292 | -0.49 |
| /sigmau_2 | 0.272 | 0.065 | 4.19 | 0.473 | 0.165 | 2.86 |
| /sigmav_2 | 0.012 | 0.001 | 22.38 | 0.006 | 0.000 | 17.76 |
| sigma_u | 0.521 | 0.062 | 8.37 | 0.687 | 0.120 | 5.71 |
| sigma_v | 0.108 | 0.002 | 44.76 | 0.080 | 0.002 | 35.52 |
| lambda | 4.846 | 0.062 | 78.15 | 8.623 | 0.120 | 71.83 |
| LLH | 753.63 | | | 682.92 | | |
| Iterations # | 196 | | | 244 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.996 | | |
| BIC | -1290.21 | | | -1161.36 | | |
| *N* | 1098 | | | 732 | | |

### 3.5.2 Consistency with economic theory or industry knowledge

Tables 3.5.1 and 3.5.2 show that, for the long period, both the SFACD and SFATLG models produce the expected signs for the main log-output coefficients, which are statistically significant. The coefficient on the log share of underground cables is also negative and statistically significant. In the short period, however, the RMD output in the SFACD model is not statistically significant, and the coefficient on undergrounding is positive in both the SFACD and SFATLG models.

Table 3.5.3 presents the output elasticities for both the long- and short-period models. Table 3.5.4 reports the monotonicity violations in the SFATLG model for both the long- and short-period models.

#### Table 3.5.3 Kumb90-AJTTnz-HN: Output elasticities

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *SFACD* | | | | | | | | |
| Full Sample | 0.657 | 0.124 | 0.273 | 1.054 | 0.597 | 0.285 | 0.079 | 0.961 |
| *SFATLG* | | | | | | | | |
| Australia | 0.843 | 0.260 | 0.042 | 1.145 | 0.413 | 0.344 | 0.103 | 0.861 |
| New Zealand | 0.576 | 0.150 | 0.393 | 1.118 | 0.464 | 0.506 | 0.029 | 1.000 |
| Ontario | 0.611 | -0.003 | 0.346 | 0.954 | 0.401 | 0.110 | 0.463 | 0.974 |
| Full sample | 0.650 | 0.101 | 0.296 | 1.046 | 0.423 | 0.283 | 0.251 | 0.958 |

#### Table 3.5.4 Kumb90-AJTTnz-HN: Monotonicity violations in SFATLG models (%)

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *By DNSP* | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| CIT | 0.0 | 5.6 | 83.3 | 83.3 | 0.0 | 50.0 | 0.0 | 50.0 |
| END | 0.0 | 0.0 | 22.2 | 22.2 | 0.0 | 0.0 | 0.0 | 0.0 |
| ENX | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ERG | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ESS | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| JEN | 0.0 | 77.8 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| PCR | 0.0 | 0.0 | 11.1 | 11.1 | 0.0 | 0.0 | 100.0 | 100.0 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 33.3 | 33.3 |
| AND | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| *By jurisdiction* | | | | | | | | |
| Australia | 0.0 | 6.4 | 47.4 | 47.4 | 0.0 | 3.8 | 25.6 | 29.5 |
| New Zealand | 6.1 | 5.3 | 3.8 | 15.2 | 0.0 | 0.0 | 34.6 | 34.6 |
| Ontario | 0.0 | 54.6 | 0.4 | 55.0 | 0.0 | 13.8 | 0.0 | 13.8 |
| Full sample | 1.9 | 29.0 | 11.5 | 41.0 | 0.0 | 7.4 | 16.3 | 23.6 |

Across all four specifications, the sum of output elasticities is close to one, indicating near-constant returns to scale. Notably, the total elasticity in the long-period models slightly exceeds one. Customer numbers consistently have the highest elasticity, followed by RMD in the long period models and circuit length in the short period models. In the long-period model, 47.4 per cent of the Australian sample and 41.0 per cent of the total sample exhibit monotonicity violations. In the short-period model, the MVs are 29.5 per cent for the Australian sample and 23.6 per cent for the total sample. These results indicate that the Kumb90-AJTTnz-HN model performs better than the standard SFATLG specifications in reducing monotonicity violations.

### 3.5.3 Convergence & Specification Tests

Both the SFACD and SFATLG models were estimated for the long and short periods, with convergence achieved within 71 to 224 iterations. Tables 3.5.1 and 3.5.2 report the BIC, pseudo-adjusted $R^2$, and the number of iterations for each model. Additional diagnostic statistics are presented in Table 3.5.5.

Table 3.5.5 Kumb90-AJTTnz-HN: Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value** | *Stat.* | *p-value** |
| ***SFACD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers)(1) | 0.45 | | 0.27 | |
| Shapiro–Wilk W test(2) | 0.978 | 0.000 | 0.981 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF(3) | 24.98 | | 25.89 | |
| Condition number(3) | 1084.2 | | 1619.5 | |
| *Specification* | | | | |
| Link test(4) | 2.92 | 0.004 | -1.51 | 0.130 |
| ***SFATLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.36 | | 0.41 | |
| Shapiro–Wilk W test | 0.983 | 0.000 | 0.982 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 714.08 | | 717.50 | |
| Condition number | 1641.0 | | 2427.5 | |
| Specification | | | | |
| Link test | 2.28 | 0.023 | -0.95 | 0.342 |
| Joint parameter tests | | | | |
| Higher-order output terms | 60.63 | 0.000 | 59.96 | 0.000 |

Note: * Null hypothesis is rejected in these tests, if the p-value is less than 0.05. Equivalently, the reported statistic exceeds the critical value for that statistic; (1) Severe outliers comprise about .0002% of the normal population; (2) The null hypothesis is that residuals are normally distributed; (3) Collinearity is potentially a problem if VIF>10 or the Condition number > 30; (4) Absolute value of t-statistic on hatsq. The null hypothesis is that the model is correctly specified.

Residual diagnostics indicate that severe outliers are rare, fewer than 0.5 per cent across all models. However, the Shapiro–Wilk test rejects the normality of residuals. Multicollinearity is moderate in the SFACD model but high in the SFATLG model, primarily due to the inclusion of interaction and squared terms. The link test suggests potential misspecification in all models and functional forms, except for the SFACD short-period model. Joint tests support the SFATLG specification, with the higher-order terms statistically significant in both periods.

### 3.5.4 Efficiency Scores

Table 3.5.6 presents the average SFACD and SFATLG efficiency scores for each Australian DNSP in both the long- and short-period analyses. In the long period, the SFACD model produces an average efficiency score that is 8.2 per cent lower than its standard counterpart, while the SFATLG model shows an average score 1.4 per cent higher. In the short period, the SFACD model yields an average efficiency score 0.1 per cent higher than the standard model. In contrast, the SFATLG model shows a substantial difference, 94.2 per cent higher than the standard short-period SFATLG model, which did not converge.

When comparing average efficiency scores, the correlation between the Kumb90-AJTTnz-HN and standard models varies by specification. For the SFACD model, the correlations are very high (0.937 for the long period and 0.958 for the short period) indicating strong alignment. For the SFATLG model, the correlations are lower: 0.627 in the long period and just 0.377 in the short period.

Table 3.5.6 Kumb90-AJTTnz-HN Average Efficiency Scores by Australian DNSP

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *SFACD* | *Rank* | *SFATLG* | *Rank* | *SFACD* | *Rank* | *SFATLG* | *Rank* |
| EVO | 0.447 | 13 | 0.364 | 13 | 0.541 | 13 | 0.612 | 12 |
| AGD | 0.634 | 10 | 0.560 | 12 | 0.638 | 11 | 0.574 | 13 |
| CIT | 0.789 | 4 | 0.654 | 8 | 0.744 | 6 | 0.945 | 3 |
| END | 0.677 | 9 | 0.579 | 11 | 0.716 | 7 | 0.686 | 10 |
| ENX | 0.712 | 7 | 0.658 | 7 | 0.713 | 8 | 0.638 | 11 |
| ERG | 0.477 | 12 | 0.680 | 6 | 0.569 | 12 | 0.705 | 9 |
| ESS | 0.548 | 11 | 0.824 | 4 | 0.665 | 10 | 0.835 | 6 |
| JEN | 0.684 | 8 | 0.637 | 10 | 0.695 | 9 | 0.753 | 8 |
| PCR | 0.904 | 2 | 0.978 | 1 | 0.959 | 1 | 0.960 | 2 |
| SAP | 0.863 | 3 | 0.930 | 2 | 0.946 | 2 | 0.976 | 1 |
| AND | 0.738 | 5 | 0.758 | 5 | 0.797 | 5 | 0.786 | 7 |
| TND | 0.715 | 6 | 0.644 | 9 | 0.833 | 4 | 0.911 | 5 |
| UED | 0.926 | 1 | 0.871 | 3 | 0.924 | 3 | 0.927 | 4 |
| Australia | 0.701 | | 0.703 | | 0.749 | | 0.793 | |

Figure 3.5.1 compares the average efficiency scores from the standard LSECD, LSETLG, SFACD, and SFATLG models for the long-period sample, alongside the average scores from

the Kumb90-AJTTnz-HN model and the average opex partial factor productivity (OPFP) measures. The results are reasonably consistent across all approaches.

The efficiency scores for Australian DNSPs from the long-period SFACD and SFATLG models show strong correlations with the OPFP measures, at 0.731 and 0.750, respectively. These correlations are higher than that of the standard SFACD model (0.686) and comparable to the standard SFATLG model (0.734).

Figure 3.5.1 Average Efficiency Scores by DNSP (2006–2023)

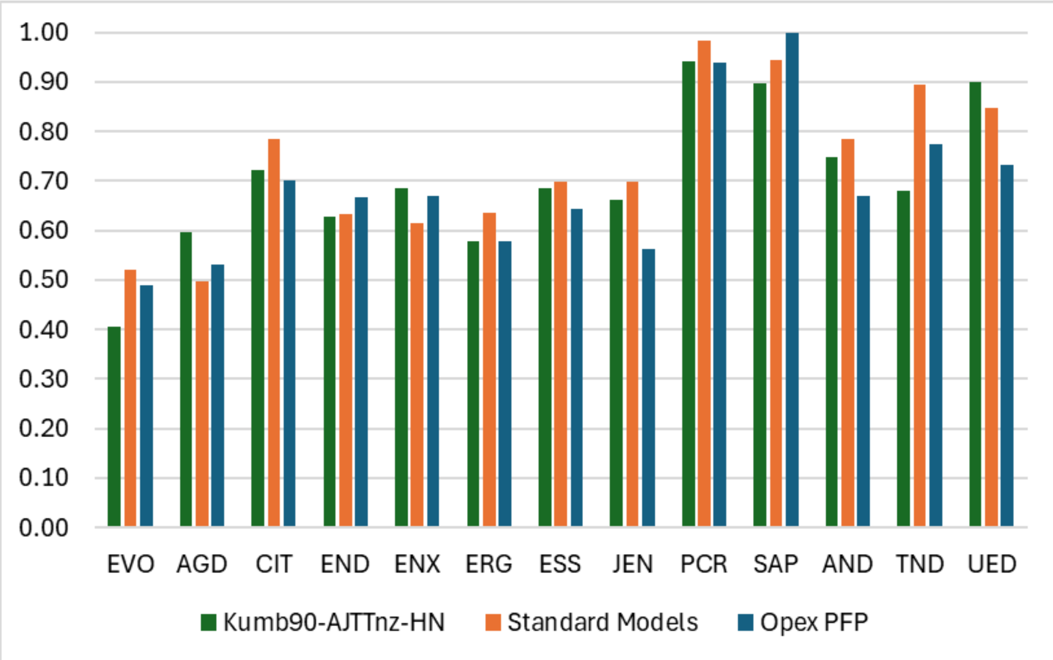
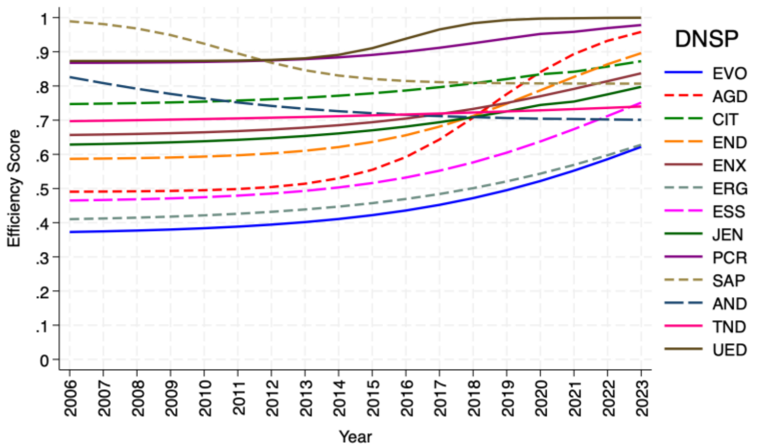


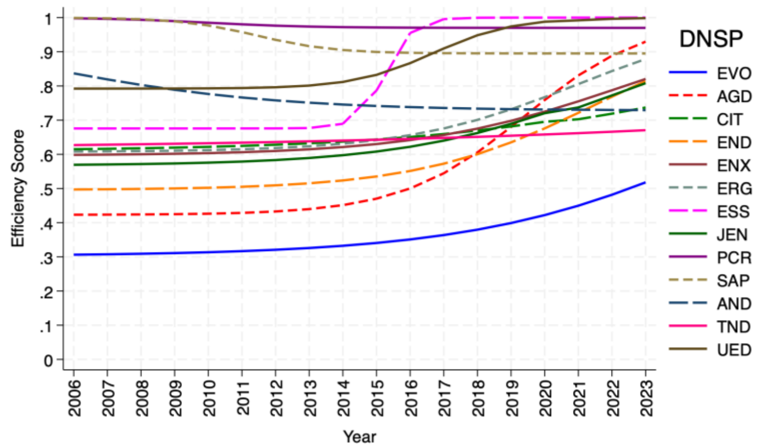

Figure 3.5.2 illustrate the trends in efficiency scores over time for all models. Figure 3.5.3 shows scatter charts of the residuals of these models plotted against fitted values of the dependent variable.

### 3.5.5 Concluding Comments

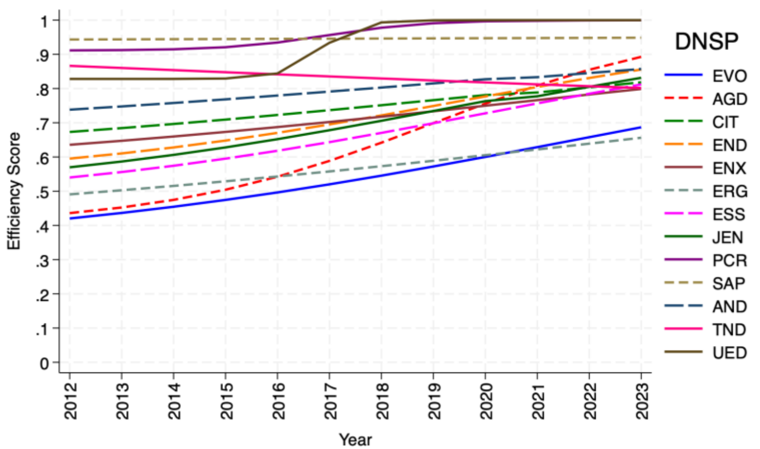
The Kumb90-AJTTnz-HN models produced the expected output coefficient values in the long-period analysis, however, this was not observed in the short period. Nevertheless, the models for both periods displayed consistent output elasticities, indicating near-constant returns to scale, and generated meaningful efficiency scores. They also outperformed the standard specifications in reducing monotonicity violations, and their efficiency scores showed a strong correlation with the opex partial factor productivity index.

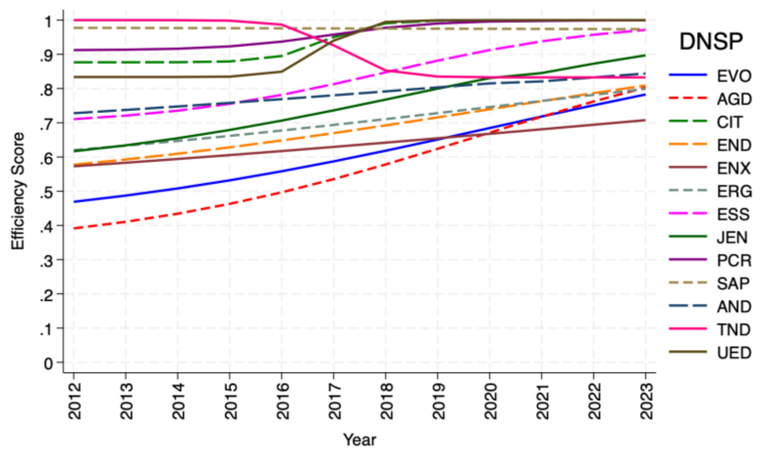
Figure 3.5.2 Kumb90-AJTTnz-HN Efficiency Trends by DNSP



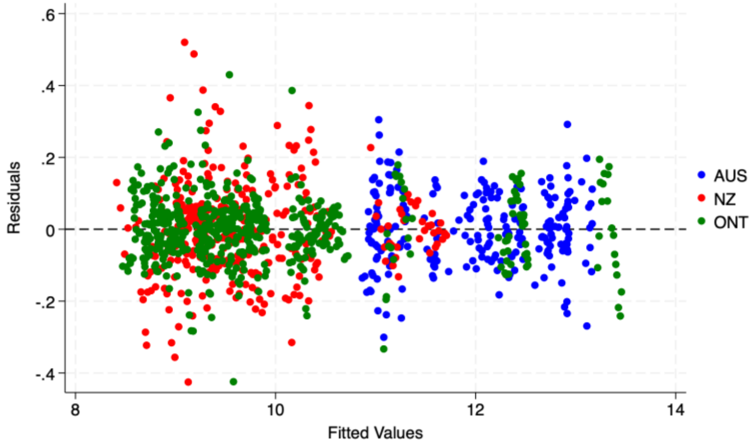

| *SFACD Long Period* | *SFATLG Long Period* |
|---|---|



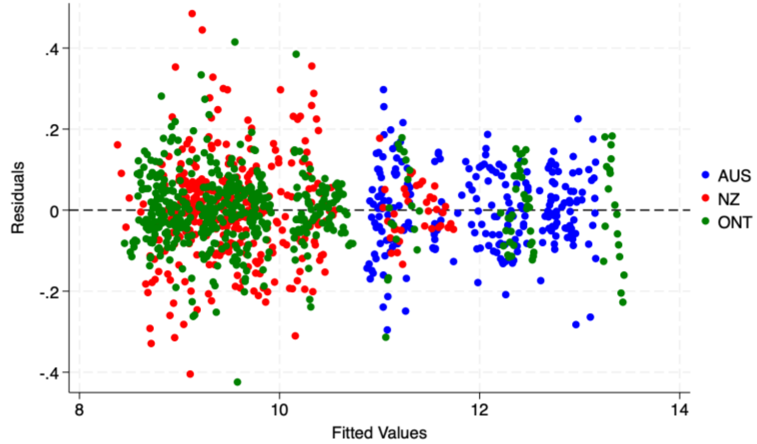




| *SFACD Short Period* | *SFATLG Short Period* |
|---|---|

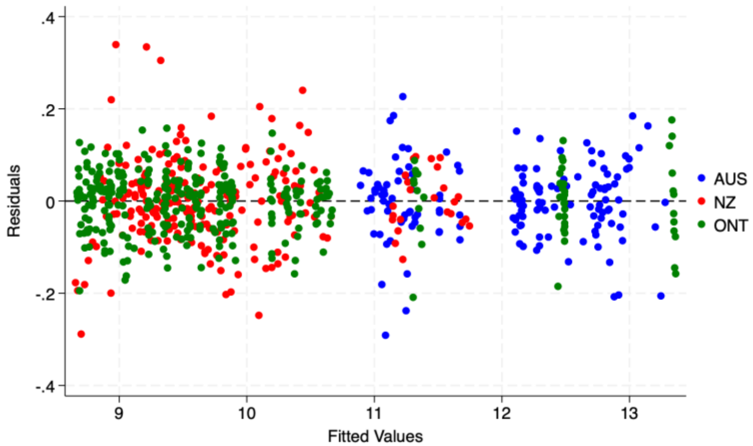
Figure 3.5.3 Kumb90-AJTTnz-HN Residual plots



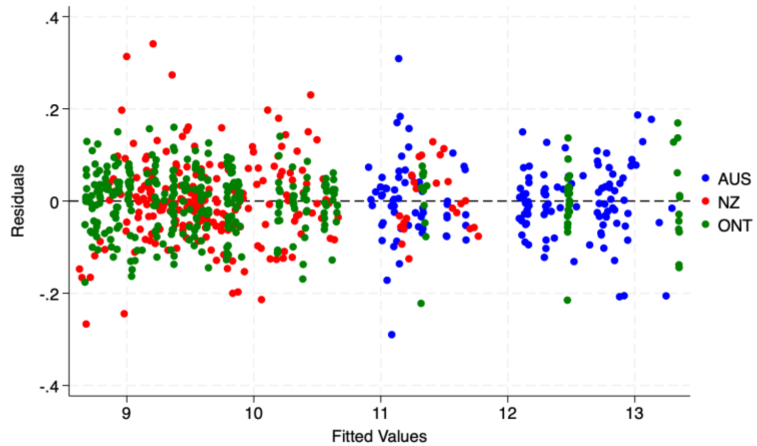

*SFACD Long Period*




*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

## 3.6 Kumb90-AJTTnz-HN-GTC: Australian DNSP Specific & New Zealand Jurisdiction Time Trend as *z*-variables & General Technical Change

In this specification, the Australian DNSP-specific time trends and the New Zealand jurisdictional time trend variable are included as z variables. Instead of the 'yr' variable, the GTC dummy variables are used.

### 3.6.1 Estimation Results

The results of estimating the Cobb-Douglas and Translog with both the long and short samples are presented in Table 3.6.1 and 3.6.2.

### 3.6.2 Consistency with economic theory or industry knowledge

As shown in Tables 3.6.1 and 3.6.2, the SFACD and SFATLG models for both the long and short periods generally produce output coefficients with the expected signs, and most are statistically significant. The main exception is the RMD output, which is statistically significant only in the SFATLG short-period model.

The coefficient on the log share of underground cables is negative, as expected, in all models except the SFATLG short-period model, where it is positive and statistically significant. This result runs counter to expectations and suggests a possible issue with that specification.

Table 3.6.3 reports the output elasticities for both the long- and short-period models. In all four specifications, the sum of elasticities is close to one, indicating near-constant returns to scale. Notably, the total elasticity slightly exceeds one in the long-period models. Customer numbers consistently have the highest elasticity, followed by RMD in the long-period models and circuit length in the short-period models.

Table 3.6.4 reports the monotonicity violations in the SFATLG model for both the long- and short-period models. In the long-period model, 81.6 per cent of the Australian sample and 65.0 per cent of the total sample exhibit monotonicity violations. In the short-period model, the corresponding figures are 66.7 per cent for the Australian sample and 55.6 per cent for the total sample. These results indicate that the Kumb90-AJTTnz-HN-GTC model performs worse than the standard SFATLG specification in the long period, but better in the short period, in terms of reducing monotonicity violations.

Table 3.6.1 Kumb90-AJTTnz-HN-GTC SFACD Parameter Estimates

| | Long Period | | | Short Period | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.824 | 0.098 | 8.37 | 0.599 | 0.107 | 5.58 |
| ly2 | 0.106 | 0.051 | 2.07 | 0.282 | 0.045 | 6.32 |
| ly3 | 0.141 | 0.080 | 1.75 | 0.078 | 0.083 | 0.94 |
| lz1 | -0.091 | 0.038 | -2.38 | -0.009 | 0.046 | -0.20 |
| gtc2 | 0.030 | 0.012 | 2.54 | | | |
| gtc3 | 0.080 | 0.013 | 6.19 | | | |
| gtc4 | 0.095 | 0.014 | 6.57 | 0.015 | 0.009 | 1.64 |
| gtc5 | 0.094 | 0.017 | 5.52 | 0.006 | 0.011 | 0.57 |
| gtc6 | 0.058 | 0.020 | 2.86 | -0.046 | 0.013 | -3.50 |
| jur2 | 0.119 | 0.117 | 1.01 | -0.279 | 0.101 | -2.77 |
| jur3 | 0.401 | 0.082 | 4.91 | 0.266 | 0.084 | 3.16 |
| _cons | 9.422 | 0.119 | 78.94 | 9.918 | 0.124 | 79.68 |
| ***Bt*** | | | | | | |
| t_dnsp2 | 0.091 | 0.036 | 2.54 | 0.103 | 0.021 | 4.90 |
| t_dnsp2 | 0.322 | 0.089 | 3.62 | 0.195 | 0.034 | 5.79 |
| t_dnsp3 | 0.021 | 0.073 | 0.29 | 0.083 | 0.038 | 2.20 |
| t_dnsp4 | 0.182 | 0.068 | 2.67 | 0.128 | 0.036 | 3.57 |
| t_dnsp5 | 0.097 | 0.064 | 1.51 | 0.088 | 0.032 | 2.77 |
| t_dnsp6 | 0.095 | 0.034 | 2.79 | 0.068 | 0.019 | 3.60 |
| t_dnsp7 | 0.134 | 0.052 | 2.59 | 0.167 | 0.041 | 4.06 |
| t_dnsp8 | 0.058 | 0.058 | 1.01 | 0.128 | 0.033 | 3.89 |
| t_dnsp9 | 0.117 | 0.165 | 0.71 | 0.823 | 1.003 | 0.82 |
| t_dnsp10 | -0.294 | 0.198 | -1.49 | -0.003 | 0.158 | -0.02 |
| t_dnsp11 | -0.045 | 0.076 | -0.59 | 0.076 | 0.045 | 1.68 |
| t_dnsp12 | 0.016 | 0.042 | 0.38 | -0.076 | 0.067 | -1.15 |
| t_dnsp13 | 0.838 | 0.629 | 1.33 | 0.724 | 1.142 | 0.63 |
| t_nz | -0.097 | 0.019 | -5.01 | -0.086 | 0.008 | -10.34 |
| _cons | -0.875 | 0.347 | -2.52 | 0.877 | 0.174 | 5.05 |
| /sigmau_2 | 0.497 | 0.156 | 3.19 | 1.938 | . | . |
| /sigmav_2 | 0.011 | 0.001 | 22.18 | 0.006 | 0.000 | 17.80 |
| sigma_u | 0.705 | 0.111 | 6.37 | 1.392 | . | . |
| sigma_v | 0.107 | 0.002 | 44.36 | 0.079 | 0.002 | 35.60 |
| lambda | 6.581 | 0.110 | 59.67 | 17.634 | . | . |
| LLH | 754.88 | | | 682.82 | | |
| Iterations # | 83 | | | 129 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.997 | | |
| BIC | -1306.72 | | | -1194.15 | | |
| *N* | 1098 | | | 732 | | |

Table 3.6.2 Kumb90-AJTTnz-HN-GTC SFATLG Parameter Estimates

| | Long Period | | | Short Period | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| ***Frontier*** | | | | | | |
| ly1 | 0.821 | 0.097 | 8.46 | 0.545 | 0.090 | 6.08 |
| ly2 | 0.111 | 0.041 | 2.69 | 0.270 | 0.041 | 6.53 |
| ly3 | 0.128 | 0.090 | 1.42 | 0.168 | 0.072 | 2.32 |
| ly11 | 1.920 | 0.552 | 3.48 | 1.184 | 0.598 | 1.98 |
| ly12 | -0.442 | 0.131 | -3.38 | -0.348 | 0.144 | -2.42 |
| ly13 | -1.313 | 0.443 | -2.96 | -0.785 | 0.479 | -1.64 |
| ly22 | 0.256 | 0.059 | 4.31 | 0.400 | 0.062 | 6.43 |
| ly23 | 0.271 | 0.109 | 2.48 | -0.035 | 0.114 | -0.31 |
| ly33 | 0.863 | 0.356 | 2.42 | 0.768 | 0.383 | 2.00 |
| lz1 | -0.035 | 0.037 | -0.94 | 0.112 | 0.045 | 2.51 |
| gtc2 | 0.034 | 0.012 | 2.86 | | | |
| gtc3 | 0.085 | 0.013 | 6.58 | | | |
| gtc4 | 0.108 | 0.015 | 7.28 | 0.017 | 0.009 | 1.83 |
| gtc5 | 0.115 | 0.017 | 6.64 | 0.004 | 0.012 | 0.32 |
| gtc6 | 0.084 | 0.020 | 4.11 | -0.057 | 0.014 | -3.92 |
| jur2 | 0.293 | 0.066 | 4.46 | -0.138 | 0.099 | -1.39 |
| jur3 | 0.624 | 0.065 | 9.54 | 0.331 | 0.101 | 3.28 |
| _cons | 9.191 | 0.078 | 117.65 | 9.863 | 0.111 | 88.51 |
| ***Bt*** | | | | | | |
| t_dnsp1 | 0.144 | 0.039 | 3.66 | 0.073 | 0.014 | 5.22 |
| t_dnsp2 | 0.473 | 0.088 | 5.37 | 0.134 | 0.026 | 5.12 |
| t_dnsp3 | 0.087 | 0.071 | 1.21 | 0.126 | 0.079 | 1.60 |
| t_dnsp4 | 0.277 | 0.056 | 4.94 | 0.083 | 0.020 | 4.14 |
| t_dnsp5 | 0.288 | 0.092 | 3.14 | 0.065 | 0.023 | 2.81 |
| t_dnsp6 | 0.251 | 0.063 | 4.01 | 0.073 | 0.023 | 3.13 |
| t_dnsp7 | 2.094 | 0.876 | 2.39 | 0.951 | 0.473 | 2.01 |
| t_dnsp8 | 0.256 | 0.077 | 3.34 | 0.107 | 0.027 | 3.98 |
| t_dnsp9 | 1.314 | 1.329 | 0.99 | 0.178 | 0.110 | 1.63 |
| t_dnsp10 | -0.681 | 0.356 | -1.91 | -0.023 | 0.259 | -0.09 |
| t_dnsp11 | 0.240 | 0.110 | 2.17 | 0.056 | 0.026 | 2.13 |
| t_dnsp12 | 0.045 | 0.049 | 0.91 | -0.028 | 0.021 | -1.34 |
| t_dnsp13 | 0.815 | 0.275 | 2.96 | 0.256 | 0.114 | 2.24 |
| t_nz | -0.109 | 0.019 | -5.76 | -0.073 | 0.009 | -8.43 |
| _cons | -1.697 | 0.300 | -5.66 | 2.850 | 0.907 | 3.14 |
| /sigmau_2 | 0.379 | 0.091 | 4.16 | 45.971 | 79.843 | 0.58 |
| /sigmav_2 | 0.011 | 0.000 | 22.36 | 0.006 | 0.000 | 17.93 |
| sigma_u | 0.615 | 0.074 | 8.32 | 6.780 | 5.888 | 1.15 |
| sigma_v | 0.105 | 0.002 | 44.72 | 0.076 | 0.002 | 35.86 |
| lambda | 5.879 | 0.074 | 79.68 | 89.070 | 5.888 | 15.13 |
| LLH | 776.74 | | | 711.13 | | |
| Iterations # | 324 | | | 276 | | |
| Pseudo Adj $R^2$ | 0.994 | | | 0.997 | | |
| BIC | -1308.44 | | | -1204.59 | | |
| *N* | 1098 | | | 732 | | |

Table 3.6.3 Kumb90-AJTTnz-HN-GTC Output elasticities

| | Long Period | | | | Short Period | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| <u>*SFACD*</u> | | | | | | | | |
| Full Sample | 0.824 | 0.106 | 0.141 | 1.071 | 0.599 | 0.282 | 0.078 | 0.958 |
| <u>*SFATLG*</u> | | | | | | | | |
| Australia | 1.188 | 0.282 | -0.244 | 1.226 | 0.670 | 0.376 | -0.026 | 1.020 |
| New Zealand | 0.690 | 0.197 | 0.242 | 1.129 | 0.412 | 0.589 | -0.003 | 0.998 |
| Ontario | 0.743 | -0.023 | 0.221 | 0.941 | 0.577 | 0.012 | 0.367 | 0.956 |
| Full sample | 0.821 | 0.111 | 0.128 | 1.060 | 0.545 | 0.270 | 0.168 | 0.983 |

Table 3.6.4 Kumb90-AJTTnz-HN-GTC Monotonicity violations in SFATLG models (%)

| | Long Period | | | | Short Period | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| <u>*By DNSP*</u> | | | | | | | | |
| EVO | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 58.3 | 58.3 |
| CIT | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 0.0 | 100.0 |
| END | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ENX | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 83.3 | 83.3 |
| ERG | 0.0 | 0.0 | 0.0 | 0.0 | 25.0 | 0.0 | 0.0 | 25.0 |
| ESS | 0.0 | 0.0 | 61.1 | 61.1 | 0.0 | 0.0 | 100.0 | 100.0 |
| JEN | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 91.7 | 100.0 | 100.0 |
| PCR | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| SAP | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| AND | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 33.3 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| <u>*By jurisdiction*</u> | | | | | | | | |
| Australia | 0.0 | 17.9 | 81.6 | 81.6 | 1.9 | 14.7 | 57.1 | 66.7 |
| New Zealand | 9.9 | 5.3 | 25.7 | 35.7 | 10.5 | 0.0 | 48.2 | 58.8 |
| Ontario | 0.0 | 61.7 | 18.8 | 76.8 | 0.0 | 48.3 | 0.3 | 48.6 |
| Full sample | 3.1 | 34.8 | 34.3 | 65.0 | 3.7 | 26.1 | 27.3 | 55.6 |

### 3.6.3 Convergence & Specification Tests

Both the SFACD and SFATLG models were estimated for the long and short periods, with convergence achieved between 83 and 324 iterations. Tables 3.6.1 and 3.6.2 report the BIC, pseudo-adjusted $R^2$, and the number of iterations for each model. Additional diagnostic statistics are presented in Table 3.6.5.

Residual diagnostics indicate that severe outliers are rare, affecting fewer than 0.8 per cent of observations across both models. However, the Shapiro–Wilk test rejects the normality of residuals. Multicollinearity is moderate in the SFACD model but high in the SFATLG model, primarily due to the inclusion of interaction and squared terms. The link test suggests potential misspecification in all models. The functional form tests support the SFATLG specification, with higher-order terms statistically significant in both periods.

Table 3.6.5 Kumb90-AJTTnz-HN-GTC Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value** | *Stat.* | *p-value** |
| ***SFACD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers)(1) | 0.73 | | 0.41 | |
| Shapiro–Wilk W test(2) | 0.965 | 0.000 | 0.979 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF(3) | 24.98 | | 20.50 | |
| Condition number(3) | 1084.23 | | 22.56 | |
| *Specification* | | | | |
| Link test(4) | 3.17 | 0.002 | -2.96 | 0.003 |
| ***SFATLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.54 | | 0.27 | |
| Shapiro–Wilk W test | 0.971 | 0.000 | 0.980 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 714.08 | | 621.85 | |
| Condition number | 1641.03 | | 366.68 | |
| Specification | | | | |
| Link test | 2.39 | 0.017 | -2.47 | 0.013 |
| Joint parameter tests | | | | |
| Higher-order output terms | 76.19 | 0.000 | 24.37 | 0.000 |

Note: * Null hypothesis is rejected in these tests, if the p-value is less than 0.05. Equivalently, the reported statistic exceeds the critical value for that statistic; (1) Severe outliers comprise about .0002% of the normal population; (2) The null hypothesis is that residuals are normally distributed; (3) Collinearity is potentially a problem if VIF>10 or the Condition number > 30; (4) Absolute value of t-statistic on hatsq. The null hypothesis is that the model is correctly specified.

### 3.6.4 Efficiency Scores

Table 3.6.6 presents the average SFACD and SFATLG efficiency scores for each Australian DNSP in both the long- and short-period analyses. The average efficiency rankings are broadly consistent across the SFACD and SFATLG models in both periods and closely align with those from the standard ABR24 models.

Over the long period, the SFACD model reports an average efficiency score 10.3 per cent lower than its standard counterpart, while the SFATLG model is 0.7 per cent lower. In the short period, the SFACD model produces an average score 0.3 per cent below that of the standard model. However, the SFATLG model shows an average efficiency score 82.9 per cent higher than the standard short-period model, which did not converge.

Regarding the alignment of average scores, the correlation between the Kumb90-AJTTnz-HN-GTC and standard models varies across specifications. For SFACD, the correlations are very strong (0.903 in the long period and 0.961 in the short) indicating close agreement. For SFATLG, the correlations are weaker: 0.481 in the long period and just 0.259 in the short period.

Table 3.6.6 Kumb90-AJTTnz-HN-GTC Average Efficiency Scores by Australian DNSP

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *SFACD* | *Rank* | *SFATLG* | *Rank* | *SFACD* | *Rank* | *SFATLG* | *Rank* |
| EVO | 0.425 | 13 | 0.334 | 13 | 0.533 | 13 | 0.493 | 13 |
| AGD | 0.633 | 10 | 0.591 | 10 | 0.621 | 11 | 0.613 | 12 |
| CIT | 0.757 | 4 | 0.606 | 9 | 0.736 | 6 | 0.850 | 5 |
| END | 0.653 | 9 | 0.558 | 11 | 0.703 | 7 | 0.648 | 11 |
| ENX | 0.706 | 6 | 0.688 | 6 | 0.703 | 7 | 0.663 | 10 |
| ERG | 0.441 | 12 | 0.633 | 8 | 0.574 | 12 | 0.720 | 7 |
| ESS | 0.528 | 11 | 0.825 | 4 | 0.679 | 10 | 0.898 | 2 |
| JEN | 0.685 | 7 | 0.636 | 7 | 0.690 | 9 | 0.676 | 9 |
| PCR | 0.882 | 2 | 0.935 | 2 | 0.964 | 1 | 0.896 | 3 |
| SAP | 0.839 | 3 | 0.938 | 1 | 0.939 | 2 | 0.965 | 1 |
| AND | 0.740 | 5 | 0.770 | 5 | 0.797 | 5 | 0.723 | 6 |
| TND | 0.671 | 8 | 0.548 | 12 | 0.838 | 4 | 0.685 | 8 |
| UED | 0.941 | 1 | 0.881 | 3 | 0.924 | 3 | 0.886 | 4 |
| Australia | 0.685 | | 0.688 | | 0.746 | | 0.747 | |

Figure 3.6.1 presents the average efficiency scores from the standard LSECD, LSETLG, SFACD, and SFATLG models for the long-period sample, alongside the average scores from the Kumb90-AJTTnz-HN-GTC model and the opex partial factor productivity (OPFP) measures. The results are reasonably consistent across all approaches, although this specification shows the greatest variation compared to the other Kumb models. This is reflected in the correlation between the efficiency scores from the long-period SFACD and SFATLG models and the OPFP measures, which are 0.681 and 0.679, respectively. These correlations are slightly lower than that of the standard SFACD model (0.686) and the standard SFATLG model (0.734).

Figure 3.6.2 illustrates the trends in efficiency scores over time for all models and periods. Figure 3.6.3 displays the scatter of residuals plotted against the fitted values of the dependent variable.

### 3.6.5 Concluding Comments

The Kumb90-AJTTnz-HN-GTC models present issues with the coefficient on RMD and exhibit excessive monotonicity violations, making them unsuitable as a replacement for the standard models.

Figure 3.6.1 Average Efficiency Scores by DNSP (2006–2023)

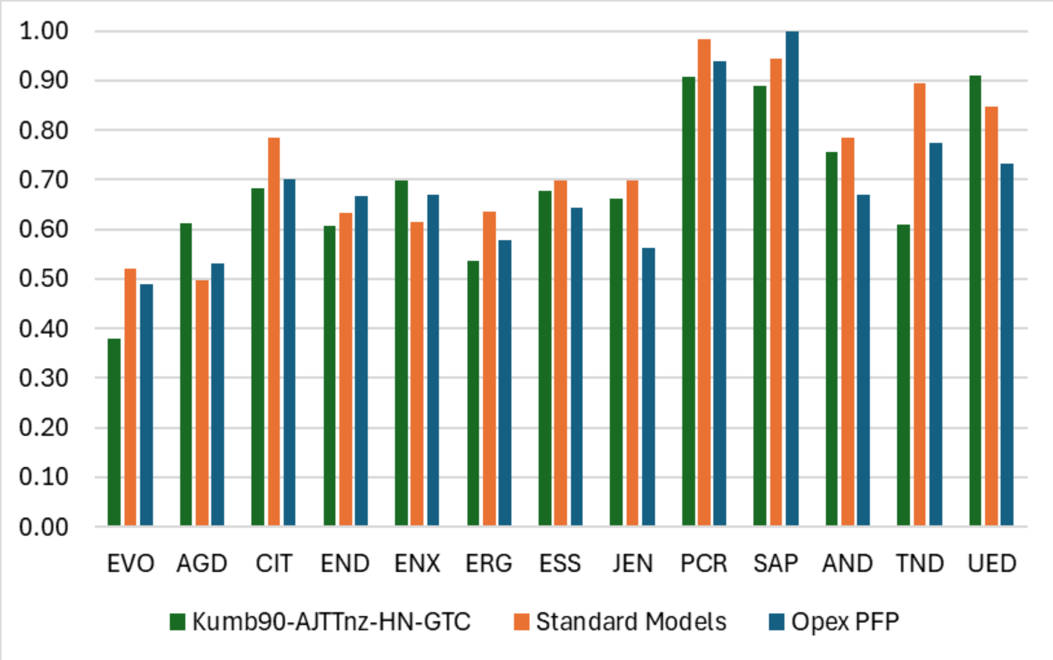
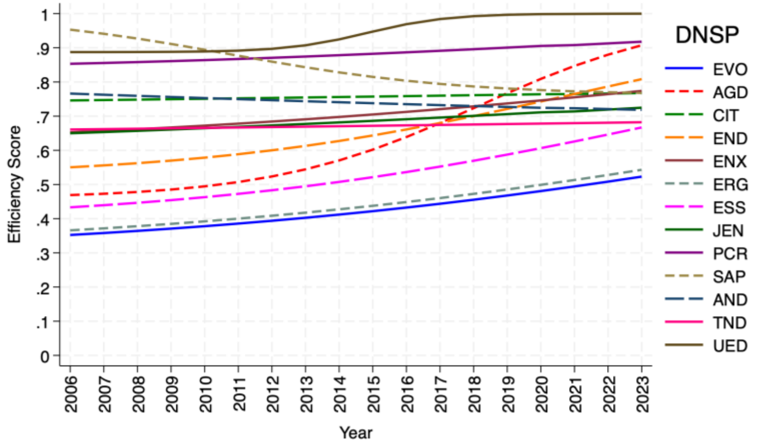
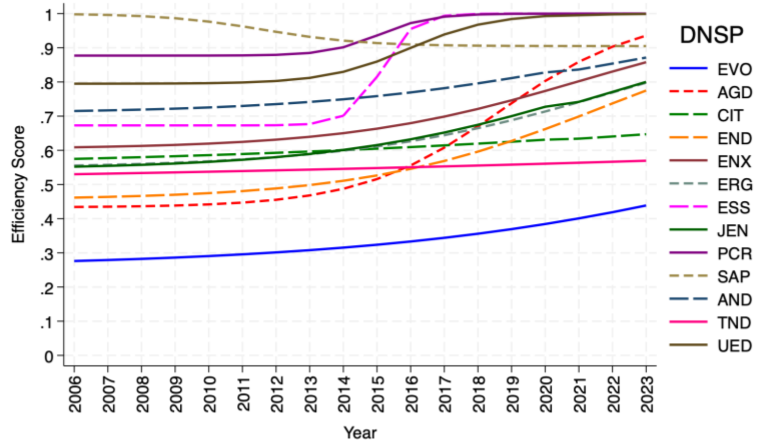


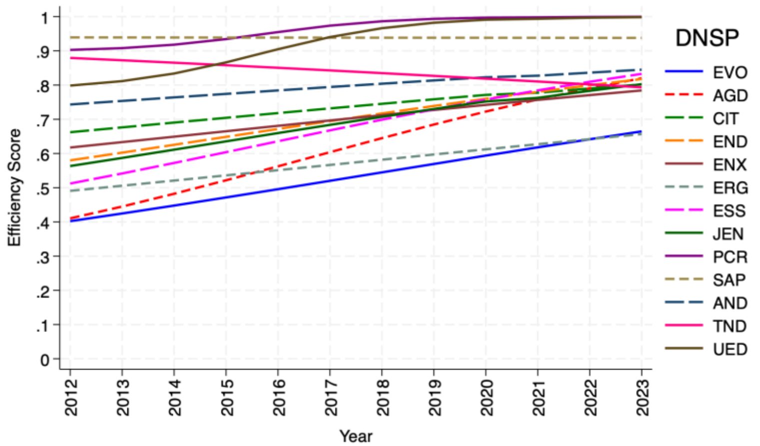
Figure 3.6.2 Kumb90-AJTTnz-HN-GTC Efficiency Trends by DNSP

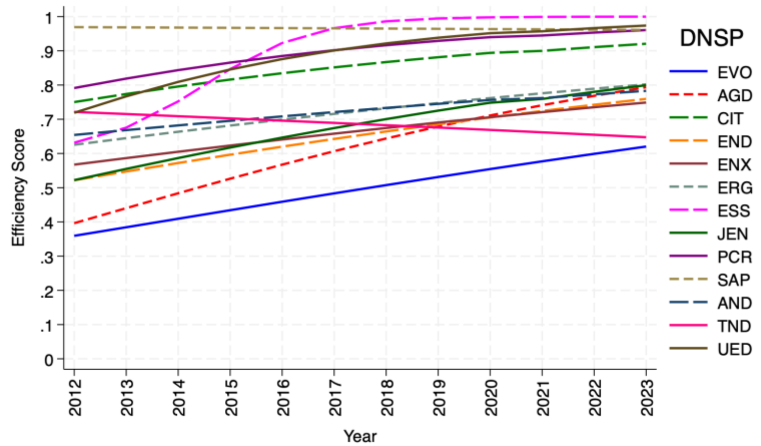



*SFACD Long Period*

*SFATLG Long Period*

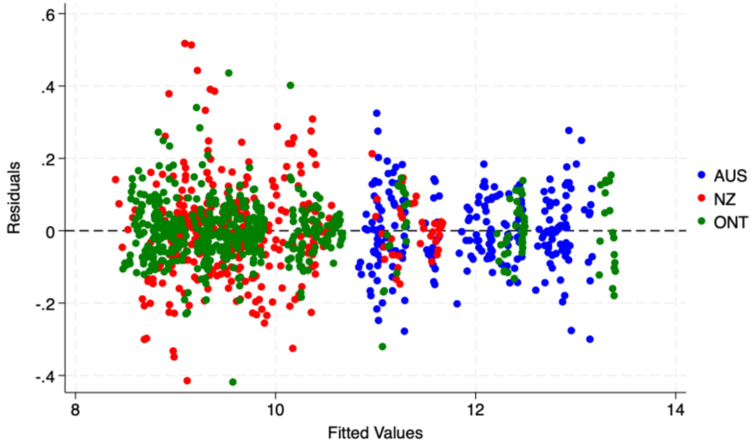


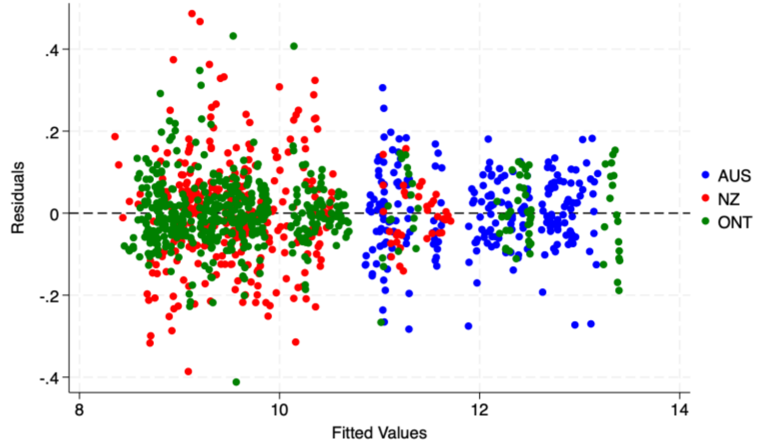

*SFACD Short Period*

*SFATLG Short Period*

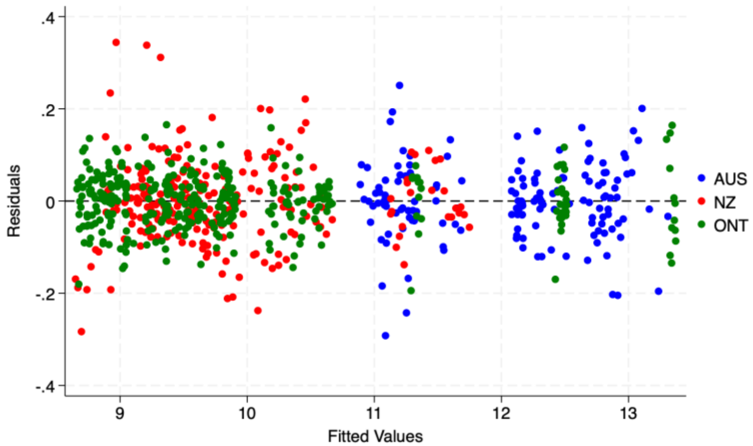
Figure 3.6.3 Kumb90-AJTTnz-HN-GTC Residual plots



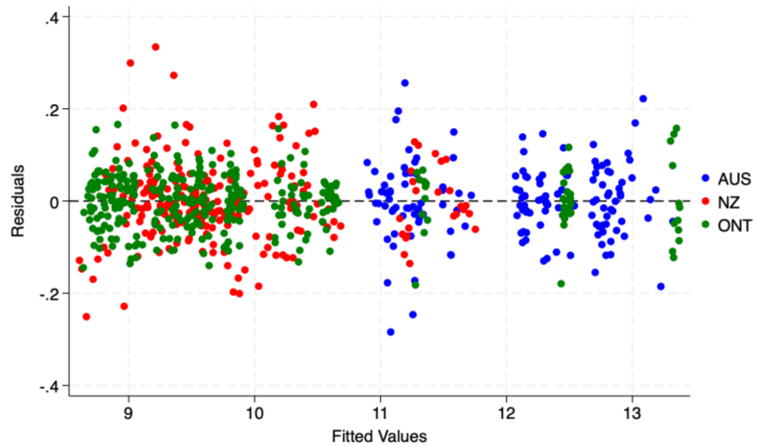

*SFACD Long Period*




*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

# 4 Colombi et al. (2014): Four Components Model

This section presents the empirical results obtained from estimating the four-component SFA specification of Colombi et al. (2014) discussed in Section 3.1.4 of the draft report *"Electricity Distribution Benchmarking Opex Model Development- Phase 2"*.

In this approach, the residual, after excluding inefficiency, has a transitory component which is the idiosyncratic disturbance, and a non-transitory component, which is interpreted as the effect of unobserved heterogeneity. The one-sided random component associated with inefficiency, also has transitory and non-transitory components. This is intended to allow for a more refined understanding of the unobserved elements in a regression's residuals by distinguishing between systemic and situational factors. This method is implemented using the three-step procedure explained in in Section 3.1.4 of the draft report. Recall, this procedure is:

(a) Predict combined transitory error ($v_{it}$) and transitory inefficiency ($u_{it}$) via random effects regression: **xtreg y xlist, re**; then use postestimation commands: **predict esl, e** (to predict the composite transitory elements) and: **predict lam, u** (to predict lambda = $\alpha + \eta + E(\eta)$);

(b) Predict persistent (in)efficiency via cross-sectional SFA without regressors: **frontier lam, distribution(hnormal)**. Then use: predict **ineff_persistent, u** (to predict the persistent inefficiency, $E(\eta|e)$; and: predict **eff_persistent, te** (to predict persistent efficiency , $E(\exp(-\eta)|e)$

(c) Predict transitory (in)efficiency via cross-sectional SFA without regressors: frontier **esl, distribution(hnormal)**. Then: **predict ineff_transitory, u** (to predict transitory inefficiency, $E(u|e)$); and: **predict eff_transitory, te** (to predict transitory efficiency, $E(\exp(-u)|e)$)

The models presented here include the standard time trend but exclude the jurisdictional dummy variables, because the model determines a persistent unobserved efficiency effect, which when aggregated between jurisdictions, will imply persistent jurisdictional differences.

## 4.1 Estimation results

Tables 4.1 and 4.2 present the estimated models.

### 4.1.1 Consistency with economic theory or industry knowledge

Tables 4.1 and 4.2 show the estimation results for the Cobb–Douglas and Translog models over the long period indicate that the coefficients on the main log output variables have the expected signs and are statistically significant. However, in the short period, the coefficient on the log of customer numbers is not statistically significant. The coefficient on the log share of undergrounding is negative and statistically significant in the long period, but not statistically significant in the short period.

Table 4.1 4Comp SFACD Parameter Estimates

| | Long Period (2006-2023) | | | Short Period (2012-2023) | | |
|---|---|---|---|---|---|---|
| | *Coeff* | *std. err.* | *t-ratio* | *Coeff* | *std. err.* | *t-ratio* |
| *ly1* | 0.227 | 0.080 | 2.830 | 0.171 | 0.106 | 1.620 |
| *ly2* | 0.164 | 0.034 | 4.850 | 0.244 | 0.039 | 6.260 |
| *ly3* | 0.564 | 0.063 | 8.910 | 0.528 | 0.083 | 6.340 |
| *lz1* | -0.153 | 0.034 | -4.560 | -0.041 | 0.042 | -0.970 |
| *yr* | 0.011 | 0.001 | 11.360 | 0.003 | 0.001 | 2.160 |
| *_cons* | -12.068 | 1.974 | -6.110 | 4.013 | 2.914 | 1.380 |
| *sigma_u* | 0.178 | | | 0.172 | | |
| *sigma_e* | 0.128 | | | 0.114 | | |
| *rho* | 0.657 | | | 0.695 | | |
| $R^2$ | | | | | | |
| *Within* | 0.356 | | | 0.101 | | |
| *Between* | 0.980 | | | 0.981 | | |
| *Overall* | 0.972 | | | 0.975 | | |
| *Pseudo Adj.* $R^2$ | 0.991 | | | 0.993 | | |
| *N* | 1,098 | | | 732 | | |
| # Parameters | 6 | | | 6 | | |

Table 4.2 4Comp SFATLG Parameter Estimates

| | Long Period (2006-2023) | | | Short Period (2012-2023) | | |
|---|---|---|---|---|---|---|
| | *Coeff* | *std. err.* | *t-ratio* | *Coeff* | *std. err.* | *t-ratio* |
| *ly1* | 0.279 | 0.084 | 3.300 | 0.154 | 0.113 | 1.350 |
| *ly2* | 0.170 | 0.035 | 4.860 | 0.252 | 0.042 | 6.000 |
| *ly3* | 0.536 | 0.070 | 7.690 | 0.589 | 0.092 | 6.420 |
| *ly11* | 0.772 | 0.484 | 1.590 | -0.182 | 0.623 | -0.290 |
| *ly12* | -0.150 | 0.131 | -1.140 | 0.295 | 0.162 | 1.820 |
| *ly13* | -0.753 | 0.390 | -1.930 | -0.477 | 0.508 | -0.940 |
| *ly22* | 0.058 | 0.068 | 0.860 | -0.008 | 0.079 | -0.100 |
| *ly23* | 0.135 | 0.100 | 1.350 | -0.208 | 0.126 | -1.650 |
| *ly33* | 0.618 | 0.325 | 1.900 | 0.863 | 0.425 | 2.030 |
| *lz1* | -0.145 | 0.039 | -3.740 | -0.054 | 0.051 | -1.050 |
| *yr* | 0.011 | 0.001 | 9.890 | 0.005 | 0.002 | 3.090 |
| *_cons* | -11.640 | 0.035 | 4.860 | 0.513 | 3.188 | 0.160 |
| *sigma_u* | 0.169 | | | 0.160 | | |
| *sigma_e* | 0.122 | | | 0.095 | | |
| *rho* | 0.657 | | | 0.740 | | |
| $R^2$ | | | | | | |
| *Within* | 0.378 | | | 0.188 | | |
| *Between* | 0.976 | | | 0.978 | | |
| *Overall* | 0.968 | | | 0.972 | | |
| *Pseudo Adj.* $R^2$ | 0.991 | | | 0.994 | | |
| *N* | 1,098 | | | 732 | | |
| # Parameters | 16 | | | 16 | | |

Table 4.3 presents the output elasticities for the models in the long and short period. The sum of output elasticities across all four models is close to 1, suggesting near constant returns to scale. The negative output elasticity for customer numbers in the short period for the Australian sample indicates a violation of the monotonicity condition.

### Table 4.3 4Comp Output Elasticities

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *SFACD* | | | | | | | | |
| Full Sample | 0.243 | 0.178 | 0.545 | 0.967 | 0.171 | 0.244 | 0.528 | 0.943 |
| *SFATLG* | | | | | | | | |
| Australia | 0.098 | 0.244 | 0.492 | 0.834 | -0.404 | 0.42 | 0.774 | 0.790 |
| NZ | 0.426 | 0.157 | 0.490 | 1.073 | 0.726 | 0.244 | 0.115 | 1.085 |
| Ontario | 0.264 | 0.146 | 0.586 | 0.995 | 0.029 | 0.182 | 0.817 | 1.028 |
| Full sample | 0.279 | 0.170 | 0.536 | 0.985 | 0.154 | 0.252 | 0.589 | 0.995 |

Table 4.4 reports the monotonicity violations in the TLG models for both the long and short periods. The model shows a frequency of monotonicity violations in the long period for the Australian DNSPs of 34.2 per cent. For all DNSPs, 13.0 per cent of observations exhibit monotonicity violations.

### Table 4.4 4Comp Monotonicity violations in SFATLG models (%)

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *By DNSP* | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| AGD | 5.6 | 0.0 | 0.0 | 5.6 | 100.0 | 0.0 | 0.0 | 100.0 |
| CIT | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| END | 88.9 | 0.0 | 0.0 | 88.9 | 100.0 | 0.0 | 0.0 | 100.0 |
| ENX | 33.3 | 0.0 | 0.0 | 33.3 | 100.0 | 0.0 | 0.0 | 100.0 |
| ERG | 100.0 | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| ESS | 100.0 | 0.0 | 0.0 | 100.0 | 83.3 | 0.0 | 0.0 | 83.3 |
| JEN | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| PCR | 5.6 | 0.0 | 0.0 | 5.6 | 100.0 | 0.0 | 0.0 | 100.0 |
| SAP | 100.0 | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| AND | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| TND | 11.1 | 0.0 | 0.0 | 11.1 | 100.0 | 0.0 | 0.0 | 100.0 |
| UED | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| *By jurisdiction* | | | | | | | | |
| Australia | 34.2 | 0.0 | 0.0 | 34.2 | 98.7 | 0.0 | 0.0 | 98.7 |
| NZ | 0.0 | 0.0 | 0.0 | 0.0 | 10.5 | 0.0 | 33.3 | 43.9 |
| Ontario | 12.1 | 0.0 | 0.0 | 12.1 | 35.9 | 0.0 | 0.0 | 35.9 |
| Full sample | 13.0 | 0.0 | 0.0 | 13.0 | 41.4 | 0.0 | 10.4 | 51.8 |

These results are intermediate between the standard LSETLG and SFATLG models for Australian DNSPs, but an improvement over those models for the sample as a whole

(Quantonomics 2024a, 148). In the short period, the issue becomes more severe, with 98.7 per cent of Australian observations and 51.8 per cent of the total sample affected. These results indicate that the model is not viable in the short period.

### 4.1.2 Specification Statistics

Tables 4.1 and 4.2 report the adjusted R-squared values for each model, all of which exceed 0.99, indicating a very high degree of explanatory power. Additional diagnostic statistics are presented in Table 4.5.

Table 4.5 4Comp Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value* | *Stat.* | *p-value* |
| ***SFACD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.18 | | 0.27 | |
| Shapiro–Wilk W test | 6.147 | 0.000 | 6.237 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 24.10 | | 24.95 | |
| Condition number | 947.51 | | 1418.82 | |
| ***SFATLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.18 | | 0.41 | |
| Shapiro–Wilk W test | 5.934 | 0.000 | 6.296 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 821.59 | | 829.92 | |
| Condition number | 1592.134 | | 2365.40 | |
| *Joint parameter tests* | | | | |
| Higher-order output terms | 19.74 | 0.003 | 53.63 | 0.000 |

Residual normality tests show that severe outliers (based on the IQR method) are rare (less than 0.5 per cent) for both SFACD and SFATLG models across both long and short periods. However, the Shapiro–Wilk test rejects normality, indicating the residuals deviate from a normal distribution. The SFACD models show moderate multicollinearity with average VIFs around 25 and high condition numbers. SFATLG models show much higher multicollinearity due to the inclusion of interaction and squared terms in the Translog form. The Translog specification is supported: in both periods, joint tests confirm the significance of higher-order terms at the 5 per cent level.

### 4.1.3 Efficiency Scores

Table 4.6 presents the average SFACD and SFATLG efficiency scores for each Australian DNSP in both the long and short period analyses. Figure 4.1 illustrates the trends in efficiency scores over time.

In this model, the overall efficiency score is calculated as the product of persistent inefficiency and transitory efficiency scores. As shown in Table 4.6, the efficiency scores are extremely high, with no DNSP scoring below 0.9. In the short period, all DNSPs appear to operate at full efficiency throughout 2012–2023. In the long period, some variation is visible, but all scores remain above 0.8 over 2006–2023

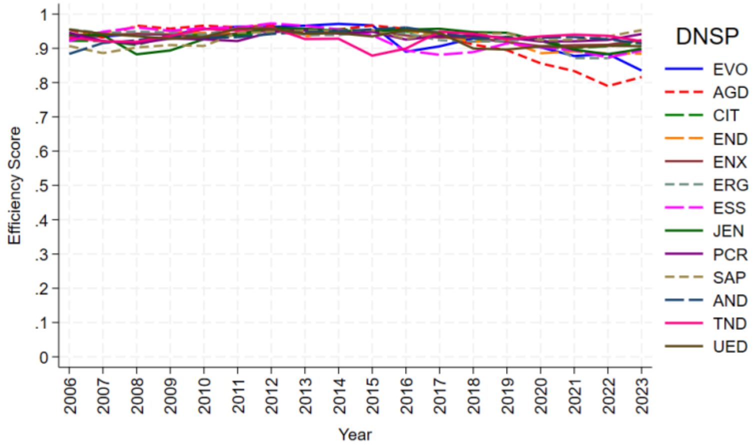
Table 4.6 Average Efficiency Scores by Australian DNSP

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *CD* | *Rank* | *TLG* | *Rank* | *CD* | *Rank* | *TLG* | *Rank* |
| EVO | 0.927 | 11 | 0.929 | 11 | 0.997 | 1 | 0.997 | 4 |
| AGD | 0.921 | 13 | 0.925 | 13 | 0.997 | 3 | 0.997 | 1 |
| CIT | 0.932 | 4 | 0.934 | 4 | 0.997 | 9 | 0.997 | 10 |
| END | 0.931 | 8 | 0.934 | 5 | 0.997 | 8 | 0.997 | 5 |
| ENX | 0.934 | 1 | 0.937 | 1 | 0.997 | 6 | 0.997 | 2 |
| ERG | 0.931 | 5 | 0.934 | 6 | 0.997 | 2 | 0.997 | 8 |
| ESS | 0.926 | 12 | 0.929 | 12 | 0.997 | 4 | 0.997 | 9 |
| JEN | 0.930 | 10 | 0.932 | 10 | 0.997 | 5 | 0.997 | 3 |
| PCR | 0.933 | 3 | 0.934 | 2 | 0.997 | 13 | 0.997 | 11 |
| SAP | 0.931 | 7 | 0.933 | 9 | 0.997 | 12 | 0.997 | 12 |
| AND | 0.933 | 2 | 0.934 | 3 | 0.997 | 7 | 0.997 | 6 |
| TND | 0.931 | 6 | 0.933 | 7 | 0.997 | 10 | 0.997 | 13 |
| UED | 0.930 | 9 | 0.933 | 8 | 0.997 | 11 | 0.997 | 7 |
| Australia | 0.930 | | 0.932 | | 0.997 | | 0.997 | |

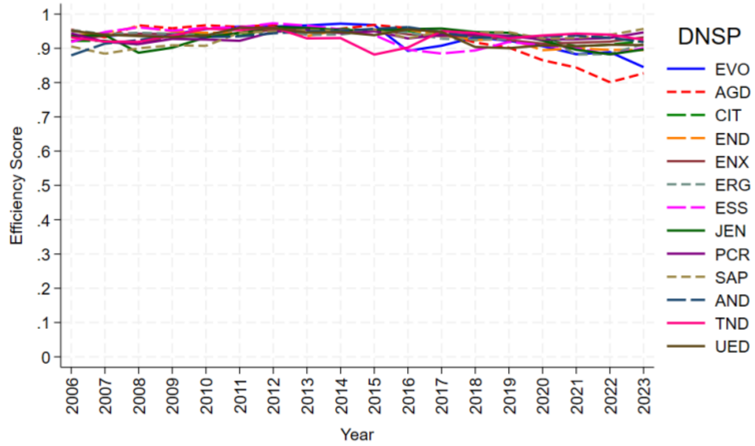
### 4.1.4 Concluding comments

These high efficiency levels may be because this model may attribute a substantial portion of the variation to firm-specific effects rather than inefficiency.

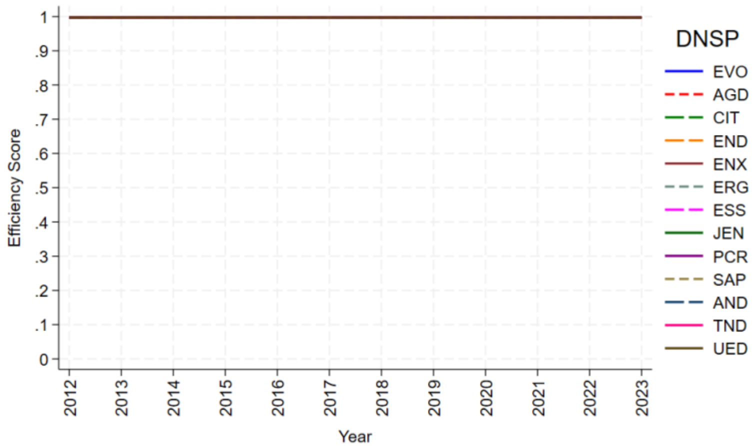
Figure 4.1: Efficiency Trends by DNSP



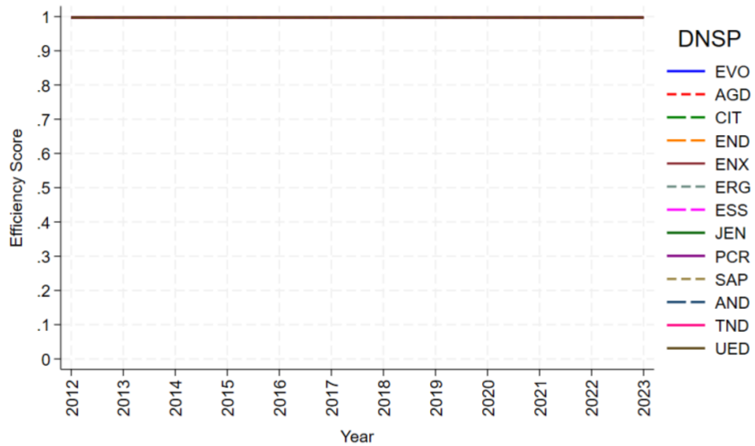

*SFACD Long Period*




*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

# Chapter 2: Fixed Effect time-varying inefficiency models

# 1 LSE Models Time Varying Models

The standard LSE time invarying opex cost function has the specification:

$$c_{it} = \alpha + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \lambda t + \sum_{k=2}^{13} \gamma_k d_k + \varepsilon_{it} \quad (1.1)$$

where $i$ refers to firm $i$; $c_{it}$ is the log opex cost of firm $i$ in period $t$; $\boldsymbol{x_{it}}$ is the vector of the values of the explanatory variables for firm $i$ in period $t$;[10] the parameter $\lambda$ represents the coefficient for the time trend variable, capturing the rate of technical change, trends in omitted OEFs and changes in efficiency over time, and $d_k$ represent firm-specific dummy variables for each of the 13 Australian DNSPs;[11] and $\varepsilon_{it}$ is a white noise disturbance.

The technical efficiency measures are based on the estimates of $\gamma_k$ parameters. The technical efficiency of firm $k$ is obtained using the formula:

$$\theta_k = \exp[\min(0, \gamma_2, \dots, \gamma_{13}) - \gamma_k] \quad (1.2)$$

The time varying LSE opex cost function extends Equation 1.1 to allow for time-varying inefficiency by introducing interaction terms between the time trend variable and the firm-specific dummy variables. In the linear case:

$$c_{it} = \alpha + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \lambda t + \sum_{k=2}^{13} d_k(\gamma_k + \gamma_{kt} t) + \gamma_{1t} t + \varepsilon_{it} \quad (1.3)$$

It is feasible to have both the time-trend variable ($t$) and the time-interactions with the inefficiency effects ($d_k t$ ) because the 13 Australian DNSPs are a subset of the total sample of DNSPs. In this case, the cost efficiency of firm $k$ in period $t$ is obtained using the formula:

$$\theta_{kt} = \exp[\min(\gamma_{1t} t, \gamma_2 + \gamma_{2t} t, \dots, \gamma_{13} + \gamma_{13t} t) - (\gamma_{kt} + \gamma_{kt} t)] \quad (1.4)$$

More specifically, by incorporating DNSP-specific time trends for each Australian DNSP, the estimated value of $\lambda$ represents the average time trend for the 2 remaining jurisdictions (New Zealand and Ontario). This is assumed to be the rate of technical change applicable to Australian DNSPs. This model allows for a specific time trend for each Australian DNSP, rather than for Australian DNSPs to be grouped together as a whole. However, the model does not decompose each Australian DNSP's time trend further into separate estimates of technical change and efficiency change.

In this section, we present empirical results for four alternative specifications for the standard LSE model using time-varying approaches:

[10] The explanatory variables include the log of output variables—customer numbers, circuit length, and RMD—the log of the share of underground cables, which is a proxy for operational environmental factors (OEF), and jurisdictional dummy variables for the New Zealand and Ontario DNSPs.

[11] DNSP 1 has been arbitrarily chosen as the base firm so that $\gamma_1 = 0$. The choice of base has no effect because the inefficiency score is calculated relative to the minimum $\gamma$.

- LSE-ADTT: allows for time-varying inefficiency through interaction terms between the time trend variable and Australian DNSP-specific dummy variables. This specification is discussed in Quantonomics (2023). Technical change is proxied by a general time trend variable applying to all DNSPs (including Ontario and New Zealand).
- LSE-ADTT–GTC: a variation of the LSE-ADTT model that incorporates a general index of technical change (GTC) instead of the general time trend.
- LSE-AJTT: in addition to the time trend for each Australian DNSP, separate time trends for NZ and Ontario are included.
- LSE-AJTT-GTC: a variation of the LSE-AJTT model that incorporates a general index of technical change (GTC) instead of the general time trend.

## 1.1 LSE-ADTT : LSE time-varying inefficiency through interaction of Australian DNSP-specific fixed effects and the time trend variable

Tables 1.1.1 and 1.1.2 present the estimation results for both long and short periods.

### 1.1.1 Consistency with economic theory or industry knowledge

The estimation tables show that that:

- In both the LSECD and LSETLG models, across both the long and short periods, the primary coefficients of the output variables have the expected signs and are statistically significant.
- The variable representing underground cables sharing (*lz1*) has a negative and statistically significant coefficient across all models.

Table 1.1.3 presents the estimated output elasticities for the LSECD and LSETLG models in the long and short periods. Across all specifications, the sum of the elasticities is close to one, indicating approximate constant returns to scale. The output elasticities are largely consistent between the long and short periods for each model. The LSECD models place greater emphasis on customer numbers and less on RMD, whereas the LSETLG models place greater emphasis on customer numbers followed closely by RMD.

Table 1.1.1 Parameter Estimates LSECD Models

| | Long Period | | | Short Period | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *ly1* | 0.544 | 0.074 | 7.32 | 0.546 | 0.073 | 7.50 |
| *ly2* | 0.227 | 0.034 | 6.59 | 0.262 | 0.032 | 8.19 |
| *ly3* | 0.194 | 0.064 | 3.03 | 0.159 | 0.067 | 2.36 |
| *lz1* | -0.091 | 0.025 | -3.56 | -0.085 | 0.025 | -3.41 |
| *yr* | 0.013 | 0.002 | 7.72 | 0.011 | 0.002 | 4.64 |
| *jur2* | -48.711 | 32.863 | -1.48 | -112.818 | 47.041 | -2.40 |
| *jur3* | -48.479 | 32.864 | -1.48 | -112.565 | 47.042 | -2.39 |
| *d2* | 36.923 | 46.606 | 0.79 | 42.032 | 57.776 | 0.73 |
| *d3* | -38.963 | 37.320 | -1.04 | -56.351 | 50.054 | -1.13 |
| *d4* | -1.625 | 38.707 | -0.04 | -27.159 | 52.249 | -0.52 |
| *d5* | -32.882 | 35.771 | -0.92 | -59.034 | 49.805 | -1.19 |
| *d6* | 4.873 | 39.458 | 0.12 | -32.258 | 55.489 | -0.58 |
| *d7* | -12.406 | 42.188 | -0.29 | -4.452 | 54.849 | -0.08 |
| *d8* | -22.482 | 40.630 | -0.55 | -21.747 | 50.545 | -0.43 |
| *d9* | -33.363 | 37.184 | -0.90 | -80.926 | 51.084 | -1.58 |
| *d10* | -70.505 | 38.678 | -1.82 | -102.676 | 53.580 | -1.92 |
| *d11* | -51.399 | 37.115 | -1.38 | -68.687 | 50.880 | -1.35 |
| *d12* | -32.053 | 42.519 | -0.75 | -72.300 | 61.445 | -1.18 |
| *d13* | -9.403 | 38.906 | -0.24 | -40.358 | 54.288 | -0.74 |
| *dt1* | -0.024 | 0.016 | -1.47 | -0.056 | 0.023 | -2.39 |
| *dt2* | -0.042 | 0.017 | -2.56 | -0.077 | 0.017 | -4.53 |
| *dt3* | -0.005 | 0.009 | -0.53 | -0.028 | 0.009 | -3.08 |
| *dt4* | -0.023 | 0.010 | -2.25 | -0.042 | 0.012 | -3.64 |
| *dt5* | -0.008 | 0.007 | -1.06 | -0.027 | 0.009 | -3.08 |
| *dt6* | -0.027 | 0.011 | -2.39 | -0.040 | 0.015 | -2.67 |
| *dt7* | -0.018 | 0.013 | -1.35 | -0.054 | 0.014 | -3.74 |
| *dt8* | -0.013 | 0.012 | -1.08 | -0.045 | 0.010 | -4.69 |
| *dt9* | -0.008 | 0.009 | -0.87 | -0.016 | 0.010 | -1.55 |
| *dt10* | 0.011 | 0.010 | 1.03 | -0.005 | 0.013 | -0.39 |
| *dt11* | 0.001 | 0.009 | 0.14 | -0.022 | 0.010 | -2.18 |
| *dt12* | -0.008 | 0.014 | -0.61 | -0.020 | 0.020 | -1.02 |
| *dt13* | -0.020 | 0.011 | -1.85 | -0.036 | 0.014 | -2.62 |
| *_cons* | 32.937 | 32.689 | 1.01 | 101.667 | 46.800 | 2.17 |
| *rho* | 0.766 | | | 0.676 | | |
| *R2* | 0.992 | | | 0.995 | | |
| *Adj Pseudo* $R^2$ | 0.980 | | | 0.982 | | |
| *N* | 1,098 | | | 732 | | |

Table 1.1.2 Parameter Estimates LSETLG Models

| | *LSETLG - Long Period* | | | *LSETLG- Short Period* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *ly1* | 0.380 | 0.078 | 4.85 | 0.380 | 0.079 | 4.81 |
| *ly2* | 0.230 | 0.034 | 6.84 | 0.263 | 0.030 | 8.79 |
| *ly3* | 0.345 | 0.066 | 5.20 | 0.313 | 0.068 | 4.61 |
| *ly11* | -0.243 | 0.527 | -0.46 | 0.200 | 0.572 | 0.35 |
| *ly12* | 0.295 | 0.123 | 2.41 | 0.177 | 0.126 | 1.40 |
| *ly13* | -0.103 | 0.419 | -0.25 | -0.436 | 0.440 | -0.99 |
| *ly22* | -0.045 | 0.043 | -1.04 | 0.015 | 0.040 | 0.36 |
| *ly23* | -0.227 | 0.101 | -2.25 | -0.180 | 0.103 | -1.75 |
| *ly33* | 0.388 | 0.335 | 1.16 | 0.689 | 0.338 | 2.04 |
| *lz1* | -0.102 | 0.028 | -3.62 | -0.084 | 0.025 | -3.37 |
| *yr* | 0.015 | 0.002 | 8.98 | 0.012 | 0.002 | 5.75 |
| *jur2* | -55.968 | 32.252 | -1.74 | -123.549 | 43.815 | -2.82 |
| *jur3* | -55.798 | 32.253 | -1.73 | -123.335 | 43.816 | -2.81 |
| *d2* | 30.354 | 45.203 | 0.67 | 28.712 | 54.165 | 0.53 |
| *d3* | -43.465 | 36.702 | -1.18 | -64.222 | 46.948 | -1.37 |
| *d4* | -7.814 | 38.080 | -0.21 | -42.119 | 49.200 | -0.86 |
| *d5* | -36.390 | 34.886 | -1.04 | -71.023 | 46.804 | -1.52 |
| *d6* | 5.434 | 38.705 | 0.14 | -39.812 | 51.941 | -0.77 |
| *d7* | -15.756 | 41.415 | -0.38 | -13.744 | 51.365 | -0.27 |
| *d8* | -30.175 | 39.969 | -0.75 | -34.372 | 48.024 | -0.72 |
| *d9* | -37.392 | 36.503 | -1.02 | -87.508 | 48.091 | -1.82 |
| *d10* | -72.892 | 37.832 | -1.93 | -109.511 | 50.142 | -2.18 |
| *d11* | -56.650 | 36.444 | -1.55 | -76.323 | 47.882 | -1.59 |
| *d12* | -35.532 | 41.506 | -0.86 | -83.483 | 57.478 | -1.45 |
| *d13* | -12.922 | 38.081 | -0.34 | -52.057 | 50.850 | -1.02 |
| *dt1* | -0.028 | 0.016 | -1.72 | -0.061 | 0.022 | -2.81 |
| *dt2* | -0.043 | 0.016 | -2.69 | -0.075 | 0.016 | -4.71 |
| *dt3* | -0.006 | 0.009 | -0.69 | -0.029 | 0.009 | -3.31 |
| *dt4* | -0.024 | 0.010 | -2.32 | -0.040 | 0.011 | -3.55 |
| *dt5* | -0.010 | 0.007 | -1.39 | -0.026 | 0.009 | -3.05 |
| *dt6* | -0.030 | 0.011 | -2.79 | -0.041 | 0.014 | -2.93 |
| *dt7* | -0.020 | 0.013 | -1.52 | -0.054 | 0.014 | -3.99 |
| *dt8* | -0.013 | 0.012 | -1.07 | -0.044 | 0.010 | -4.42 |
| *dt9* | -0.009 | 0.009 | -1.07 | -0.018 | 0.010 | -1.78 |
| *dt10* | 0.008 | 0.010 | 0.82 | -0.007 | 0.012 | -0.57 |
| *dt11* | 0.000 | 0.009 | 0.03 | -0.023 | 0.010 | -2.36 |
| *dt12* | -0.010 | 0.013 | -0.77 | -0.020 | 0.019 | -1.07 |
| *dt13* | -0.021 | 0.010 | -2.08 | -0.036 | 0.013 | -2.72 |
| *_cons* | 35.857 | 32.076 | 1.12 | 108.695 | 43.583 | 2.49 |
| *rho* | 0.753 | | | 0.637 | | |
| *R2* | 0.992 | | | 0.995 | | |
| *Adj. Pseudo* $R^2$ | 0.982 | | | 0.986 | | |
| *N* | 1,098 | | | 732 | | |

Table 1.1.3 Output elasticities

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| LSECD | | | | | | | | |
| Full Sample | 0.544 | 0.227 | 0.194 | 0.964 | 0.546 | 0.262 | 0.159 | 0.967 |
| LSETLG | | | | | | | | |
| Australia | 0.353 | 0.290 | 0.366 | 1.009 | 0.356 | 0.310 | 0.331 | 0.997 |
| New Zealand | 0.675 | 0.235 | 0.029 | 0.939 | 0.659 | 0.309 | −0.034 | 0.933 |
| Ontario | 0.199 | 0.199 | 0.542 | 0.940 | 0.208 | 0.213 | 0.532 | 0.953 |
| Full sample | 0.380 | 0.230 | 0.345 | 0.954 | 0.380 | 0.263 | 0.313 | 0.956 |

Table 1.1.4 presents the monotonicity violations in the LSETLG model for both the long and short periods. In the long period, one DNSP (CIT) shows 100 per cent of its observations affected by MVs. In contrast, during the short period, no DNSP has more than 50 per cent of observations affected. This represents an improvement compared to the standard LSETLG models, where three DNSPs had more than 50 per cent of observations affected in the long period, and six DNSPs in the short period.

Table 1.1.4 Monotonicity violations in LSETLG models (%)

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| By DNSP | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| CIT | 100.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| END | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ENX | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ERG | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ESS | 0.0 | 0.0 | 44.4 | 44.4 | 0.0 | 0.0 | 16.7 | 16.7 |
| JEN | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| PCR | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| By jurisdiction | | | | | | | | |
| Australia | 7.7 | 0.0 | 3.4 | 11.1 | 0.0 | 0.0 | 1.3 | 1.3 |
| New Zealand | 0.0 | 0.0 | 42.7 | 42.7 | 0.0 | 0.0 | 52.6 | 52.6 |
| Ontario | 6.3 | 0.0 | 0.0 | 6.3 | 10.3 | 0.0 | 0.0 | 10.3 |
| Full sample | 4.6 | 0.0 | 14.0 | 18.7 | 4.9 | 0.0 | 16.7 | 21.6 |

Interestingly, unlike the standard LSETLG specification, the current model shows a higher number of MVs for Australian DNSPs in the long period than in the short period. Considering the observations from other jurisdictions, we note that New Zealand shows a high incidence of monotonicity violations in both the long and short periods, with more than 50 per cent of observations affected in the short period.

### 1.1.2 Specification Statistics

Tables 1.1.1 and 1.1.2 show the $R^2$-Adjusted for each model. All models report a pseudo-$R^2$ of 0.98 or higher, indicating strong goodness-of-fit. Other diagnostic statistics are shown in Table 1.1.5.

Table 1.1.5 LSE Models Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value* | *Stat.* | *p-value* |
| ***CD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.27 | | 0.00 | |
| Shapiro–Wilk W test | 0.967 | 0.000 | 0.977 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 311,380 | | 710,855 | |
| Condition number | 9,061 | | 13,637 | |
| ***TLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.18 | | 0.00 | |
| Shapiro–Wilk W test | 0.978 | 0.000 | 0.989 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 264,608 | | 604,380 | |
| Condition number | 13,100 | | 19,730 | |
| *Joint parameter tests* | | | | |
| Higher-order output terms | 47.07 | 0.000 | 78.59 | 0.000 |

Residual normality tests show that severe outliers (based on the IQR method) are rare (less than 0.3 per cent) for both SFACD and SFATLG models across both long and short periods. However, the Shapiro–Wilk test rejects normality, indicating the residuals deviate from a normal distribution. The Translog specification is supported: in both periods, joint tests confirm the significance of higher-order terms at the 5 per cent level.

One of the key concerns when estimating time-varying inefficiency in the LSE models, particularly through the inclusion of interaction terms between the time trend and dummy variables, is the presence of multicollinearity as the inclusion of time trend interactions with jurisdictional dummies adds another layer, significantly intensifying the correlation between explanatory variables.[12]

[12] While multicollinearity does not bias coefficient estimates, it raises concerns about the stability of those estimates. As multicollinearity increases, the standard errors of the coefficients tend to be inflated, making the estimates more sensitive to small changes in the data. This can lead to coefficients with incorrect signs or implausible magnitudes, undermining the reliability of the model (Greene 2012, 129).

In the LSE models presented in this section, multicollinearity is particularly strong in the interaction terms involving the time trend and dummy variables, as show the Average VIF and Condition number values.

### 1.1.3 Efficiency Scores

Table 1.1.6 presents the average efficiency scores from the LSECD and LSETLG models for each Australian DNSP in both the long and short periods. The average efficiency rankings are broadly consistent between the models and closely align with those from the standard ABR24 models.

Table 1.1.6 *Average* Efficiency Scores by Australian DNSP

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *LSECD* | *Rank* | *LSETLG* | *Rank* | *LSECD* | *Rank* | *LSETLG* | *Rank* |
| EVO | 0.503 | 13 | 0.459 | 13 | 0.497 | 13 | 0.478 | 13 |
| AGD | 0.578 | 11 | 0.549 | 12 | 0.604 | 12 | 0.596 | 11 |
| CIT | 0.763 | 6 | 0.696 | 7 | 0.703 | 6 | 0.702 | 7 |
| END | 0.665 | 9 | 0.657 | 8 | 0.682 | 8 | 0.693 | 8 |
| ENX | 0.678 | 8 | 0.653 | 9 | 0.672 | 9 | 0.663 | 9 |
| ERG | 0.555 | 12 | 0.554 | 11 | 0.607 | 11 | 0.638 | 10 |
| ESS | 0.663 | 10 | 0.703 | 6 | 0.698 | 7 | 0.755 | 6 |
| JEN | 0.709 | 7 | 0.573 | 10 | 0.665 | 10 | 0.585 | 12 |
| PCR | 0.977 | 1 | 0.980 | 1 | 1.000 | 1 | 1.000 | 1 |
| SAP | 0.942 | 2 | 0.945 | 2 | 0.913 | 2 | 0.926 | 2 |
| AND | 0.831 | 5 | 0.790 | 4 | 0.804 | 5 | 0.774 | 5 |
| TND | 0.836 | 4 | 0.794 | 3 | 0.845 | 4 | 0.823 | 3 |
| UED | 0.910 | 3 | 0.753 | 5 | 0.905 | 3 | 0.807 | 4 |
| Australia | 0.739 | | 0.700 | | 0.738 | | 0.726 | |

For the long period, the LSECD model shows an average efficiency score that is 2.6 per cent lower than its standard counterpart, while the LSETLG model is 2.4 per cent lower. For the short period, the LSECD is just 0.5 per cent higher and the SFATLG model shows has average score of just 0.1 per cent lower than the standard short-period model.

The alignment of average efficiency scores between the LSE-ADTT and standard models is strong, with correlations of 0.999 (long-period LSECD), 0.994 (long-period LSETLG), 0.999 (short-period LSECD), and 0.937 (short-period LSETLG), indicating solid agreement. A similar pattern is observed for efficiency rankings, with correlations of 1.000, 0.995, 0.995, and 0.868, respectively.

Figure 1.1.1 show the average efficiency scores across the standard LSECD, LSETLG, SFACD and SFATLG models, in the long period sample, and compares them to the average efficiency scores of the LSE-ADTT and the average opex partial factor productivity (OPFP) measures. The results are reasonably similar across all approaches.

The efficiency scores for Australian DNSPs from the long-period LSECD and LSETLG models show strong correlations with the OPFP measures, at 0.760 and 0.821, respectively. These correlations are higher than those observed in the standard LSECD models (0.741) and comparable to the standard LSETLG model (0.798).

Figure 1.1.1 Average Efficiency Scores by DNSP (2006–2023)

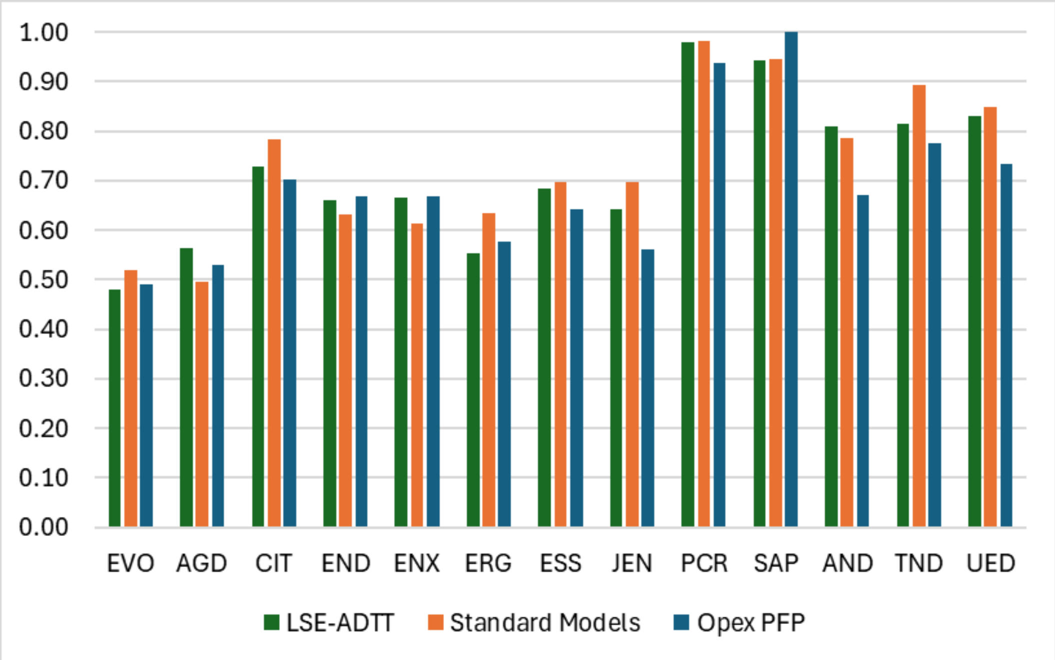
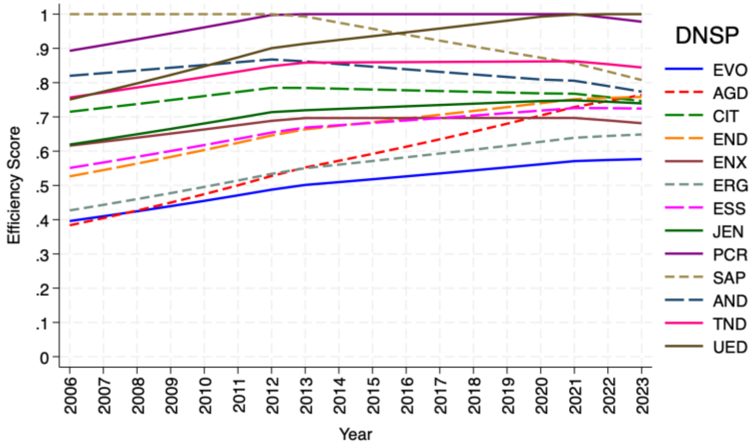



Figure 1.1.2 illustrates the trends in efficiency scores over time for all models. Figure 1.1.3 shows scatter charts of residuals plotted against fitted values of the dependent variable.

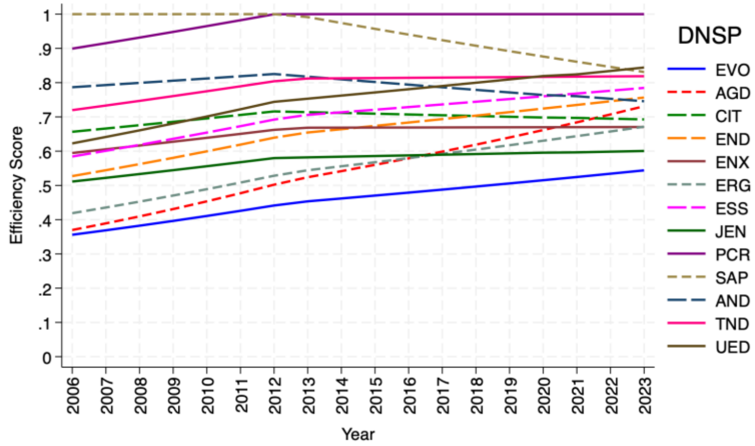
### 1.1.4 Concluding Comments

The main output variables in the LSE-ADTT model are consistently positive and statistically significant across all model specifications and time periods and the OEF variable is negative and statistically significant. The frequency of monotonicity violations is low in both Translog models for the short and long periods, and the resulting efficiency scores are broadly consistent with those obtained from the standard models. A key limitation of the LSE-ADTT model, however, is the presence of very high multicollinearity.

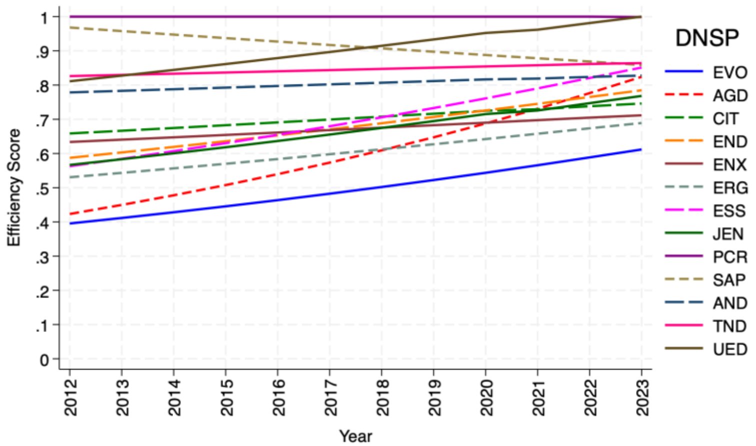
Figure 1.1.2 LSE-ADTT: Efficiency Trends by DNSP



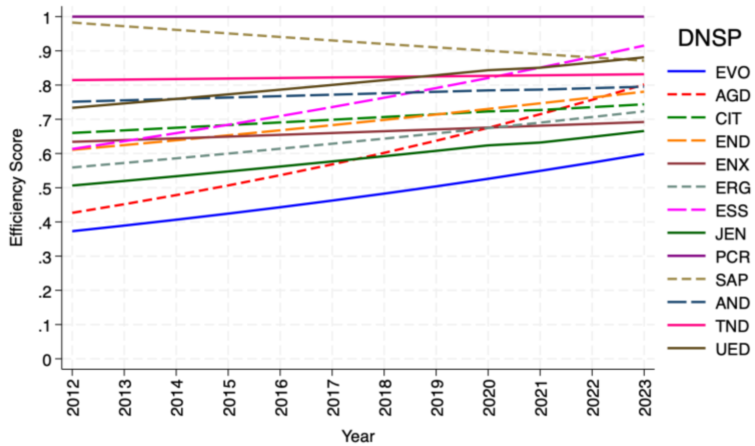

*LSECD Long Period*




*LSETLG Long Period*

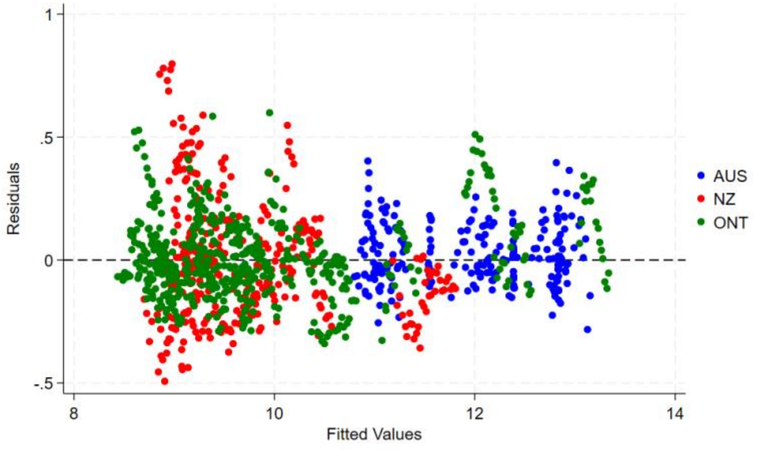



*LSECD Short Period*

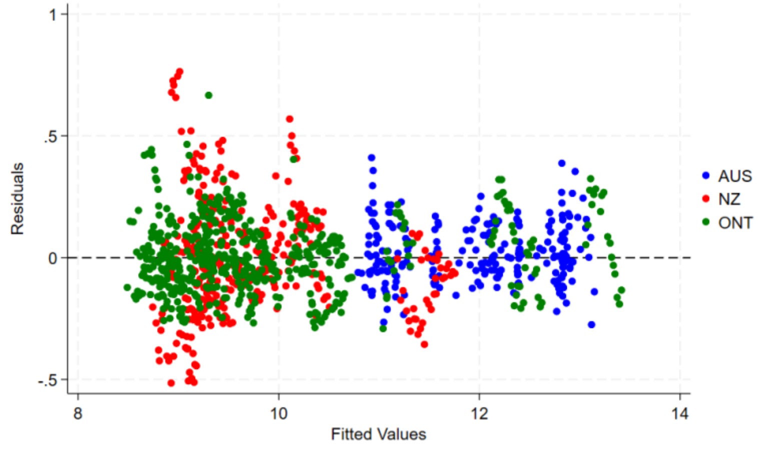



*LSETLG Short Period*

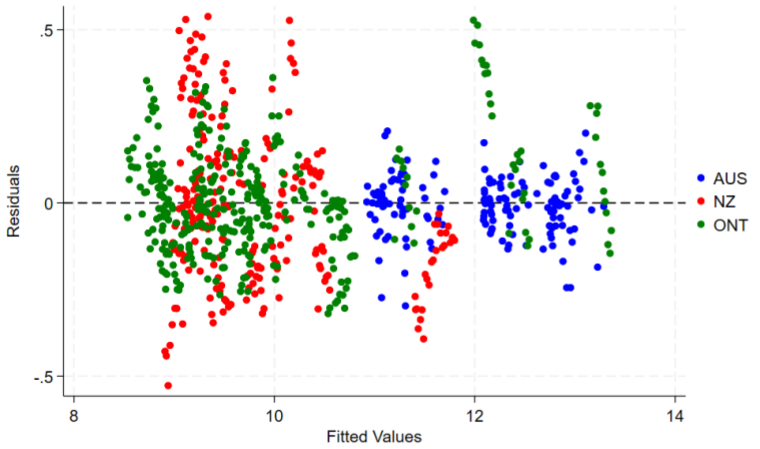
Figure 1.1.3 LSE-ADTT: Residual plots



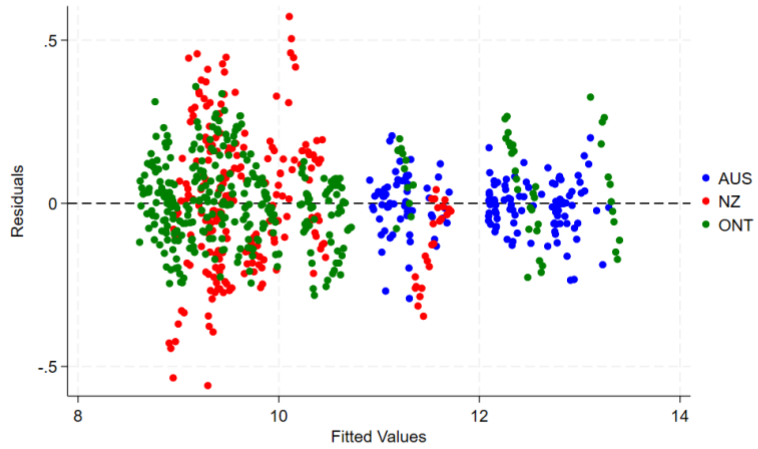

*LSECD Long Period*




*LSETLG Long Period*




*LSECD Short Period*




*LSETLG Short Period*

## 1.2 LSE-ADTT-GTC: LSE time-varying inefficiency through interaction with GTC

Tables 1.2.1 and 1.2.2 present the estimation results for both long and short periods.

### Table 1.2.1 Parameter Estimates LSECD Models

| | *LSECD-Long Period* | | | *LSECD-Short Period* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *ly1* | 0.575 | 0.068 | 8.48 | 0.560 | 0.072 | 7.82 |
| *ly2* | 0.223 | 0.030 | 7.33 | 0.265 | 0.031 | 8.58 |
| *ly3* | 0.170 | 0.059 | 2.86 | 0.143 | 0.066 | 2.17 |
| *lz1* | -0.092 | 0.022 | -4.14 | -0.078 | 0.024 | -3.32 |
| *gtc2* | 0.034 | 0.013 | 2.65 | | | |
| *gtc3* | 0.104 | 0.016 | 6.43 | | | |
| *gtc4* | 0.129 | 0.018 | 7.08 | 0.027 | 0.012 | 2.21 |
| *gtc5* | 0.146 | 0.020 | 7.39 | 0.051 | 0.016 | 3.21 |
| *gtc6* | 0.121 | 0.021 | 5.71 | 0.033 | 0.018 | 1.83 |
| *jur2* | -0.413 | 0.094 | -4.38 | -0.423 | 0.105 | -4.03 |
| *jur3* | -0.175 | 0.092 | -1.89 | -0.166 | 0.102 | -1.62 |
| *d2* | -0.128 | 0.129 | -0.99 | -0.177 | 0.126 | -1.41 |
| *d3* | -0.430 | 0.102 | -4.20 | -0.355 | 0.110 | -3.22 |
| *d4* | -0.285 | 0.107 | -2.66 | -0.325 | 0.113 | -2.87 |
| *d5* | -0.322 | 0.100 | -3.22 | -0.321 | 0.109 | -2.95 |
| *d6* | -0.104 | 0.116 | -0.90 | -0.202 | 0.126 | -1.61 |
| *d7* | -0.288 | 0.125 | -2.31 | -0.338 | 0.128 | -2.63 |
| *d8* | -0.358 | 0.112 | -3.19 | -0.288 | 0.111 | -2.60 |
| *d9* | -0.689 | 0.105 | -6.57 | -0.715 | 0.114 | -6.25 |
| *d10* | -0.655 | 0.110 | -5.93 | -0.632 | 0.119 | -5.32 |
| *d11* | -0.524 | 0.106 | -4.94 | -0.496 | 0.114 | -4.36 |
| *d12* | -0.526 | 0.119 | -4.41 | -0.546 | 0.136 | -4.03 |
| *d13* | -0.608 | 0.113 | -5.37 | -0.604 | 0.122 | -4.93 |
| *dt1* | -0.020 | 0.014 | -1.41 | -0.049 | 0.022 | -2.20 |
| *dt2* | -0.038 | 0.014 | -2.76 | -0.070 | 0.016 | -4.39 |
| *dt3* | -0.001 | 0.007 | -0.17 | -0.022 | 0.009 | -2.37 |
| *dt4* | -0.020 | 0.009 | -2.19 | -0.036 | 0.011 | -3.13 |
| *dt5* | -0.004 | 0.006 | -0.69 | -0.020 | 0.008 | -2.40 |
| *dt6* | -0.022 | 0.009 | -2.48 | -0.033 | 0.014 | -2.42 |
| *dt7* | -0.015 | 0.011 | -1.34 | -0.047 | 0.014 | -3.25 |
| *dt8* | -0.008 | 0.010 | -0.87 | -0.039 | 0.009 | -4.32 |
| *dt9* | -0.004 | 0.007 | -0.53 | -0.010 | 0.010 | -1.02 |
| *dt10* | 0.015 | 0.009 | 1.64 | 0.001 | 0.013 | 0.11 |
| *dt11* | 0.005 | 0.007 | 0.67 | -0.016 | 0.010 | -1.59 |
| *dt12* | -0.004 | 0.012 | -0.32 | -0.012 | 0.020 | -0.63 |
| *dt13* | -0.015 | 0.009 | -1.63 | -0.030 | 0.014 | -2.10 |
| *_cons* | 10.341 | 0.094 | 110.27 | 10.488 | 0.103 | 101.41 |
| *rho* | 0.699 | | | 0.654 | | |
| *R2* | 0.991 | | | 0.995 | | |
| *Adj. Pseudo* $R^2$ | 0.980 | | | 0.982 | | |
| *N* | 1,098 | | | 732 | | |

Table 1.2.2 Parameter Estimates LSETLG Models

| | *LSETLG - LP* | | | *LSETLG-SP* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *ly1* | 0.432 | 0.071 | 6.05 | 0.409 | 0.075 | 5.42 |
| *ly2* | 0.225 | 0.030 | 7.44 | 0.263 | 0.028 | 9.24 |
| *ly3* | 0.300 | 0.060 | 4.97 | 0.284 | 0.065 | 4.41 |
| *ly11* | -0.058 | 0.518 | -0.11 | 0.300 | 0.578 | 0.52 |
| *ly12* | 0.202 | 0.117 | 1.73 | 0.119 | 0.127 | 0.94 |
| *ly13* | -0.204 | 0.412 | -0.49 | -0.485 | 0.444 | -1.09 |
| *ly22* | -0.008 | 0.039 | -0.20 | 0.038 | 0.039 | 0.98 |
| *ly23* | -0.171 | 0.098 | -1.75 | -0.144 | 0.104 | -1.38 |
| *ly33* | 0.441 | 0.326 | 1.35 | 0.707 | 0.340 | 2.08 |
| *lz1* | -0.093 | 0.025 | -3.70 | -0.072 | 0.023 | -3.10 |
| *gtc2* | 0.037 | 0.013 | 2.95 | | | |
| *gtc3* | 0.112 | 0.016 | 6.94 | | | |
| *gtc4* | 0.141 | 0.018 | 7.80 | 0.033 | 0.012 | 2.76 |
| *gtc5* | 0.163 | 0.020 | 8.26 | 0.063 | 0.015 | 4.08 |
| *gtc6* | 0.142 | 0.021 | 6.70 | 0.051 | 0.017 | 2.90 |
| *jur2* | -0.465 | 0.094 | -4.93 | -0.491 | 0.093 | -5.25 |
| *jur3* | -0.280 | 0.092 | -3.03 | -0.268 | 0.091 | -2.95 |
| *d2* | -0.168 | 0.141 | -1.19 | -0.208 | 0.129 | -1.61 |
| *d3* | -0.447 | 0.104 | -4.31 | -0.405 | 0.100 | -4.04 |
| *d4* | -0.358 | 0.110 | -3.25 | -0.379 | 0.104 | -3.65 |
| *d5* | -0.369 | 0.110 | -3.36 | -0.344 | 0.110 | -3.12 |
| *d6* | -0.217 | 0.137 | -1.59 | -0.314 | 0.134 | -2.34 |
| *d7* | -0.438 | 0.146 | -3.01 | -0.463 | 0.143 | -3.23 |
| *d8* | -0.265 | 0.124 | -2.14 | -0.216 | 0.118 | -1.84 |
| *d9* | -0.762 | 0.111 | -6.88 | -0.745 | 0.114 | -6.52 |
| *d10* | -0.743 | 0.117 | -6.33 | -0.686 | 0.116 | -5.92 |
| *d11* | -0.548 | 0.115 | -4.76 | -0.487 | 0.121 | -4.01 |
| *d12* | -0.555 | 0.120 | -4.64 | -0.555 | 0.123 | -4.53 |
| *d13* | -0.525 | 0.128 | -4.10 | -0.540 | 0.129 | -4.17 |
| *dt1* | -0.022 | 0.014 | -1.60 | -0.054 | 0.020 | -2.64 |
| *dt2* | -0.038 | 0.014 | -2.80 | -0.069 | 0.015 | -4.63 |
| *dt3* | -0.002 | 0.007 | -0.26 | -0.023 | 0.009 | -2.57 |
| *dt4* | -0.019 | 0.009 | -2.15 | -0.034 | 0.011 | -3.07 |
| *dt5* | -0.005 | 0.006 | -0.88 | -0.020 | 0.008 | -2.40 |
| *dt6* | -0.024 | 0.009 | -2.70 | -0.034 | 0.013 | -2.62 |
| *dt7* | -0.016 | 0.011 | -1.42 | -0.047 | 0.014 | -3.46 |
| *dt8* | -0.008 | 0.010 | -0.82 | -0.039 | 0.010 | -4.09 |
| *dt9* | -0.005 | 0.007 | -0.66 | -0.012 | 0.010 | -1.24 |
| *dt10* | 0.013 | 0.009 | 1.50 | 0.000 | 0.012 | -0.02 |
| *dt11* | 0.005 | 0.008 | 0.59 | -0.017 | 0.010 | -1.80 |
| *dt12* | -0.005 | 0.012 | -0.40 | -0.012 | 0.018 | -0.64 |
| *dt13* | -0.017 | 0.009 | -1.75 | -0.030 | 0.013 | -2.21 |
| *_cons* | 10.339 | 0.094 | 110.33 | 10.483 | 0.091 | 114.65 |
| *rho* | 0.693 | | | 0.608 | | |
| *R2* | 0.992 | | | 0.995 | | |
| *Adj. Pseudo* $R^2$ | 0.983 | | | 0.986 | | |
| *N* | 1,098 | | | 732 | | |

### 1.2.1 Consistency with economic theory or industry knowledge

The estimation tables show that that in both the LSECD and LSETLG models, across both the long and short periods, the primary coefficients of the output variables have the expected signs and are statistically significant. The variable representing underground cables sharing (*lz1*) has a negative and statistically significant coefficient across all models.

Table 1.2.3 presents the estimated output elasticities for the LSECD and LSETLG models in the long and short periods. Across all specifications, the sum of the elasticities is close to one, indicating approximate constant returns to scale. Table 1.2.4 presents the monotonicity violations in the LSE-TLG model for both the long and short periods. In both cases, there are no violations for the Australian DNSPs. This represents an improvement compared to the previous time-varying LSE model.

#### Table 1.2.3 Output elasticities

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *LSECD* | | | | | | | | |
| Full Sample | 0.575 | 0.223 | 0.170 | 0.967 | 0.560 | 0.265 | 0.143 | 0.968 |
| *LSETLG* | | | | | | | | |
| Australia | 0.384 | 0.285 | 0.339 | 1.009 | 0.368 | 0.311 | 0.318 | 0.997 |
| New Zealand | 0.682 | 0.246 | 0.012 | 0.940 | 0.656 | 0.318 | -0.041 | 0.933 |
| Ontario | 0.289 | 0.183 | 0.472 | 0.944 | 0.266 | 0.205 | 0.482 | 0.953 |
| Full sample | 0.432 | 0.225 | 0.300 | 0.957 | 0.409 | 0.263 | 0.284 | 0.956 |

#### Table 1.2.4 Monotonicity violations in LSETLG models (%)

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *By DNSP* | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| CIT | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| END | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ENX | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ERG | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ESS | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| JEN | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| PCR | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| *By jurisdiction* | | | | | | | | |
| Australia | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| New Zealand | 0.0 | 0.0 | 48.2 | 48.2 | 0.0 | 0.0 | 55.7 | 55.7 |
| Ontario | 3.4 | 0.0 | 0.0 | 3.4 | 6.9 | 0.0 | 0.0 | 6.9 |
| Full sample | 1.6 | 0.0 | 15.0 | 16.7 | 3.3 | 0.0 | 17.3 | 20.6 |

### 1.2.2 Specification Statistics

Table 1.2.1 and 1.2.2 present the adjusted $R^2$ values for each model, all of which report pseudo-$R^2$ scores of 0.98 or higher, indicating a strong model fit. Additional diagnostic statistics are reported in Table 1.2.5.

Residual normality assessments show that severe outliers, as identified using the interquartile range (IQR) method, are rare (fewer than 0.5 per cent). However, the Shapiro–Wilk test rejects the null hypothesis of normality, suggesting that residuals deviate from a normal distribution. The Translog specification is supported in both periods, with joint significance tests confirming the relevance of higher-order terms at the five per cent level. The inclusion of the GTC terms has also substantially mitigated multicollinearity issues.

**Table 1.2.5 LSE Models Statistics Results**

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value* | *Stat.* | *p-value* |
| ***CD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.46 | | 0.00 | |
| Shapiro–Wilk W test | 0.962 | 0.000 | 0.976 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 8.90 | | 9.17 | |
| Condition number | 25.37 | | 26.62 | |
| ***TLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.36 | | 0.00 | |
| Shapiro–Wilk W test | 0.970 | 0.000 | 0.984 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 390.24 | | 399.59 | |
| Condition number | 486.61 | | 496.73 | |
| *Joint parameter tests* | | | | |
| Higher-order output terms | 52.45 | 0.000 | 83.74 | 0.000 |

### 1.2.3 Efficiency Scores

Table 1.2.6 shows the average of efficiency scores for each DNSP and model from both long and short period. Over the long period, the LSECD model reports an average efficiency score 3.2 per cent lower than its standard counterpart, and the LSETLG model produces efficiency scores 1.4 per cent lower than the standard. In the short period, the LSECD model returns an average 0.8 per cent higher, and the LSETLG model shows an average efficiency scores of 1.3 per cent higher, compared to their respective standard versions.

In terms of how closely the average efficiency levels align, the correlations between the LSE-ADTT-GTC models and the standard models are very strong. For LSECD, the correlation is nearly perfect (0.999 in both the long and short periods). For LSETLG, the correlation is also high (at 0.986 for the long period and 0.939 for the short period).

Efficiency rankings follow a similar pattern. The LSECD long-period model yields a near identical ranking to the standard version (correlation of 0.998). The LSETLG model also aligns closely, with a correlation of 0.973 in the long period. In the short period, the LSECD model shows a ranking correlation of 0.995, while the LSETLG model has a slightly lower correlation of 0.885. Overall, these results suggest strong consistency between the LSE-ADTT-GTC specifications and the standard models, both in terms of average scores and relative DNSP rankings.

Table 1.2.6 *Average* Efficiency Scores by Australian DNSP

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *LSECD* | *Rank* | *LSETLG* | *Rank* | *LSECD* | *Rank* | *LSETLG* | *Rank* |
| EVO | 0.495 | 13 | 0.459 | 13 | 0.499 | 13 | 0.486 | 13 |
| AGD | 0.574 | 11 | 0.553 | 12 | 0.607 | 11 | 0.605 | 11 |
| CIT | 0.754 | 6 | 0.710 | 6 | 0.703 | 6 | 0.717 | 7 |
| END | 0.658 | 9 | 0.655 | 9 | 0.684 | 8 | 0.700 | 8 |
| ENX | 0.676 | 8 | 0.656 | 8 | 0.677 | 9 | 0.672 | 9 |
| ERG | 0.550 | 12 | 0.572 | 11 | 0.605 | 12 | 0.656 | 10 |
| ESS | 0.658 | 9 | 0.708 | 7 | 0.698 | 7 | 0.767 | 6 |
| JEN | 0.706 | 7 | 0.595 | 10 | 0.668 | 10 | 0.602 | 12 |
| PCR | 0.979 | 1 | 0.976 | 1 | 1.000 | 1 | 1.000 | 1 |
| SAP | 0.939 | 2 | 0.950 | 2 | 0.918 | 2 | 0.940 | 2 |
| AND | 0.824 | 5 | 0.783 | 4 | 0.806 | 5 | 0.775 | 5 |
| TND | 0.829 | 4 | 0.791 | 3 | 0.845 | 4 | 0.827 | 3 |
| UED | 0.913 | 3 | 0.779 | 5 | 0.908 | 3 | 0.825 | 4 |
| Australia | 0.735 | | 0.707 | | 0.740 | | 0.736 | |

Figure 1.2.1 average efficiency scores across the standard LSECD, LSETLG, SFACD and SFATLG models, in the long period sample, and compares them to the average efficiency scores of the LSE-ADTT-GTC and the average opex partial factor productivity (OPFP) measures. The results are reasonably similar across all approaches.

The efficiency scores for Australian DNSPs from the long-period LSECD and LSETLG models show strong correlations with the OPFP measures, at 0.763 and 0.818, respectively. These correlations are higher than those observed in the standard LSECD (0.741) and LSETLG model (0.798).

Figure 1.2.2 presents the time varying LSECD and LSETLG efficiency scores for each Australian DNSP across the long and short period analysis. Most DNSPs display an upward trend in efficiency scores over the period, with some showing a more pronounced improvement while others maintain relatively steady performance. In this specification, it is particularly notable that PCR remains fully efficient throughout the entire period in the short-period models. Conversely, SAP appears to experience a gradual decline in efficiency in the long-period models, standing out as an exception to the broader trend of improvement.

Figure 1.2.1 Average Efficiency Scores by DNSP (2006–2023)

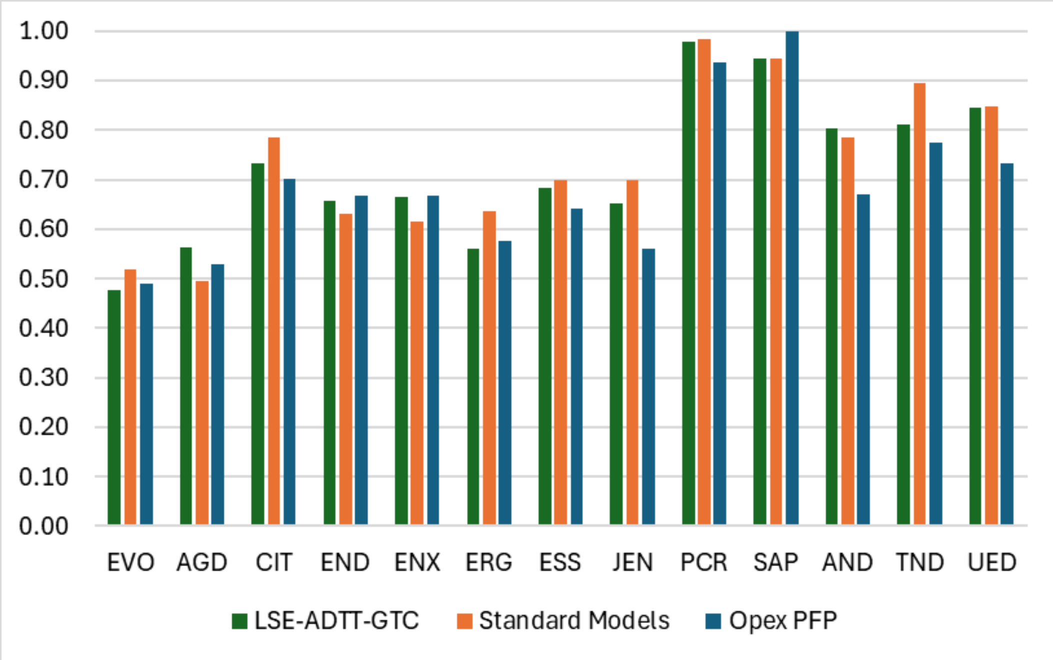
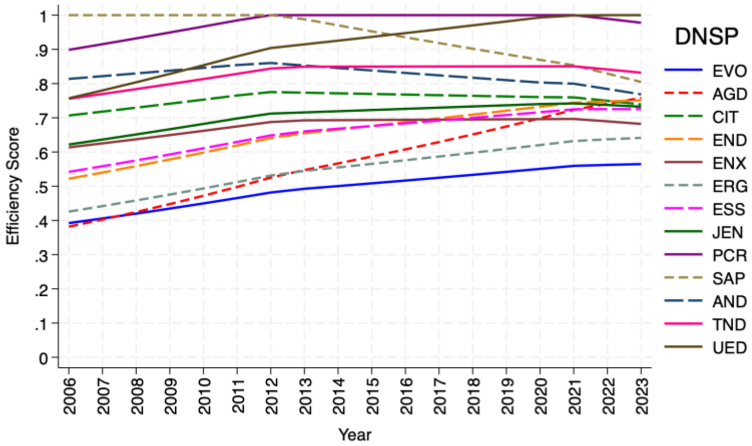



Figure 1.2.3 shows scatter charts of residuals plotted against fitted values of the dependent variable.

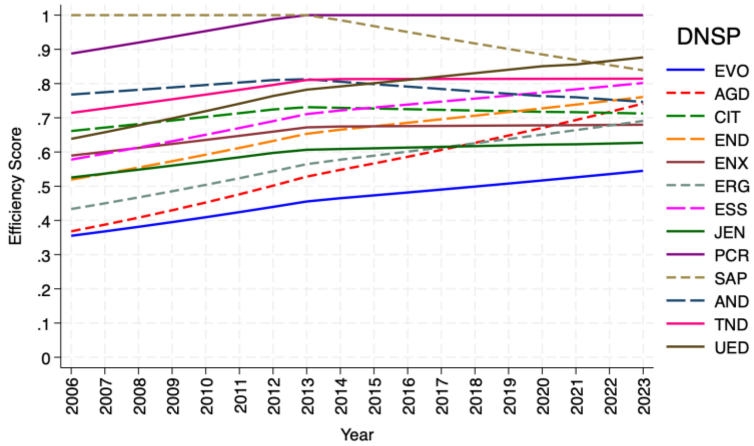
### 1.2.4 Concluding Comments

Similar to the LSE-ADTT model, the main output variables in the LSE-ADTT-GTC models are consistently positive and statistically significant across all model specifications and time periods. The OEF variable is negative and statistically significant. The frequency of monotonicity violations for Australian DNSPs is zero in both Translog models for the short and long periods, and the resulting efficiency scores are broadly consistent with those from the standard models. This model also presents a much more reasonable outcome in terms of multicollinearity.

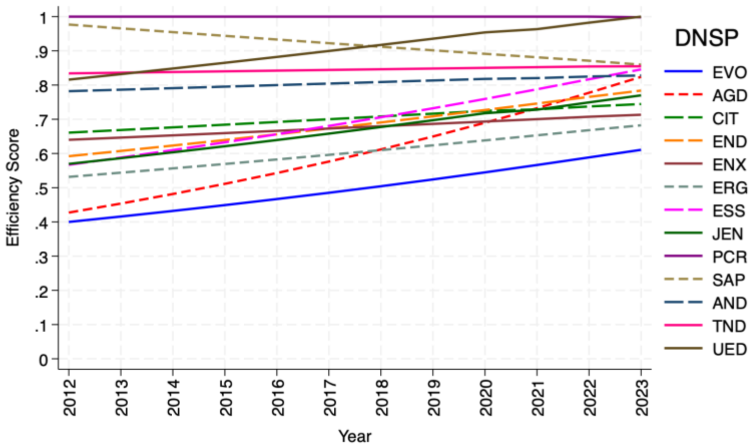
Figure 1.2.2 LSE-ADTT-GTC Efficiency Trends by DNSP



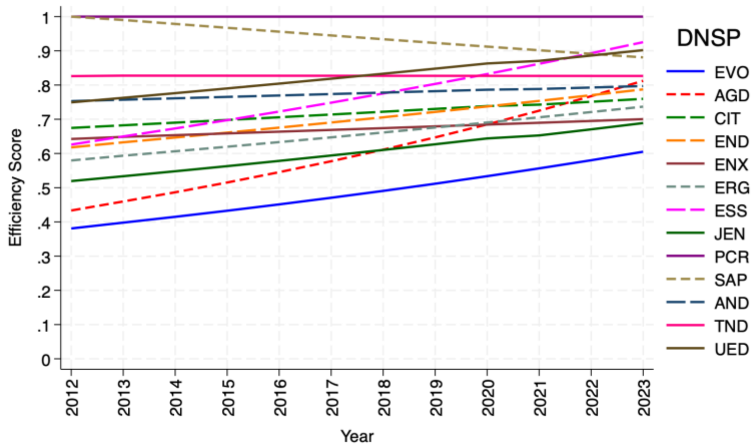

*LSECD Long Period*




*LSETLG Long Period*

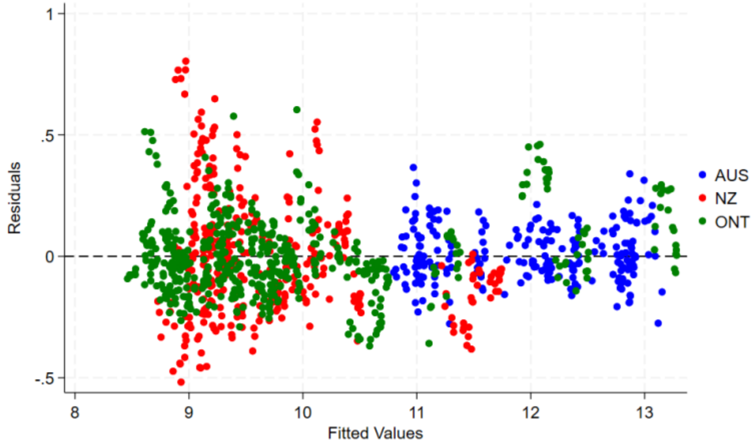



*LSECD Short Period*

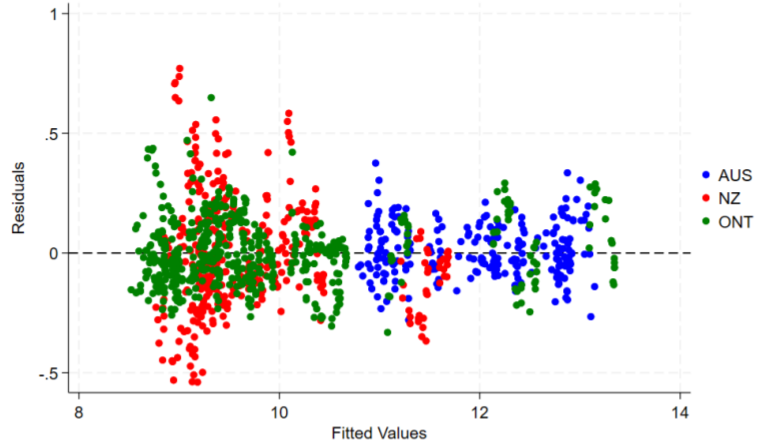



*LSETLG Short Period*

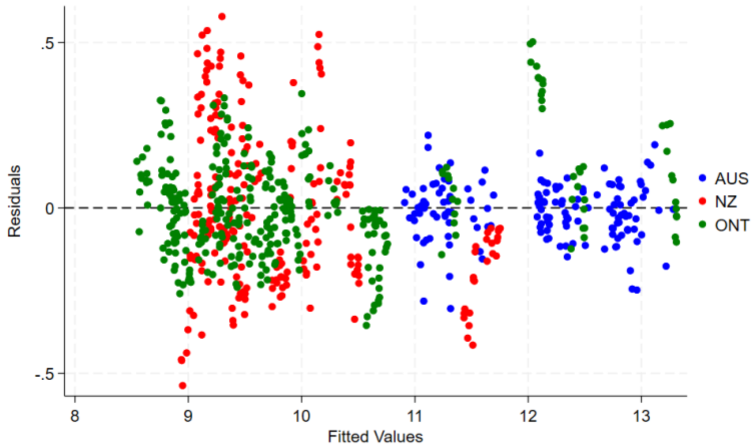
Figure 1.2.3 LSE-ADTT-GTC Residuals Plot



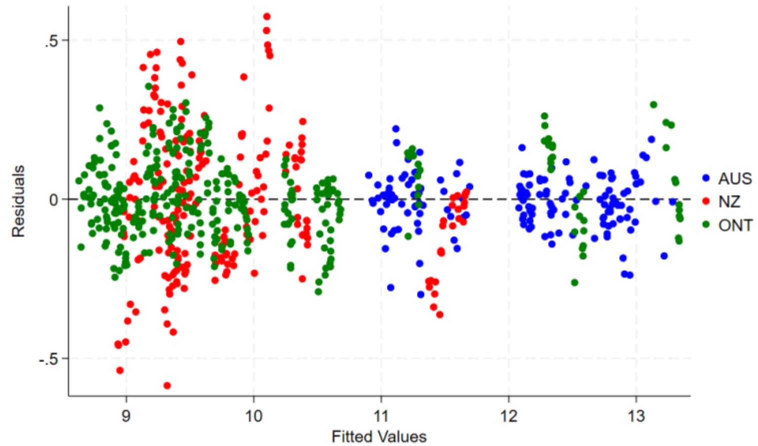

*LSECD Long Period*




*LSETLG Long Period*




*LSECD Short Period*




*LSETLG Short Period*

## 1.3 LSE-AJTT: LSE time-varying inefficiency through interaction of Australian DNSP-specific fixed effects and the time trend variable

In section 1.1, the ADTT model implicitly assumed that the general time trend variable represented the average rate of change of opex PFP for DNSPs in Ontario and NZ, and we assumed that this was equal to the underlying rate of technical change. This section presents a model which has a jurisdictional time trend variable for NZ DNSPs. This allows the average rate of change of opex PFP to differ between in Ontario and NZ. The general time trend variable now represents the average rate of change of opex PFP for Ontario, and we will assume that this represents the underlying rate of technical change.

Tables 1.3.1 and 1.3.2 present the estimation results for both long and short periods.

### 1.3.1 Consistency with economic theory or industry knowledge

The estimation tables show that that:

- In both the LSECD and LSETLG models, across both the long and short periods, the primary coefficients of the output variables have the expected signs and are statistically significant.
- The variable representing underground cables sharing (*lz1*) has a negative and statistically significant coefficient across all models.

Table 1.3.3 presents the estimated output elasticities for the LSECD and LSETLG models in the long and short periods. Across all specifications, the sum of the elasticities is close to one, indicating approximate constant returns to scale. The output elasticities are largely consistent between the long and short periods for each model. The LSECD model places greater emphasis on customer numbers and less on RMD. The LSETLG models also assign more weight to customer numbers, followed by RMD, with circuit length elasticities comparable to those of RMD.

Table 1.3.4 presents the monotonicity violations in the LSETLG model for both the long and short periods. In the long period, one DNSP (ESS) shows 100 per cent of its observations affected by MVs. In contrast, during the short period, there is no MVs for the Australian sample. This represents an improvement compared to the standard LSETLG models, where three DNSPs had more than 50 per cent of observations affected in the long period, and six DNSPs in the short period.

Interestingly, unlike the standard LSETLG specification, the current model shows a higher number of MVs for Australian DNSPs in the long period than in the short period. Considering the observations from other jurisdictions, we note that New Zealand shows a high incidence of monotonicity violations in both the long and short periods, with more than 50 per cent of observations affected.

Table 1.3.1 LSE-AJTT: Parameter Estimates LSECD Models

| | LSECD-Long Period | | | LSECD-Short Period | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *ly1* | 0.616 | 0.068 | 9.01 | 0.580 | 0.066 | 8.74 |
| *ly2* | 0.217 | 0.032 | 6.81 | 0.250 | 0.029 | 8.69 |
| *ly3* | 0.134 | 0.059 | 2.26 | 0.138 | 0.062 | 2.22 |
| *lz1* | -0.100 | 0.023 | -4.39 | -0.096 | 0.022 | -4.39 |
| *yr* | 0.004 | 0.002 | 2.16 | -0.002 | 0.002 | -0.71 |
| *jur2* | -0.416 | 0.106 | -3.92 | -0.425 | 0.092 | -4.60 |
| *jur3* | -0.166 | 0.104 | -1.60 | -0.175 | 0.090 | -1.95 |
| *d2* | -0.133 | 0.147 | -0.91 | -0.189 | 0.110 | -1.71 |
| *d3* | -0.433 | 0.118 | -3.67 | -0.370 | 0.096 | -3.87 |
| *d4* | -0.283 | 0.121 | -2.35 | -0.330 | 0.098 | -3.37 |
| *d5* | -0.325 | 0.113 | -2.88 | -0.330 | 0.095 | -3.49 |
| *d6* | -0.103 | 0.130 | -0.79 | -0.218 | 0.111 | -1.97 |
| *d7* | -0.304 | 0.140 | -2.17 | -0.362 | 0.112 | -3.22 |
| *d8* | -0.377 | 0.129 | -2.93 | -0.308 | 0.097 | -3.16 |
| *d9* | -0.703 | 0.120 | -5.87 | -0.737 | 0.100 | -7.39 |
| *d10* | -0.655 | 0.123 | -5.30 | -0.636 | 0.103 | -6.18 |
| *d11* | -0.547 | 0.120 | -4.58 | -0.510 | 0.099 | -5.15 |
| *d12* | -0.529 | 0.133 | -3.97 | -0.565 | 0.117 | -4.84 |
| *d13* | -0.626 | 0.125 | -5.00 | -0.631 | 0.105 | -6.00 |
| *dt1* | -0.015 | 0.015 | -0.99 | -0.044 | 0.020 | -2.17 |
| *dt2* | -0.034 | 0.015 | -2.21 | -0.065 | 0.015 | -4.39 |
| *dt3* | 0.004 | 0.009 | 0.43 | -0.017 | 0.008 | -2.10 |
| *dt4* | -0.015 | 0.010 | -1.57 | -0.031 | 0.010 | -3.00 |
| *dt5* | 0.000 | 0.007 | 0.05 | -0.016 | 0.008 | -2.03 |
| *dt6* | -0.018 | 0.010 | -1.75 | -0.028 | 0.013 | -2.14 |
| *dt7* | -0.010 | 0.013 | -0.78 | -0.041 | 0.013 | -3.11 |
| *dt8* | -0.004 | 0.011 | -0.36 | -0.034 | 0.009 | -3.88 |
| *dt9* | 0.001 | 0.008 | 0.13 | -0.005 | 0.009 | -0.53 |
| *dt10* | 0.019 | 0.010 | 1.97 | 0.006 | 0.012 | 0.48 |
| *dt11* | 0.010 | 0.009 | 1.16 | -0.010 | 0.009 | -1.12 |
| *dt12* | 0.000 | 0.013 | 0.01 | -0.006 | 0.018 | -0.31 |
| *dt13* | -0.011 | 0.010 | -1.08 | -0.024 | 0.012 | -1.99 |
| *t-nz* | 0.022 | 0.003 | 6.71 | 0.030 | 0.005 | 6.51 |
| *_cons* | 2.419 | 3.709 | 0.65 | 13.905 | 4.787 | 2.90 |
| *rho* | 0.732 | | | 0.597 | | |
| *R2* | 0.992 | | | 0.995 | | |
| *Adj Pseudo* $R^2$ | 0.981 | | | 0.984 | | |
| *N* | 1,098 | | | 732 | | |

Table 1.3.2 LSE-AJTT: Parameter Estimates LSETLG Models

| | *LSETLG - Long Period* | | | *LSETLG- Short Period* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *ly1* | 0.471 | 0.076 | 6.23 | 0.408 | 0.072 | 5.69 |
| *ly2* | 0.216 | 0.032 | 6.86 | 0.250 | 0.027 | 9.39 |
| *ly3* | 0.269 | 0.064 | 4.23 | 0.296 | 0.061 | 4.83 |
| *ly11* | -0.388 | 0.490 | -0.79 | -0.067 | 0.541 | -0.12 |
| *ly12* | 0.270 | 0.114 | 2.37 | 0.168 | 0.120 | 1.39 |
| *ly13* | 0.066 | 0.389 | 0.17 | -0.196 | 0.414 | -0.47 |
| *ly22* | -0.016 | 0.039 | -0.40 | 0.032 | 0.037 | 0.86 |
| *ly23* | -0.236 | 0.094 | -2.53 | -0.186 | 0.097 | -1.91 |
| *ly33* | 0.237 | 0.309 | 0.77 | 0.487 | 0.317 | 1.54 |
| *lz1* | -0.103 | 0.025 | -4.10 | -0.088 | 0.022 | -4.11 |
| *yr* | 0.006 | 0.002 | 3.20 | 0.000 | 0.002 | 0.13 |
| *jur2* | -0.471 | 0.105 | -4.49 | -0.489 | 0.087 | -5.63 |
| *jur3* | -0.273 | 0.103 | -2.65 | -0.278 | 0.084 | -3.29 |
| *d2* | -0.184 | 0.156 | -1.18 | -0.197 | 0.120 | -1.64 |
| *d3* | -0.461 | 0.118 | -3.90 | -0.420 | 0.092 | -4.57 |
| *d4* | -0.360 | 0.122 | -2.96 | -0.378 | 0.096 | -3.96 |
| *d5* | -0.375 | 0.121 | -3.09 | -0.329 | 0.102 | -3.22 |
| *d6* | -0.181 | 0.150 | -1.20 | -0.316 | 0.125 | -2.52 |
| *d7* | -0.444 | 0.158 | -2.80 | -0.464 | 0.131 | -3.54 |
| *d8* | -0.262 | 0.138 | -1.90 | -0.196 | 0.110 | -1.79 |
| *d9* | -0.774 | 0.124 | -6.22 | -0.743 | 0.105 | -7.05 |
| *d10* | -0.735 | 0.129 | -5.70 | -0.675 | 0.106 | -6.36 |
| *d11* | -0.563 | 0.127 | -4.44 | -0.459 | 0.112 | -4.09 |
| *d12* | -0.553 | 0.132 | -4.18 | -0.570 | 0.112 | -5.09 |
| *d13* | -0.530 | 0.138 | -3.85 | -0.524 | 0.119 | -4.42 |
| *dt1* | -0.019 | 0.015 | -1.23 | -0.049 | 0.020 | -2.54 |
| *dt2* | -0.034 | 0.015 | -2.29 | -0.063 | 0.015 | -4.35 |
| *dt3* | 0.002 | 0.009 | 0.27 | -0.018 | 0.008 | -2.27 |
| *dt4* | -0.016 | 0.010 | -1.63 | -0.028 | 0.010 | -2.71 |
| *dt5* | -0.001 | 0.007 | -0.21 | -0.014 | 0.008 | -1.75 |
| *dt6* | -0.022 | 0.010 | -2.11 | -0.029 | 0.013 | -2.28 |
| *dt7* | -0.011 | 0.013 | -0.91 | -0.042 | 0.013 | -3.27 |
| *dt8* | -0.004 | 0.011 | -0.33 | -0.031 | 0.009 | -3.31 |
| *dt9* | 0.000 | 0.008 | -0.04 | -0.005 | 0.009 | -0.52 |
| *dt10* | 0.017 | 0.010 | 1.77 | 0.005 | 0.011 | 0.43 |
| *dt11* | 0.009 | 0.008 | 1.08 | -0.010 | 0.009 | -1.11 |
| *dt12* | -0.002 | 0.012 | -0.14 | -0.006 | 0.017 | -0.33 |
| *dt13* | -0.013 | 0.010 | -1.30 | -0.022 | 0.012 | -1.91 |
| *t-nz* | 0.022 | 0.003 | 6.75 | 0.029 | 0.004 | 6.74 |
| *_cons* | -1.528 | 3.733 | -0.41 | 9.937 | 4.317 | 2.30 |
| *rho* | 0.725 | | | 0.572 | | |
| *R2* | 0.992 | | | 0.995 | | |
| *Adj. Pseudo $R^2$* | 0.984 | | | 0.987 | | |
| *N* | 1,098 | | | 732 | | |

Table 1.3.3 LSE-AJTT: Output elasticities

| | Long Period | | | | Short Period | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| LSECD | | | | | | | | |
| Full Sample | 0.616 | 0.217 | 0.134 | 0.967 | 0.580 | 0.250 | 0.138 | 0.969 |
| LSETLG | | | | | | | | |
| Australia | 0.419 | 0.272 | 0.320 | 1.010 | 0.286 | 0.304 | 0.397 | 0.988 |
| New Zealand | 0.703 | 0.252 | -0.022 | 0.933 | 0.647 | 0.310 | -0.030 | 0.927 |
| Ontario | 0.341 | 0.168 | 0.436 | 0.945 | 0.306 | 0.187 | 0.465 | 0.957 |
| Full sample | 0.470 | 0.216 | 0.269 | 0.955 | 0.408 | 0.250 | 0.296 | 0.954 |

Table 1.3.4 LSE-AJTT: Monotonicity violations in LSETLG models (%)

| | Long Period | | | | Short Period | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| By DNSP | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| CIT | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| END | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ENX | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ERG | 0.0 | 0.0 | 5.6 | 5.6 | 0.0 | 0.0 | 0.0 | 0.0 |
| ESS | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| JEN | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| PCR | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| By jurisdiction | | | | | | | | |
| Australia | 0.0 | 0.0 | 8.1 | 8.1 | 0.0 | 0.0 | 0.0 | 0.0 |
| New Zealand | 0.0 | 0.0 | 58.5 | 58.5 | 0.0 | 0.0 | 57.9 | 57.9 |
| Ontario | 0.0 | 0.0 | 0.0 | 0.0 | 3.4 | 0.0 | 0.0 | 3.4 |
| Full sample | 0.0 | 0.0 | 19.9 | 19.9 | 1.6 | 0.0 | 18.0 | 19.7 |

### 1.3.2 Specification Statistics

Tables 1.3.1 and 1.3.2 show the $R^2$-Adjusted for each model. All models report a pseudo-$R^2$ of 0.98 or higher, indicating strong goodness-of-fit. Other diagnostic statistics are shown in Table 1.3.5.

Residual normality tests show that severe outliers (based on the IQR method) are rare (less than 0.6 per cent) for both SFACD and SFATLG models across both long and short periods. However, the Shapiro–Wilk test rejects normality, indicating the residuals deviate from a normal distribution. The Translog specification is supported: in both periods, joint tests confirm the significance of higher-order terms at the 5 per cent level. Multicollinearity is particularly strong in the TLG models, as show the Average VIF and Condition number values.

Table 1.3.5 LSE-AJTT: LSE Models Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value* | *Stat.* | *p-value* |
| ***CD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.55 | | 0.14 | |
| Shapiro–Wilk W test | 0.966 | 0.000 | 0.977 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 9.26 | | 9.45 | |
| Condition number | 1,588.61 | | 2,371.66 | |
| ***TLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.46 | | 0.00 | |
| Shapiro–Wilk W test | 0.977 | 0.000 | 0.988 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 400.72 | | 411.94 | |
| Condition number | 2462.64 | | 3,622.83 | |
| *Joint parameter tests* | | | | |
| Higher-order output terms | 53.07 | 0.000 | 92.04 | 0.000 |

### 1.3.3 Efficiency Scores

Table 1.3.6 shows the average of efficiency scores for each DNSP and model from both long and short period. Over the long period, the LSECD model reports an average efficiency score 3.3 per cent lower than its standard counterpart, and the LSETLG model produces efficiency scores 1.6 per cent lower than the standard. In the short period, the LSECD model returns the same efficiency average, and the LSETLG model shows an average efficiency scores of 1.1 per cent higher, compared to their respective standard versions.

In terms of how closely the average efficiency levels align, the correlations between the LSE-AJTT-GTC models and the standard models are very strong. For LSECD, the correlation is nearly perfect (0.998 and 0.999 in the long and short periods). For LSETLG, the correlation is also high (at 0.980 for the long period and 0.953 for the short period).

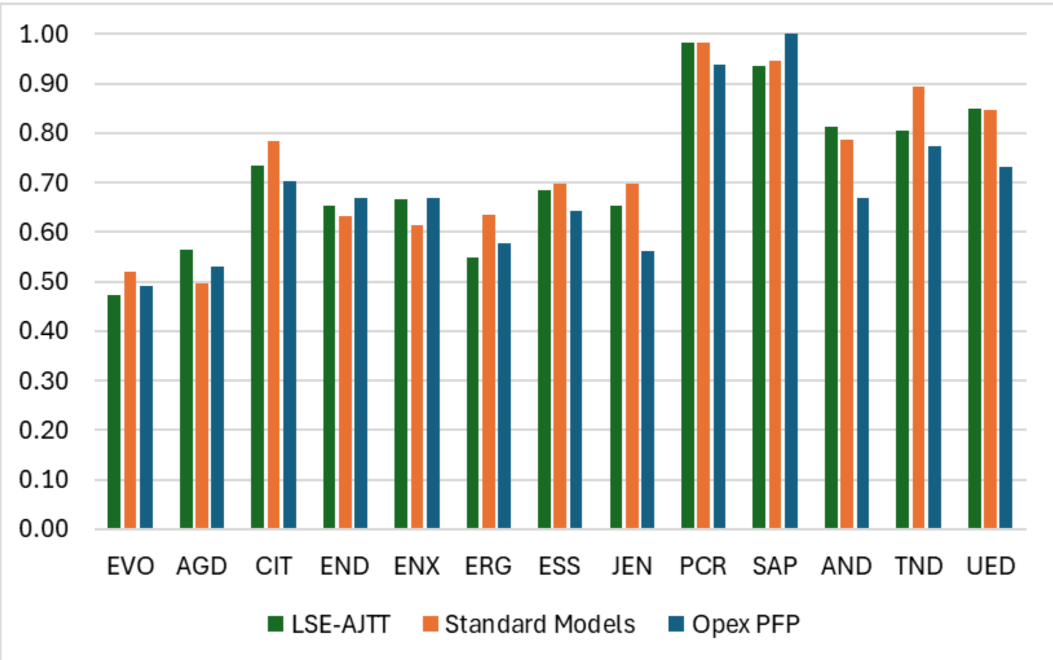
Efficiency rankings follow a similar pattern. The LSECD long-period model yields a near identical ranking to the standard version (correlation of 0.989). The LSETLG model also aligns closely, with a correlation of 0.956 in the long period. In the short period, the LSECD model shows a ranking correlation of 0.986, while the LSETLG model has a slightly lower correlation of 0.901. Overall, these results suggest strong consistency between the LSE-AJTT specifications and the standard models, both in terms of average scores and relative DNSP rankings.

Table 1.3.6 LSE-AJTT: Efficiency Scores by Australian DNSP

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *LSECD* | *Rank* | *LSETLG* | *Rank* | *LSECD* | *Rank* | *LSETLG* | *Rank* |
| EVO | 0.490 | 13 | 0.458 | 13 | 0.488 | 13 | 0.488 | 13 |
| AGD | 0.571 | 11 | 0.560 | 11 | 0.601 | 11 | 0.601 | 11 |
| CIT | 0.749 | 6 | 0.718 | 6 | 0.699 | 7 | 0.732 | 7 |
| END | 0.650 | 10 | 0.655 | 9 | 0.672 | 8 | 0.702 | 8 |
| ENX | 0.672 | 8 | 0.659 | 8 | 0.668 | 9 | 0.664 | 9 |
| ERG | 0.545 | 12 | 0.550 | 12 | 0.601 | 11 | 0.660 | 10 |
| ESS | 0.661 | 9 | 0.710 | 7 | 0.700 | 6 | 0.771 | 5 |
| JEN | 0.713 | 7 | 0.591 | 10 | 0.666 | 10 | 0.591 | 12 |
| PCR | 0.983 | 1 | 0.983 | 1 | 1.000 | 1 | 1.000 | 1 |
| SAP | 0.932 | 2 | 0.941 | 2 | 0.902 | 3 | 0.933 | 2 |
| AND | 0.836 | 4 | 0.791 | 3 | 0.799 | 5 | 0.756 | 6 |
| TND | 0.824 | 5 | 0.787 | 4 | 0.841 | 4 | 0.841 | 3 |
| UED | 0.920 | 3 | 0.780 | 5 | 0.912 | 2 | 0.815 | 4 |
| Australia | 0.734 | | 0.706 | | 0.734 | | 0.735 | |

Figure 1.3.1 average efficiency scores across the standard LSECD, LSETLG, SFACD and SFATLG models, in the long period sample, and compares them to the average efficiency scores of the LSE-AJTT and the average opex partial factor productivity (OPFP) measures. The results are reasonably similar across all approaches.

Figure 1.3.1 Average Efficiency Scores by DNSP (2006–2023)




The efficiency scores for Australian DNSPs from the long-period LSECD and LSETLG models show strong correlations with the OPFP measures, at 0.757 and 0.820, respectively.

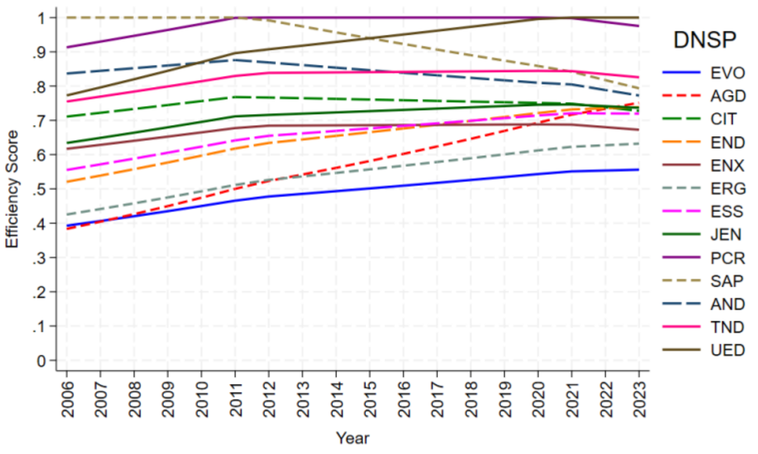
These correlations are higher than those observed in the standard LSECD (0.741) and LSETLG model (0.798).

Figure 1.3.2 presents the time varying LSECD and LSETLG efficiency scores for each Australian DNSP across the long and short period analysis. Figure 1.3.3 shows scatter charts of residuals plotted against fitted values of the dependent variable.

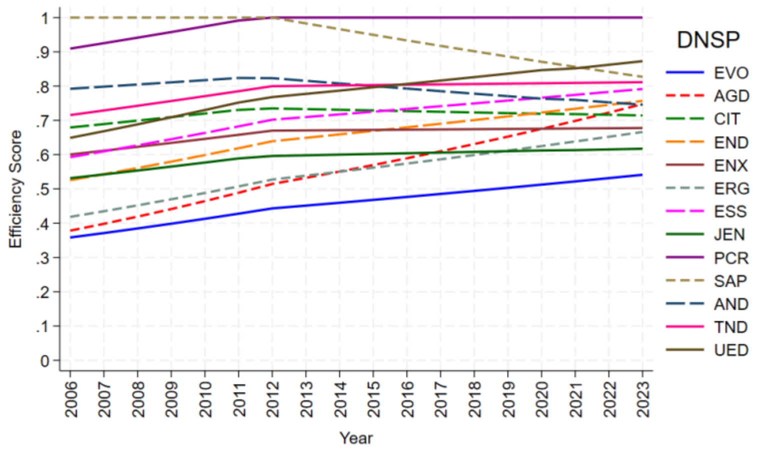
### 1.3.4 Concluding Comments

The main output variables in the LSE-AJTT model are consistently positive and statistically significant across all model specifications and time periods and the OEF variable is negative and statistically significant. The frequency of monotonicity violations is low in both Translog models for the short and long periods, and the resulting efficiency scores are broadly consistent with those obtained from the standard models. A key limitation of the LSE-AJTT model, however, is the presence of very high multicollinearity.

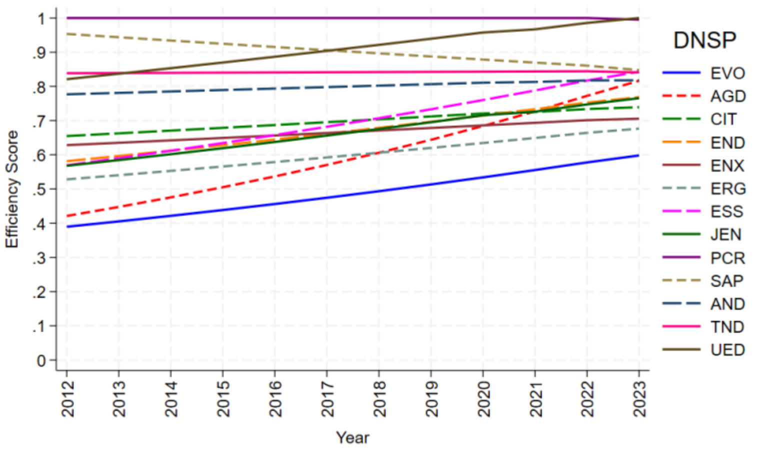
Figure 1.3.2: LSE-AJTT: Efficiency Trends by DNSP



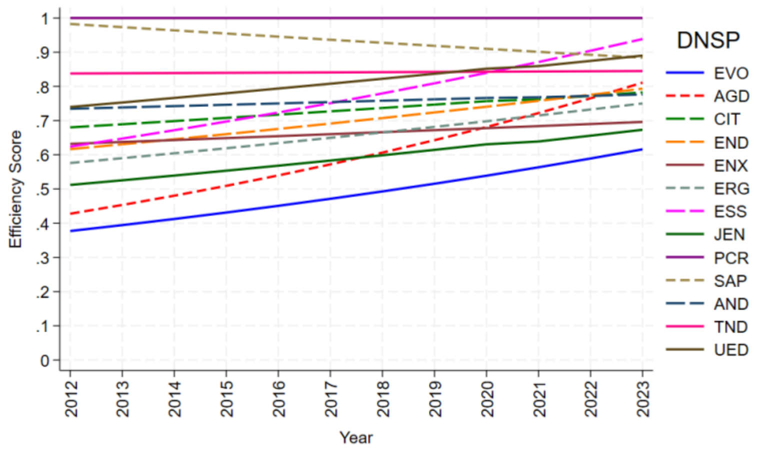

*LSECD Long Period*




*LSETLG Long Period*

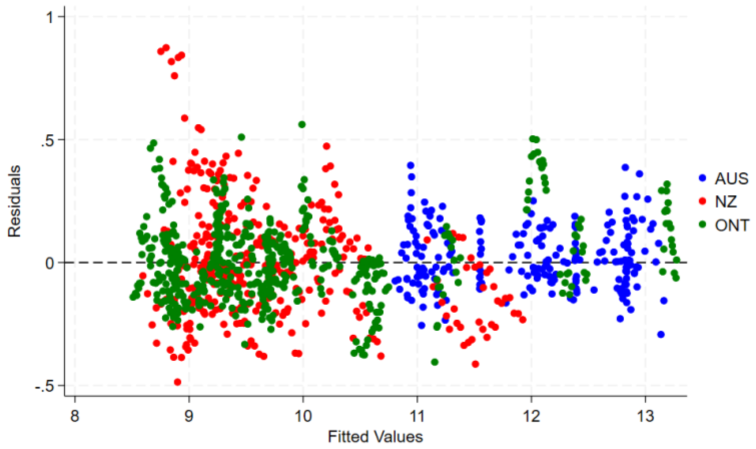



*LSECD Short Period*

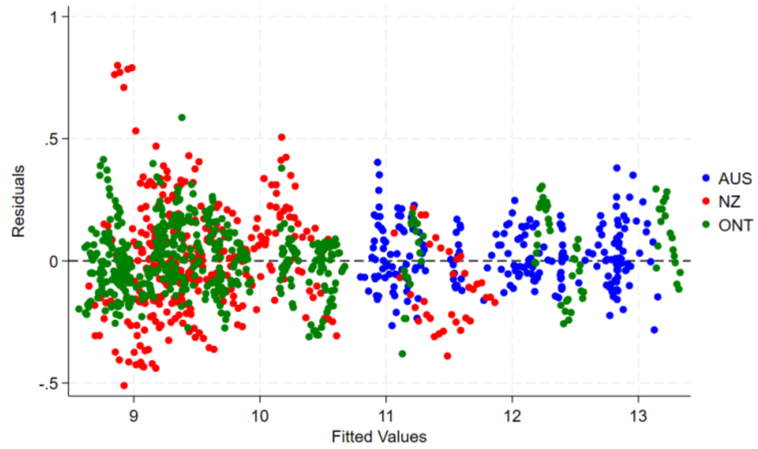



*LSETLG Short Period*

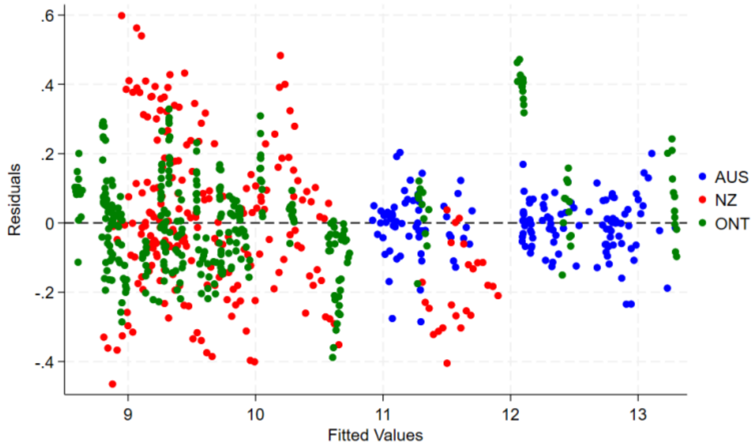
Figure 1.3.3 LSE-AJTT: Residuals Plots



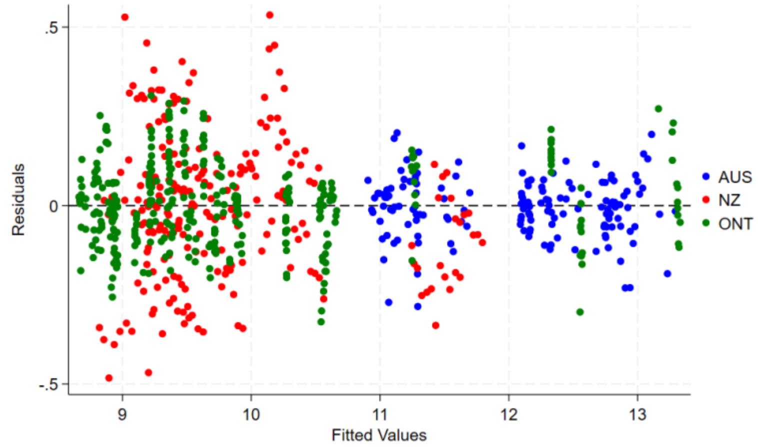

*SFACD Long Period*




*SFATLG Long Period*




*SFACD Short Period*




*SFATLG Short Period*

## 1.4 LSE-AJTT-GTC: Australian DNSP Specific & Jurisdiction Time Trends & GTC

The results of estimating the Cobb-Douglas and Translog with both the long and short samples are presented in Table 1.4.1 and 1.4.2.

### Table 1.4.1 Parameter Estimates LSECD Models

| | *Long Period* | | | *Short Period* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *ly1* | 0.646 | 0.063 | 10.18 | 0.584 | 0.065 | 8.98 |
| *ly2* | 0.211 | 0.030 | 7.10 | 0.250 | 0.028 | 8.82 |
| *ly3* | 0.112 | 0.056 | 2.01 | 0.134 | 0.061 | 2.19 |
| *lz1* | -0.104 | 0.021 | -5.00 | -0.095 | 0.021 | -4.48 |
| *gtc2* | 0.013 | 0.012 | 1.07 | | | |
| *gtc3* | 0.061 | 0.016 | 3.80 | | | |
| *gtc4* | 0.061 | 0.018 | 3.31 | 0.001 | 0.013 | 0.12 |
| *gtc5* | 0.054 | 0.021 | 2.61 | -0.004 | 0.016 | -0.23 |
| *gtc6* | 0.007 | 0.022 | 0.33 | -0.048 | 0.019 | -2.55 |
| *jur2* | -0.422 | 0.094 | -4.50 | -0.423 | 0.092 | -4.61 |
| *jur3* | -0.168 | 0.091 | -1.84 | -0.172 | 0.089 | -1.93 |
| *d2* | -0.141 | 0.128 | -1.10 | -0.189 | 0.109 | -1.73 |
| *d3* | -0.439 | 0.101 | -4.34 | -0.372 | 0.094 | -3.95 |
| *d4* | -0.286 | 0.106 | -2.71 | -0.329 | 0.098 | -3.37 |
| *d5* | -0.334 | 0.099 | -3.37 | -0.330 | 0.095 | -3.49 |
| *d6* | -0.107 | 0.113 | -0.95 | -0.216 | 0.108 | -2.00 |
| *d7* | -0.311 | 0.123 | -2.54 | -0.361 | 0.112 | -3.22 |
| *d8* | -0.392 | 0.111 | -3.54 | -0.310 | 0.095 | -3.26 |
| *d9* | -0.718 | 0.104 | -6.89 | -0.738 | 0.099 | -7.44 |
| *d10* | -0.661 | 0.109 | -6.08 | -0.636 | 0.102 | -6.21 |
| *d11* | -0.559 | 0.105 | -5.33 | -0.512 | 0.098 | -5.21 |
| *d12* | -0.534 | 0.117 | -4.56 | -0.564 | 0.117 | -4.83 |
| *d13* | -0.644 | 0.110 | -5.84 | -0.633 | 0.104 | -6.06 |
| *dt1* | -0.012 | 0.014 | -0.88 | -0.041 | 0.020 | -2.05 |
| *dt2* | -0.032 | 0.014 | -2.28 | -0.063 | 0.015 | -4.28 |
| *dt3* | 0.006 | 0.007 | 0.90 | -0.014 | 0.007 | -1.98 |
| *dt4* | -0.013 | 0.009 | -1.45 | -0.028 | 0.010 | -2.70 |
| *dt5* | 0.003 | 0.006 | 0.43 | -0.013 | 0.008 | -1.61 |
| *dt6* | -0.015 | 0.009 | -1.72 | -0.025 | 0.012 | -2.07 |
| *dt7* | -0.008 | 0.011 | -0.69 | -0.038 | 0.014 | -2.82 |
| *dt8* | -0.001 | 0.010 | -0.12 | -0.031 | 0.008 | -4.08 |
| *dt9* | 0.004 | 0.007 | 0.53 | -0.002 | 0.009 | -0.25 |
| *dt10* | 0.022 | 0.009 | 2.46 | 0.008 | 0.012 | 0.71 |
| *dt11* | 0.012 | 0.008 | 1.64 | -0.008 | 0.009 | -0.85 |
| *dt12* | 0.003 | 0.011 | 0.27 | -0.003 | 0.018 | -0.14 |
| *dt13* | -0.008 | 0.009 | -0.88 | -0.021 | 0.012 | -1.78 |
| *t_nz* | 0.025 | 0.003 | 8.34 | 0.033 | 0.004 | 7.54 |
| *_cons* | 10.383 | 0.093 | 111.88 | 10.510 | 0.090 | 116.83 |
| *rho* | 0.696 | | | 0.592 | | |
| *R2* | 0.992 | | | 0.995 | | |
| *Adj. Pseudo* $R^2$ | 0.981 | | | 0.984 | | |
| *N* | 1,098 | | | 732 | | |

Table 1.4.2 Parameter Estimates LSETLG Models

| | LSETLG - Long Period | | | LSETLG- Short Period | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *t–ratio* | *Coefficient* | *SE* | *t–ratio* |
| *ly1* | 0.527 | 0.071 | 7.45 | 0.423 | 0.070 | 6.04 |
| *ly2* | 0.208 | 0.030 | 7.01 | 0.249 | 0.026 | 9.55 |
| *ly3* | 0.222 | 0.059 | 3.76 | 0.283 | 0.060 | 4.72 |
| *ly11* | -0.231 | 0.475 | -0.49 | -0.035 | 0.538 | -0.06 |
| *ly12* | 0.210 | 0.109 | 1.94 | 0.148 | 0.120 | 1.24 |
| *ly13* | -0.019 | 0.376 | -0.05 | -0.207 | 0.412 | -0.50 |
| *ly22* | 0.008 | 0.037 | 0.22 | 0.040 | 0.037 | 1.10 |
| *ly23* | -0.204 | 0.090 | -2.28 | -0.175 | 0.096 | -1.82 |
| *ly33* | 0.283 | 0.297 | 0.95 | 0.486 | 0.314 | 1.55 |
| *lz1* | -0.101 | 0.023 | -4.33 | -0.085 | 0.021 | -4.10 |
| *gtc2* | 0.016 | 0.012 | 1.28 | | | |
| *gtc3* | 0.066 | 0.016 | 4.18 | | | |
| *gtc4* | 0.070 | 0.018 | 3.82 | 0.006 | 0.012 | 0.47 |
| *gtc5* | 0.066 | 0.020 | 3.22 | 0.004 | 0.015 | 0.28 |
| *gtc6* | 0.023 | 0.022 | 1.02 | -0.035 | 0.017 | -2.05 |
| *jur2* | -0.480 | 0.095 | -5.08 | -0.488 | 0.086 | -5.67 |
| *jur3* | -0.267 | 0.092 | -2.90 | -0.273 | 0.084 | -3.26 |
| *d2* | -0.203 | 0.141 | -1.45 | -0.200 | 0.118 | -1.70 |
| *d3* | -0.479 | 0.103 | -4.65 | -0.425 | 0.090 | -4.71 |
| *d4* | -0.358 | 0.109 | -3.29 | -0.377 | 0.095 | -3.97 |
| *d5* | -0.388 | 0.110 | -3.54 | -0.331 | 0.101 | -3.26 |
| *d6* | -0.184 | 0.134 | -1.37 | -0.316 | 0.122 | -2.60 |
| *d7* | -0.447 | 0.143 | -3.13 | -0.464 | 0.130 | -3.57 |
| *d8* | -0.302 | 0.123 | -2.46 | -0.205 | 0.108 | -1.91 |
| *d9* | -0.777 | 0.111 | -7.03 | -0.740 | 0.104 | -7.10 |
| *d10* | -0.735 | 0.116 | -6.34 | -0.674 | 0.105 | -6.43 |
| *d11* | -0.574 | 0.115 | -5.01 | -0.460 | 0.111 | -4.14 |
| *d12* | -0.545 | 0.119 | -4.59 | -0.565 | 0.112 | -5.06 |
| *d13* | -0.574 | 0.126 | -4.56 | -0.533 | 0.118 | -4.53 |
| *dt1* | -0.015 | 0.014 | -1.05 | -0.046 | 0.019 | -2.37 |
| *dt2* | -0.031 | 0.014 | -2.28 | -0.060 | 0.014 | -4.21 |
| *dt3* | 0.006 | 0.007 | 0.82 | -0.015 | 0.007 | -2.02 |
| *dt4* | -0.013 | 0.009 | -1.43 | -0.025 | 0.010 | -2.37 |
| *dt5* | 0.002 | 0.006 | 0.28 | -0.010 | 0.008 | -1.29 |
| *dt6* | -0.018 | 0.009 | -1.97 | -0.025 | 0.012 | -2.13 |
| *dt7* | -0.008 | 0.011 | -0.71 | -0.038 | 0.013 | -2.91 |
| *dt8* | -0.001 | 0.010 | -0.06 | -0.028 | 0.008 | -3.32 |
| *dt9* | 0.003 | 0.007 | 0.39 | -0.002 | 0.009 | -0.19 |
| *dt10* | 0.020 | 0.009 | 2.31 | 0.008 | 0.011 | 0.73 |
| *dt11* | 0.012 | 0.008 | 1.57 | -0.007 | 0.009 | -0.78 |
| *dt12* | 0.002 | 0.011 | 0.18 | -0.002 | 0.017 | -0.11 |
| *dt13* | -0.009 | 0.009 | -1.01 | -0.019 | 0.012 | -1.64 |
| *t_nz* | 0.026 | 0.003 | 8.69 | 0.033 | 0.004 | 7.94 |
| *_cons* | 10.380 | 0.093 | 111.17 | 10.513 | 0.084 | 125.14 |
| *rho* | 0.695 | | | 0.567 | | |
| *R2* | 0.993 | | | 0.995 | | |
| *Adj. Pseudo* $R^2$ | 0.984 | | | 0.987 | | |
| *N* | 1,098 | | | 732 | | |

### 1.4.1 Consistency with economic theory or industry knowledge

The estimation tables show that that in both the LSECD and LSETLG models, across both the long and short periods, the primary coefficients of the output variables have the expected signs and are statistically significant. The variable representing underground cables sharing (*lz1*) has a negative and statistically significant coefficient across all models.

Table 1.4.3 presents the estimated output elasticities for the LSECD and LSETLG models in the long and short periods. Across all specifications, the sum of the elasticities is close to one, indicating approximate constant returns to scale. Table 1.3.4 presents the monotonicity violations in the LSE-TLG model for both the long and short periods. The table shows that the MVs results are very similar compared to the LSE-AJTT model .

**Table 1.4.3 LSE-AJTT-GTC: Output elasticities**

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| <u>*LSECD*</u> | | | | | | | | |
| Full Sample | 0.646 | 0.211 | 0.112 | 0.969 | 0.584 | 0.250 | 0.134 | 0.969 |
| <u>*LSETLG*</u> | | | | | | | | |
| Australia | 0.496 | 0.257 | 0.261 | 1.014 | 0.303 | 0.302 | 0.384 | 0.989 |
| New Zealand | 0.726 | 0.257 | -0.049 | 0.933 | 0.647 | 0.313 | -0.034 | 0.927 |
| Ontario | 0.411 | 0.154 | 0.383 | 0.948 | 0.329 | 0.183 | 0.445 | 0.957 |
| Full sample | 0.527 | 0.208 | 0.222 | 0.957 | 0.423 | 0.249 | 0.283 | 0.955 |

**Table 1.4.4 LSE-AJTT-GTC: Monotonicity violations in LSETLG models (%)**

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| <u>*By DNSP*</u> | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AGD | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| CIT | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| END | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ENX | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ERG | 0.0 | 0.0 | 5.6 | 5.6 | 0.0 | 0.0 | 0.0 | 0.0 |
| ESS | 0.0 | 0.0 | 100.0 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| JEN | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| PCR | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| SAP | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| AND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| TND | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| UED | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| <u>*By jurisdiction*</u> | | | | | | | | |
| Australia | 0.0 | 0.0 | 8.1 | 8.1 | 0.0 | 0.0 | 0.0 | 0.0 |
| New Zealand | 0.0 | 0.0 | 67.8 | 67.8 | 0.0 | 0.0 | 57.9 | 57.9 |
| Ontario | 0.0 | 0.0 | 0.0 | 0.0 | 3.4 | 0.0 | 0.0 | 3.4 |
| Full sample | 0.0 | 0.0 | 22.9 | 22.9 | 1.6 | 0.0 | 18.0 | 19.7 |

### 1.4.2 Specification Statistics

Tables 1.4.1 and 1.4.2 present the adjusted $R^2$ values for each model, all of which report pseudo-$R^2$ scores of 0.98 or higher, indicating a strong model fit. Additional diagnostic statistics are reported in Table 1.4.5. Residual normality assessments show that severe outliers, as identified using the interquartile range (IQR) method, are rare (fewer than 0.6 per cent). However, the Shapiro–Wilk test rejects the null hypothesis of normality, suggesting that residuals deviate from a normal distribution. The Translog specification is supported in both periods, with joint significance tests confirming the relevance of higher-order terms at the five per cent level. The inclusion of the GTC terms has also substantially mitigated multicollinearity issues.

Table 1.4.5 LSE-AJTT-GTC: Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value* | *Stat.* | *p-value* |
| ***CD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.55 | | 0.27 | |
| Shapiro–Wilk W test | 0.963 | 0.000 | 0.975 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 8.81 | | 9.03 | |
| Condition number | 25.57 | | 26.67 | |
| ***TLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.55 | | 0.00 | |
| Shapiro–Wilk W test | 0.972 | 0.000 | 0.988 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 381.45 | | 391.96 | |
| Condition number | 486.86 | | 498.08 | |
| *Joint parameter tests* | | | | |
| Higher-order output terms | 57.71 | 0.000 | 93.94 | 0.000 |

### 1.4.3 Efficiency Scores

Table 1.4.6 shows the average of efficiency scores for each DNSP and model from both long and short period. Over the long period, the LSECD model reports an average efficiency score 3.7 per cent lower than its standard counterpart, and the LSETLG model produces efficiency scores 0.7 per cent lower than the standard. In the short period, the LSECD model returns the same efficiency average, and the LSETLG model shows an average efficiency scores of 1.4 per cent higher, compared to their respective standard versions.

In terms of how closely the average efficiency levels align, the correlations between the LSE-AJTT-GTC models and the standard models are very strong. For LSECD, the correlation is nearly perfect (0.997 and 0.999 in the long and short periods). For LSETLG, the correlation is also high (at 0.966 for the long period and 0.949 for the short period).

Efficiency rankings follow a similar pattern. The LSECD long-period model yields a near identical ranking to the standard version (correlation of 0.989). The LSETLG model also aligns closely, with a correlation of 0.929 in the long period. In the short period, the LSECD model shows a ranking correlation of 0.999, while the LSETLG model has a slightly lower correlation of 0.901. Overall, these results suggest strong consistency between the LSE-AJTT-GTC specifications and the standard models, both in terms of average scores and relative DNSP rankings.

Table 1.4.6 LSE-AJTT-GTC: Average Efficiency Scores by Australian DNSP

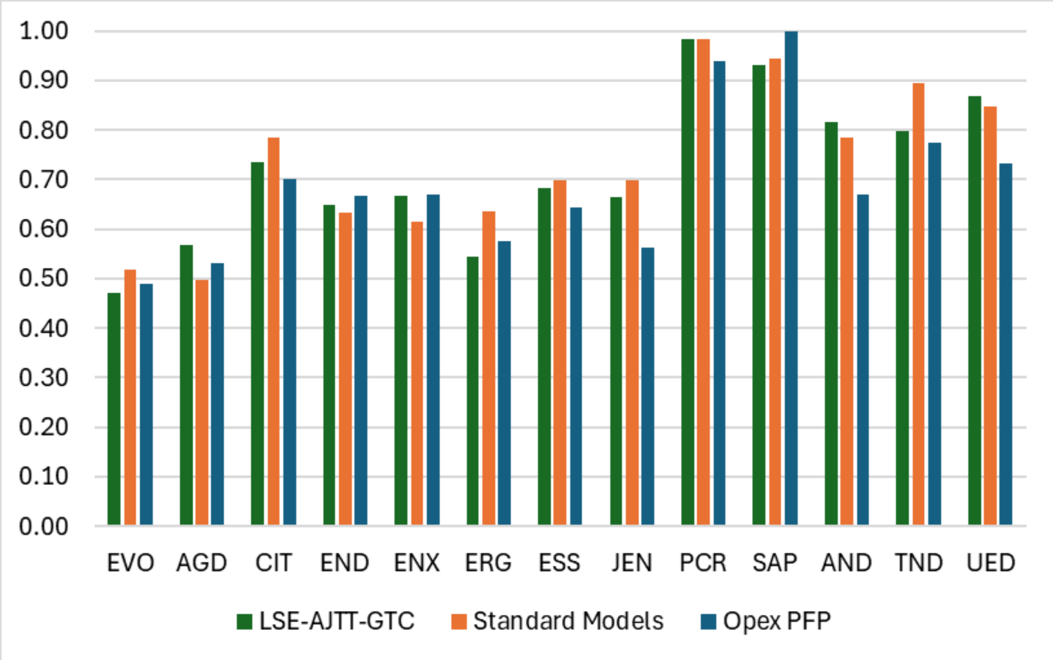
| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *LSECD* | *Rank* | *LSETLG* | *Rank* | *LSECD* | *Rank* | *LSETLG* | *Rank* |
| EVO | 0.484 | 13 | 0.456 | 13 | 0.487 | 13 | 0.489 | 13 |
| AGD | 0.568 | 11 | 0.569 | 11 | 0.600 | 11 | 0.604 | 11 |
| CIT | 0.743 | 6 | 0.729 | 6 | 0.699 | 6 | 0.737 | 7 |
| END | 0.644 | 10 | 0.652 | 9 | 0.671 | 8 | 0.702 | 8 |
| ENX | 0.670 | 8 | 0.665 | 8 | 0.667 | 9 | 0.666 | 9 |
| ERG | 0.540 | 12 | 0.550 | 12 | 0.599 | 12 | 0.661 | 10 |
| ESS | 0.658 | 9 | 0.709 | 7 | 0.698 | 7 | 0.772 | 5 |
| JEN | 0.714 | 7 | 0.614 | 10 | 0.667 | 9 | 0.598 | 12 |
| PCR | 0.985 | 1 | 0.984 | 1 | 1.000 | 1 | 1.000 | 1 |
| SAP | 0.926 | 2 | 0.938 | 2 | 0.900 | 3 | 0.934 | 2 |
| AND | 0.835 | 4 | 0.798 | 4 | 0.800 | 5 | 0.758 | 6 |
| TND | 0.818 | 5 | 0.778 | 5 | 0.840 | 4 | 0.839 | 3 |
| UED | 0.924 | 3 | 0.812 | 3 | 0.913 | 2 | 0.823 | 4 |
| Australia | 0.731 | | 0.712 | | 0.734 | | 0.737 | |

Figure 1.4.1 average efficiency scores across the standard LSECD, LSETLG, SFACD and SFATLG models, in the long period sample, and compares them to the average efficiency scores of the LSE-AJTT and the average opex partial factor productivity (OPFP) measures. The results are reasonably similar across all approaches.

The efficiency scores for Australian DNSPs from the long-period LSECD and LSETLG models show strong correlations with the OPFP measures, at 0.756 and 0.812, respectively. These correlations are higher than those observed in the standard LSECD (0.741) and LSETLG model (0.798).

Figure 1.4.2 presents the time varying LSECD and LSETLG efficiency scores for each Australian DNSP across the long and short period analysis. Figure 1.4.3 shows scatter charts of residuals plotted against fitted values of the dependent variable.

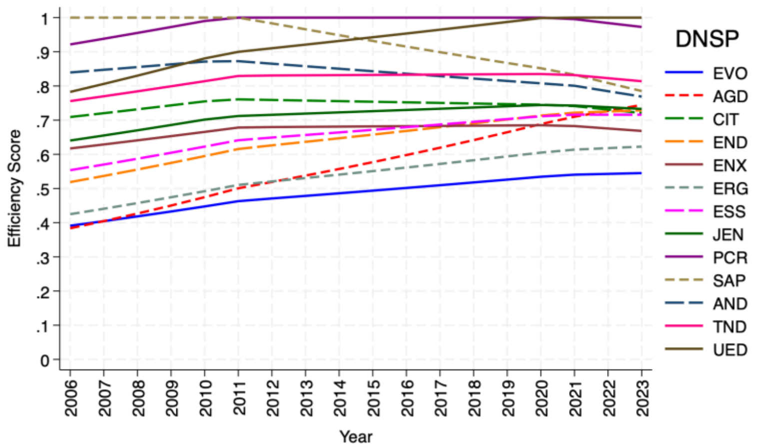
Figure 1.4.1 Average Efficiency Scores by DNSP (2006–2023)



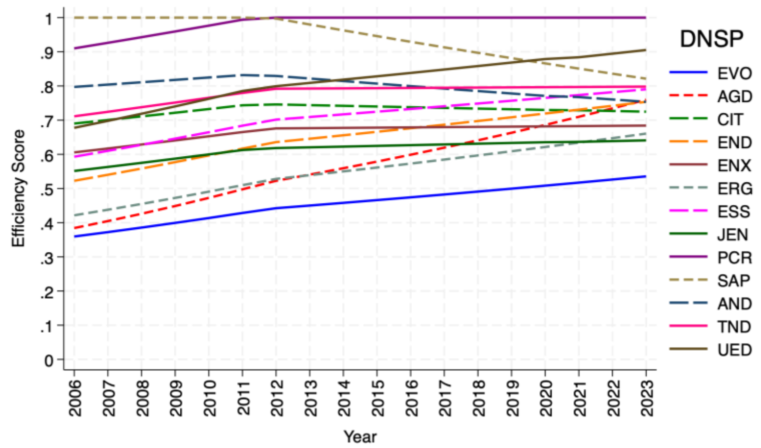

### 1.4.4 Concluding Comments

The main output variables in the LSE-AJTT-GTC models are consistently positive and statistically significant across all model specifications and time periods. The OEF variable is negative and also statistically significant. For Australian DNSPs, the frequency of monotonicity violations is zero in the short-period Translog model and very low, at 8.5 per cent, in the long-period model. The resulting efficiency scores are broadly consistent with those produced by the standard models. This specification also yields a much more reasonable outcome with respect to multicollinearity.

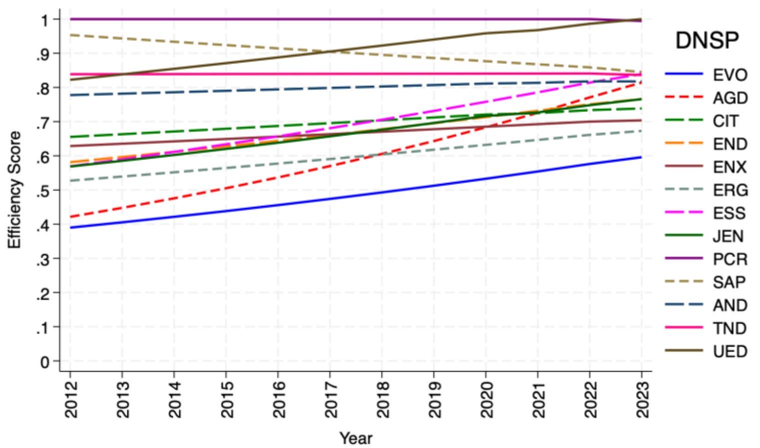
Figure 1.4.2 LSE-AJTT-GTC Efficiency Trends by DNSP



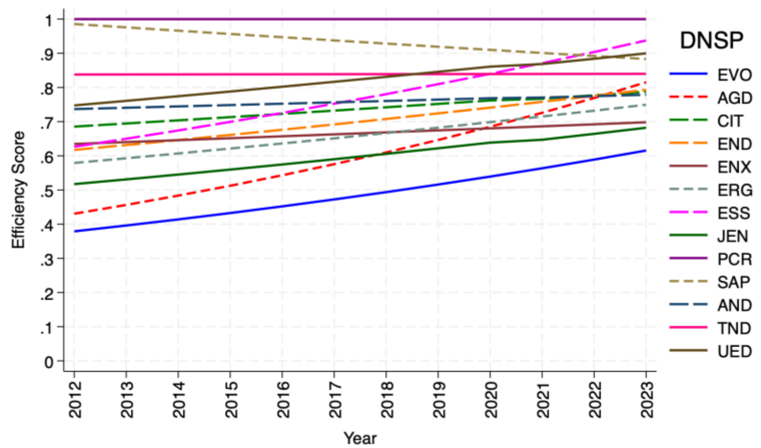

*LSECD Long Period*




*LSETLG Long Period*

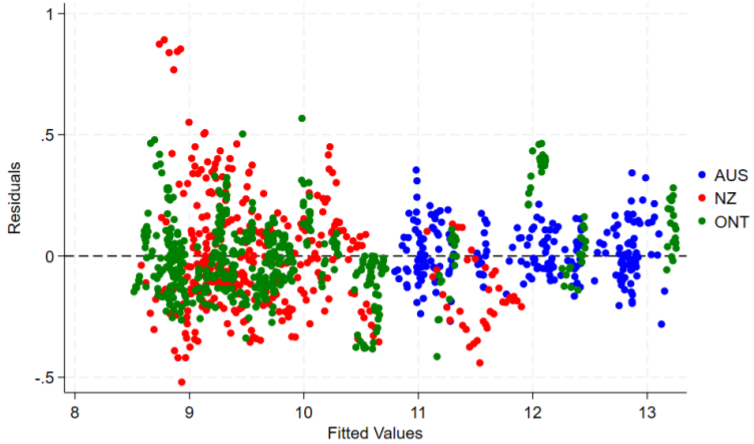



*LSECD Short Period*

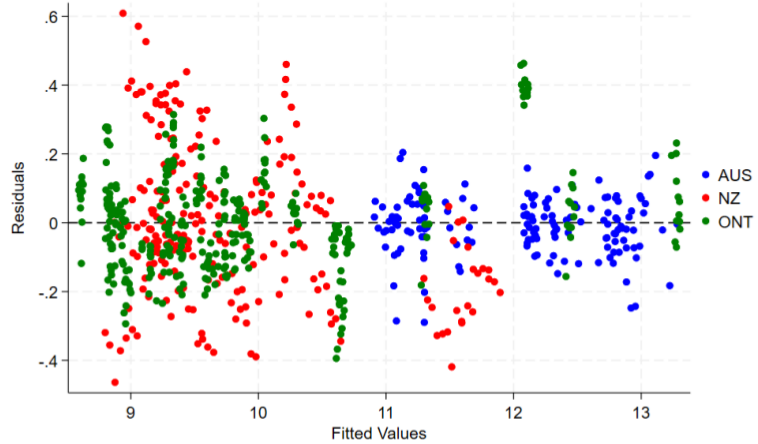



*LSETLG Short Period*

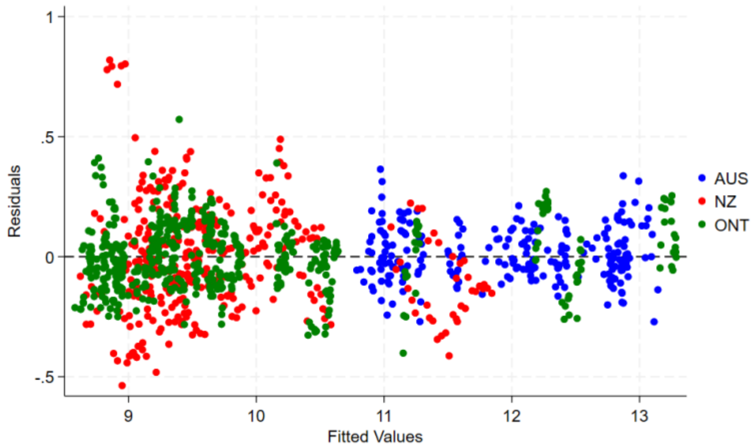
Figure 1.4.3 LSE-AJTT-GTC Residual Plots



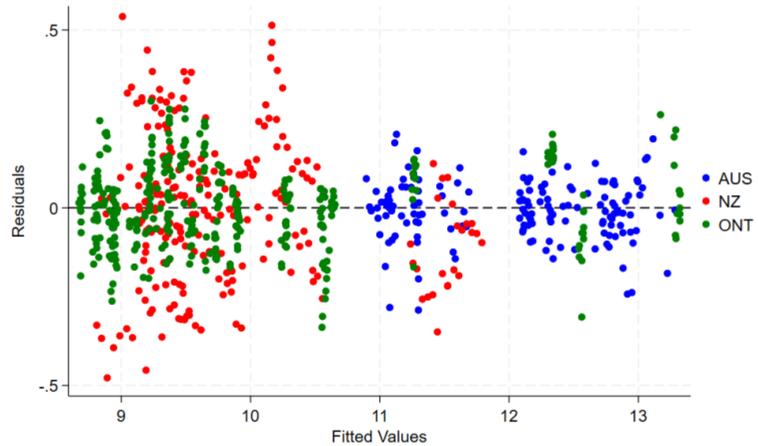

*LSECD Long Period*




*LSETLG Long Period*




*LSECD Short Period*




*LSETLG Short Period*

## 2 Fixed Effects - Cornwell, Schmidt & Sickles Models

In FECSS model, inefficiency is captured through a fixed effect for each firm combined with a firm-specific quadratic time trend. This is estimated using the Stata command: ***y xlist*, model(fecss)**. This model is discussed in 3.1.2 of the Draft report.

In this section, we test two different FECSS specifications, the first one using the standard technical change variable and in the second one we consider a variation of the FECSS model that incorporates a general index of technical change (GTC).

### 2.1 FECSS Model

Tables 2.1.1 and 2.1.2 present the estimation results for both long and short periods.

Table 2.1.1 Estimation Results (2006-2023)

| | *Cobb Douglas* | | | *Translog* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *z* | *Coefficient* | *SE* | *z* |
| ln(Custnum) | 0.196 | 0.297 | 0.66 | 0.231 | 0.353 | 0.66 |
| ln(CircLen) | 0.046 | 0.109 | 0.42 | 0.091 | 0.134 | 0.67 |
| ln(RMDemand) | 0.006 | 0.109 | 0.06 | 0.063 | 0.129 | 0.49 |
| x1*x1/2 | | | | 0.706 | 0.796 | 0.88 |
| x1*x2 | | | | 0.064 | 0.258 | 0.25 |
| x1*x3 | | | | -0.695 | 0.581 | -1.20 |
| x2*x2/2 | | | | -0.026 | 0.146 | -0.18 |
| x2*x3 | | | | 0.036 | 0.142 | 0.26 |
| x3*x3/2 | | | | 0.513 | 0.498 | 1.03 |
| ln(ShareUGC) | 0.054 | 0.060 | 0.90 | 0.058 | 0.061 | 0.96 |
| Year | -0.080 | 0.085 | -0.95 | -0.124 | 0.090 | -1.38 |
| sigma_u | 1.115 | | | 1.081 | | |
| sigma_v | 0.076 | | | 0.076 | | |
| Pseudo Adj. $R^2$ | 0.838 | | | 0.721 | | |
| N | 1098 | | | 1098 | | |

Table 2.1.2 Estimation Results (2012-2023)

| | Cobb Douglas | | | Translog | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *z* | *Coefficient* | *SE* | *z* |
| ln(Custnum) | -0.103 | 0.488 | -0.21 | -0.468 | 0.571 | -0.82 |
| ln(CircLen) | 0.289 | 0.166 | 1.75 | 0.503 | 0.227 | 2.24 |
| ln(RMDemand) | 0.080 | 0.183 | 0.44 | 0.042 | 0.223 | 0.19 |
| x1*x1/2 | | | | 0.282 | 1.412 | 0.20 |
| x1*x2 | | | | -0.254 | 0.437 | -0.58 |
| x1*x3 | | | | -0.797 | 1.050 | -0.76 |
| x2*x2/2 | | | | 0.353 | 0.252 | 1.40 |
| x2*x3 | | | | 0.137 | 0.249 | 0.55 |
| x3*x3/2 | | | | 0.643 | 0.880 | 0.73 |
| ln(ShareUGC) | -0.020 | 0.111 | -0.18 | -0.037 | 0.113 | -0.33 |
| Year | 0.026 | 0.085 | 0.30 | 0.054 | 0.088 | 0.62 |
| sigma_u | 0.951 | | | 1.579 | | |
| sigma_v | 0.062 | | | 0.062 | | |
| Pseudo Adj. $R^2$ | 0.987 | | | 0.972 | | |
| # Parameters | 7 | | | 13 | | |
| N | 732 | | | 732 | | |

## 2.1.1 Consistency with economic theory or industry knowledge

Considering both the Cobb-Douglas and Translog models across both periods, none of the coefficients are statistically significant at the 5 per cent level, except for the coefficient on circuit length in the Translog model during the short period. Consequently, the estimated output elasticities are inconsistent with expectations, as shown in Table 2.1.3.

Table 2.1.3 Output elasticities

| | Long Period | | | | Short Period | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| CD | | | | | | | | |
| Full Sample | 0.196 | 0.046 | 0.006 | 0.248 | -0.103 | 0.289 | 0.08 | 0.266 |
| TLG | | | | | | | | |
| Australia | 0.458 | 0.218 | -0.254 | 0.422 | -1.832 | 0.983 | -0.042 | -0.892 |
| New Zealand | 0.409 | 0.015 | 0.054 | 0.478 | -0.014 | 0.610 | 0.017 | 0.613 |
| Ontario | 0.013 | 0.083 | 0.210 | 0.306 | -0.155 | 0.219 | 0.096 | 0.160 |
| Full sample | 0.231 | 0.090 | 0.063 | 0.384 | -0.468 | 0.503 | 0.042 | 0.077 |

The weight assigned to each output is generally very low, resulting in total output elasticities that fall well below the expected value of approximately one. In some cases, outputs present negative elasticities, indicating violations of monotonicity. Further details on these monotonicity violations in the TLG models are provided in Table 2.1.4.

As shown in Table 2.1.4, the incidence of monotonicity violations is excessive in both the long and short periods—reaching 100 per cent for the Australian sample and over 75 per cent for the full sample in both periods.

Table 2.1.4 Monotonicity violations in LSETLG models

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *By DNSP* | | | | | | | | |
| EVO | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 91.7 | 100.0 |
| AGD | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| CIT | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| END | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 33.3 | 100.0 |
| ENX | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| ERG | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| ESS | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| JEN | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| PCR | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 75.0 | 100.0 |
| SAP | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| AND | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| TND | 0.0 | 0.0 | 94.4 | 94.4 | 100.0 | 0.0 | 0.0 | 100.0 |
| UED | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| *By jurisdiction* | | | | | | | | |
| Australia | 0.0 | 0.0 | 99.6 | 99.6 | 100.0 | 0.0 | 61.5 | 100.0 |
| New Zealand | 0.0 | 58.2 | 40.4 | 87.7 | 45.2 | 0.0 | 56.1 | 71.9 |
| Ontario | 50.0 | 10.9 | 12.8 | 66.7 | 43.7 | 20.7 | 16.4 | 71.6 |
| Full sample | 23.8 | 23.3 | 39.9 | 80.2 | 56.1 | 9.8 | 38.4 | 77.7 |

### 2.1.2 Specification Statistics

Tables 2.1.1 and 2.1.2 present the adjusted pseudo-$R^2$ values for each model. Overall, the short-period models demonstrated a stronger fit, with an average pseudo-$R^2$ of 0.980, compared to 0.780 for the long-period models. Table 2.1.5 presents the results of additional statistical tests.

Residual normality assessments show that severe outliers—identified using the interquartile range (IQR) method—are absent (zero per cent) in both the SFACD and SFATLG models across short and long periods. However, the Shapiro–Wilk test rejects the null hypothesis of normality, indicating that residuals deviate from a normal distribution. Multicollinearity is moderate in the SFACD models and extreme in the SFATLG models. Lastly, the Translog specification is not supported: in both periods, joint tests reject the statistical significance of higher-order terms at the five per cent level.

Table 2.1.5 LSE Models Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value* | *Stat.* | *p-value* |
| ***CD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.00 | | 0.00 | |
| Shapiro–Wilk W test | 0.949 | 0.000 | 0.971 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 24.98 | | 25.89 | |
| Condition number | 1084.23 | | 1619.52 | |
| ***TLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.00 | | 0.00 | |
| Shapiro–Wilk W test | 0.969 | 0.000 | 0.904 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 714.08 | | 717.50 | |
| Condition number | 1641.03 | | 2427.54 | |
| *Joint parameter tests* | | | | |
| Higher-order output terms | 6.56 | 0.363 | 6.10 | 0.413 |

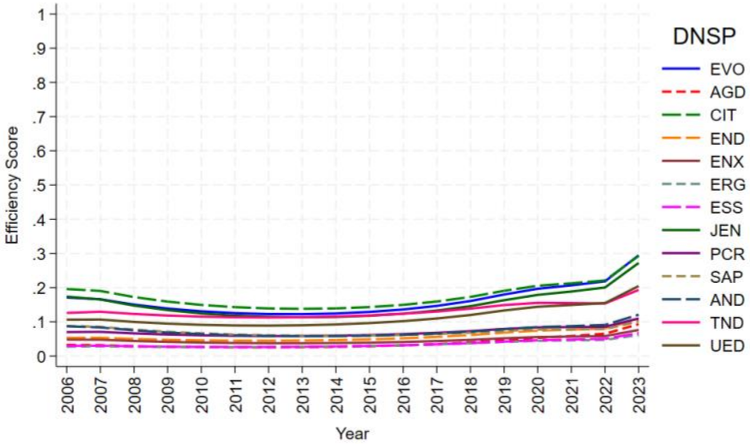
### 2.1.3 Efficiency Scores

Table 2.1.6 presents the average efficiency scores and rankings of Australian DNSPs under two model specifications for both the long and short periods. Figure 2.1.1 shows the time varying efficiency trends. The efficiency scores are notably low, and the rankings differ significantly from those observed in other models.

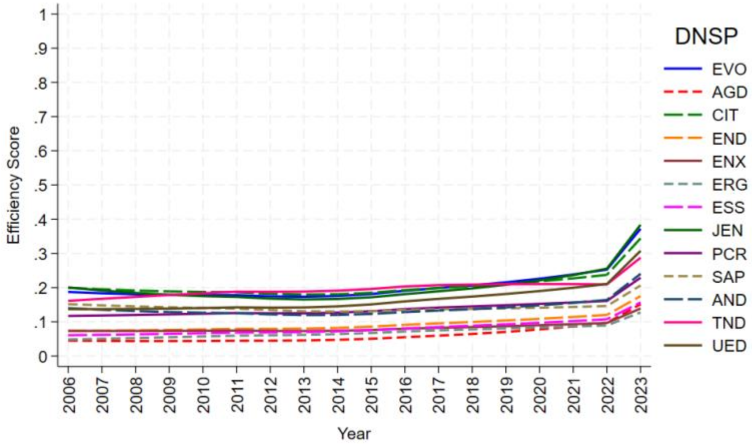
Table 2.1.6 Efficiency Scores

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *CD* | *Rank* | *TLG* | *Rank* | *CD* | *Rank* | *TLG* | *Rank* |
| EVO | 0.162 | 2 | 0.205 | 2 | 0.130 | 2 | 0.082 | 2 |
| AGD | 0.039 | 11 | 0.062 | 13 | 0.035 | 13 | 0.001 | 13 |
| CIT | 0.176 | 1 | 0.206 | 1 | 0.123 | 3 | 0.043 | 6 |
| END | 0.059 | 9 | 0.094 | 9 | 0.056 | 11 | 0.007 | 11 |
| ENX | 0.047 | 10 | 0.083 | 10 | 0.042 | 12 | 0.003 | 12 |
| ERG | 0.034 | 13 | 0.070 | 12 | 0.058 | 10 | 0.060 | 3 |
| ESS | 0.035 | 12 | 0.082 | 11 | 0.060 | 9 | 0.055 | 4 |
| JEN | 0.152 | 3 | 0.203 | 3 | 0.115 | 4 | 0.045 | 5 |
| PCR | 0.071 | 8 | 0.139 | 8 | 0.090 | 6 | 0.036 | 7 |
| SAP | 0.072 | 7 | 0.143 | 6 | 0.081 | 7 | 0.031 | 8 |
| AND | 0.074 | 6 | 0.140 | 7 | 0.079 | 8 | 0.025 | 9 |
| TND | 0.132 | 4 | 0.198 | 4 | 0.156 | 1 | 0.132 | 1 |
| UED | 0.115 | 5 | 0.167 | 5 | 0.096 | 5 | 0.017 | 10 |
| Australia | 0.090 | | 0.138 | | 0.086 | | 0.041 | |

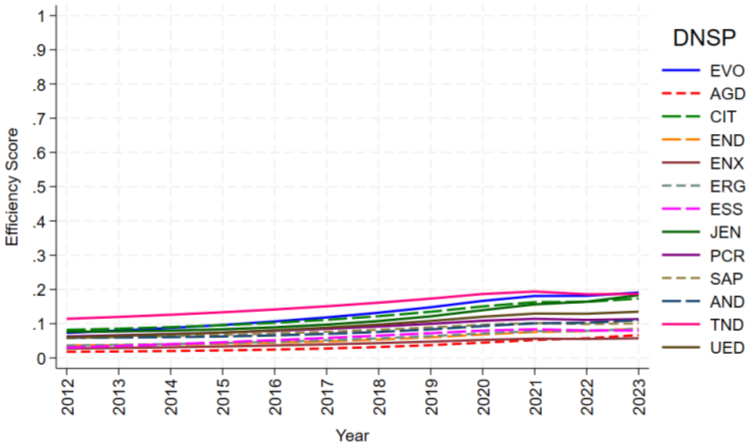
## Figure 2.1.1 Efficiency Trends by DNSP



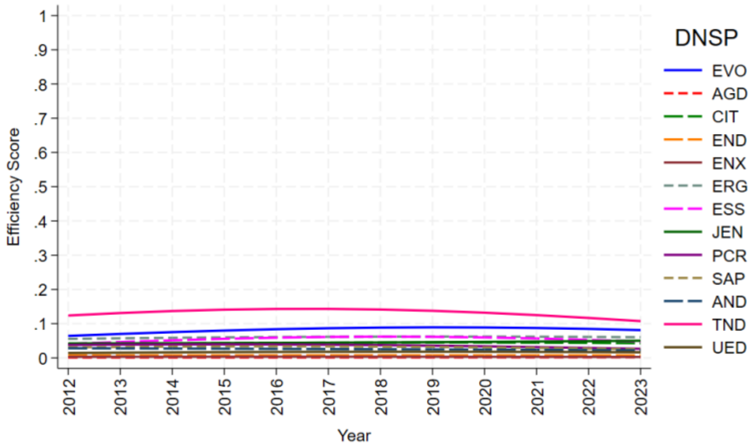

*CD Long Period*




*TLG Long Period*




*CD Short Period*




*TLG Short Period*

## 2.2 Fixed Effects Cornwell, Schmidt & Sickles with GTC (FECSS- GTC)

Tables 2.2.1 and 2.2.2 present the estimation results for both long and short periods.

### Table 2.2.1 Estimation Results (2006-2023)

| | *Cobb Douglas* | | | *Translog* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *z* | *Coefficient* | *SE* | *z* |
| ln(Custnum) | 0.350 | 0.302 | 1.16 | 0.292 | 0.350 | 0.83 |
| ln(CircLen) | 0.054 | 0.108 | 0.50 | 0.097 | 0.134 | 0.73 |
| ln(RMDemand) | 0.087 | 0.110 | 0.79 | 0.173 | 0.131 | 1.32 |
| x1*x1/2 | | | | 0.240 | 0.767 | 0.31 |
| x1*x2 | | | | 0.186 | 0.257 | 0.72 |
| x1*x3 | | | | -0.440 | 0.565 | -0.78 |
| x2*x2/2 | | | | -0.070 | 0.147 | -0.47 |
| x2*x3 | | | | -0.036 | 0.139 | -0.26 |
| x3*x3/2 | | | | 0.326 | 0.487 | 0.67 |
| ln(ShareUGC) | 0.058 | 0.059 | 0.98 | 0.066 | 0.060 | 1.09 |
| gtc2 | -0.005 | 0.015 | -0.33 | -0.004 | 0.015 | -0.23 |
| gtc3 | 0.012 | 0.024 | 0.48 | 0.013 | 0.024 | 0.55 |
| gtc4 | -0.004 | 0.030 | -0.14 | -0.001 | 0.030 | -0.04 |
| gtc5 | -0.030 | 0.036 | -0.84 | -0.028 | 0.036 | -0.76 |
| gtc6 | -0.087 | 0.043 | -2.03 | -0.087 | 0.043 | -2.03 |
| sigma_u | 0.687 | | | 0.650 | | |
| sigma_v | 0.0757 | | | 0.076 | | |
| Pseudo Adj. $R^2$ | 0.983 | | | 0.984 | | |
| # Parameters | 12 | | | 18 | | |
| N | 1098 | | | 1098 | | |

### Table 2.2.2 Estimation Results (2012-2023)

| | *Cobb Douglas* | | | *Translog* | | |
|---|---|---|---|---|---|---|
| *Variable* | *Coefficient* | *SE* | *z* | *Coefficient* | *SE* | *z* |
| ln(Custnum)=x1 | -0.151 | 0.479 | -0.32 | -0.558 | 0.554 | -1.01 |
| ln(CircLen)=x2 | 0.263 | 0.163 | 1.61 | 0.476 | 0.221 | 2.15 |
| ln(RMDemand)=x3 | 0.171 | 0.181 | 0.94 | 0.161 | 0.220 | 0.73 |
| x1*x1/2 | | | | 0.426 | 1.378 | 0.31 |
| x1*x2 | | | | -0.242 | 0.429 | -0.56 |
| x1*x3 | | | | -1.038 | 1.029 | -1.01 |
| x2*x2/2 | | | | 0.330 | 0.248 | 1.33 |
| x2*x3 | | | | 0.163 | 0.243 | 0.67 |
| x3*x3/2 | | | | 0.788 | 0.862 | 0.91 |
| ln(ShareUGC) | -0.035 | 0.108 | -0.33 | -0.050 | 0.111 | -0.45 |
| gtc4 | -0.006 | 0.013 | -0.45 | -0.008 | 0.013 | -0.60 |
| gtc5 | -0.029 | 0.019 | -1.49 | -0.031 | 0.019 | -1.57 |
| gtc6 | -0.093 | 0.026 | -3.66 | -0.098 | 0.026 | -3.80 |
| sigma_u | 0.929 | | | 1.671 | | |
| sigma_v | 0.060 | | | 0.060 | | |
| Pseudo Adj. $R^2$ | 0.968 | | | 0.994 | | |
| # Parameters | 9 | | | 15 | | |
| N | 732 | | | 732 | | |

### 2.2.1 Consistency with economic theory or industry knowledge

The majority of the coefficients are not statistically significant at the 5 per cent level. Exceptions include the coefficient on variable gtc6 in the TLG model for the long period and in both models for the short period, as well as the coefficient on CL in the Translog model for the short period. Consequently, the estimated output elasticities are inconsistent with expectations, as shown in Table 2.2.3.

Table 2.2.3 Output elasticities

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *CD* | | | | | | | | |
| Full Sample | 0.350 | 0.054 | 0.087 | 0.491 | -0.151 | 0.263 | 0.171 | 0.282 |
| *TLG* | | | | | | | | |
| Australia | 0.350 | 0.236 | -0.144 | 0.441 | -2.045 | 0.977 | -0.064 | -1.131 |
| New Zealand | 0.559 | 0.000 | 0.156 | 0.715 | 0.013 | 0.549 | 0.167 | 0.729 |
| Ontario | 0.090 | 0.099 | 0.326 | 0.515 | -0.266 | 0.203 | 0.258 | 0.195 |
| Full sample | 0.292 | 0.097 | 0.173 | 0.562 | -0.558 | 0.476 | 0.161 | 0.079 |

The weight assigned to each output is generally very low, resulting in total output elasticities that fall well below the expected value of approximately one. In some cases, outputs present negative elasticities, indicating violations of monotonicity. Further details on these monotonicity violations in the TLG models are provided in Table 2.2.4, which show the incidence of monotonicity violations is excessive in both the long and short periods for the Australian sample.

Table 2.2.4 Monotonicity violations in LSETLG models

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *Cust.* | *CL* | *RMD* | *Total* | *Cust.* | *CL* | *RMD* | *Total* |
| *By DNSP* | | | | | | | | |
| EVO | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 91.7 | 100.0 |
| AGD | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| CIT | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| END | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 33.3 | 100.0 |
| ENX | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| ERG | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| ESS | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| JEN | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| PCR | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 75.0 | 100.0 |
| SAP | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 0.0 | 100.0 |
| AND | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| TND | 0.0 | 0.0 | 61.1 | 61.1 | 100.0 | 0.0 | 0.0 | 100.0 |
| UED | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 0.0 | 100.0 | 100.0 |
| *By jurisdiction* | | | | | | | | |
| Australia | 0.0 | 0.0 | 81.6 | 81.6 | 100.0 | 0.0 | 61.5 | 100.0 |
| New Zealand | 0.0 | 61.4 | 10.5 | 71.9 | 44.7 | 0.0 | 25.9 | 56.1 |
| Ontario | 18.8 | 4.4 | 6.1 | 26.8 | 44.8 | 20.7 | 1.4 | 65.5 |
| Full sample | 8.9 | 21.2 | 23.6 | 52.6 | 56.6 | 9.8 | 21.9 | 69.9 |

### 2.2.2 Specification Statistics

Tables 2.2.1 and 2.2.2 present the pseudo adjusted $R^2$ values for each model. All models—across both the long and short periods—demonstrate a strong fit, with adjusted $R^2$ values exceeding 0.96.

Table 2.2.5 summarises the results of additional statistical tests. Residual normality assessments indicate that severe outliers, based on the interquartile range (IQR) method, are absent (zero per cent) in both the SFACD and SFATLG models, for both periods. However, the Shapiro–Wilk test rejects the null hypothesis of normality, suggesting that residuals deviate from a normal distribution.

Multicollinearity is reduced in both models with the inclusion of the GTC terms. Finally, the Translog specification is not supported: in both the long and short periods, joint tests reject the statistical significance of higher-order terms at the five per cent level.

Table 2.2.5 LSE Models Statistics Results

| | *Long Period* | | *Short Period* | |
|---|---|---|---|---|
| | *Stat.* | *p-value* | *Stat.* | *p-value* |
| ***CD*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.00 | | 0.00 | |
| Shapiro–Wilk W test | 0.949 | 0.000 | 0.944 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 14.23 | | 18.24 | |
| Condition number | 17.67 | | 17.83 | |
| ***TLG*** | | | | |
| *Normality of residuals* | | | | |
| IQR (% severe outliers) | 0.00 | | 3.83 | |
| Shapiro–Wilk W test | 0.971 | 0.000 | 0.863 | 0.000 |
| *Multicollinearity* | | | | |
| Average VIF | 636.09 | | 740.04 | |
| Condition number | 342.54 | | 341.50 | |
| *Joint parameter tests* | | | | |
| Higher-order output terms | 6.90 | 0.330 | 7.51 | 0.276 |

### 2.2.3 Efficiency Scores

Table 2.2.6 presents the average efficiency scores and rankings of Australian DNSPs under two model specifications for both the long and short periods. Figure 2.2.1 shows the time varying efficiency trends. The efficiency scores are notably low, and the rankings differ significantly from those observed in other models.

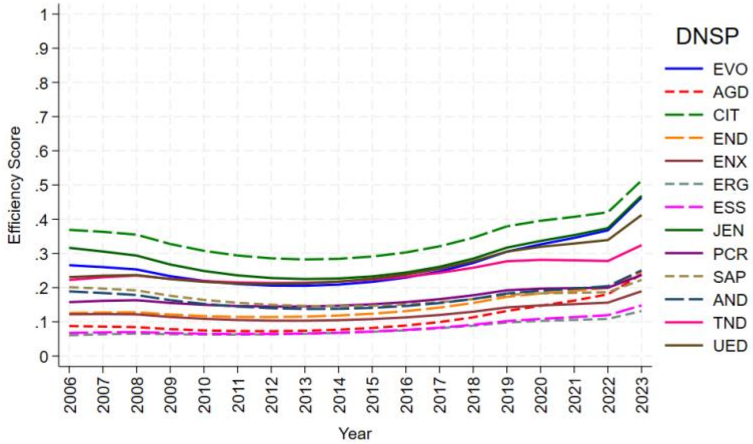
Table 2.2.6 Efficiency Scores

| | *Long Period* | | | | *Short Period* | | | |
|---|---|---|---|---|---|---|---|---|
| *Sample* | *CD* | *Rank* | *TLG* | *Rank* | *CD* | *Rank* | *TLG* | *Rank* |
| EVO | 0.269 | 3 | 0.305 | 4 | 0.138 | 2 | 0.091 | 2 |
| AGD | 0.108 | 11 | 0.096 | 13 | 0.039 | 13 | 0.001 | 13 |
| CIT | 0.347 | 1 | 0.335 | 1 | 0.134 | 3 | 0.044 | 6 |
| END | 0.146 | 9 | 0.154 | 9 | 0.061 | 11 | 0.006 | 11 |
| ENX | 0.126 | 10 | 0.131 | 10 | 0.046 | 12 | 0.002 | 12 |
| ERG | 0.080 | 13 | 0.110 | 12 | 0.062 | 10 | 0.053 | 3 |
| ESS | 0.084 | 12 | 0.129 | 11 | 0.063 | 9 | 0.046 | 5 |
| JEN | 0.290 | 2 | 0.310 | 2 | 0.121 | 4 | 0.046 | 4 |
| PCR | 0.169 | 8 | 0.233 | 6 | 0.094 | 6 | 0.031 | 7 |
| SAP | 0.173 | 6 | 0.232 | 7 | 0.085 | 7 | 0.026 | 8 |
| AND | 0.170 | 7 | 0.230 | 8 | 0.082 | 8 | 0.023 | 9 |
| TND | 0.244 | 5 | 0.308 | 3 | 0.166 | 1 | 0.141 | 1 |
| UED | 0.261 | 4 | 0.265 | 5 | 0.103 | 5 | 0.015 | 10 |
| Australia | 0.269 | 3 | 0.218 | | 0.092 | | 0.040 | |

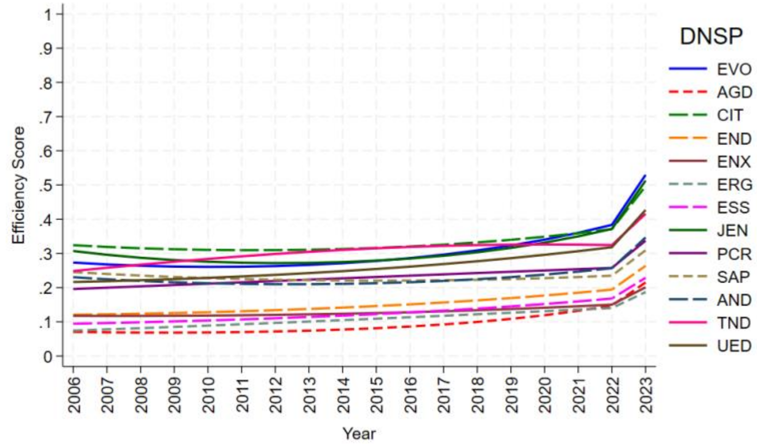
## 2.3 Concluding Comment

The FECSS specifications failed to produce meaningful results, as evidenced by output parameters that are not statistically different from zero, a very high frequency of monotonicity violations, and unrealistically low efficiency scores.

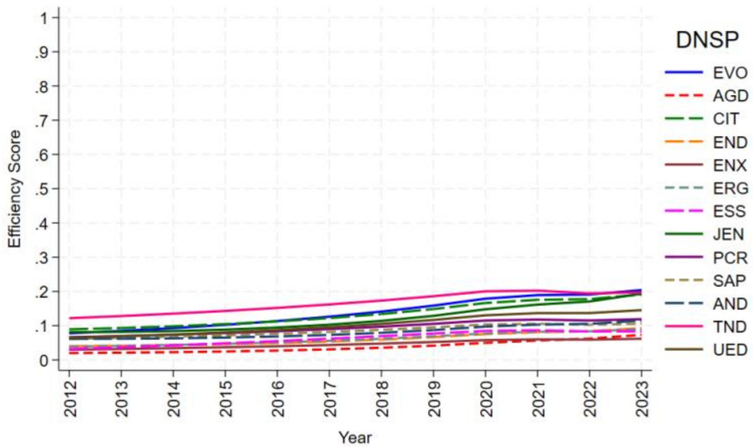
## Figure 2.2.1 Efficiency Trends by DNSP



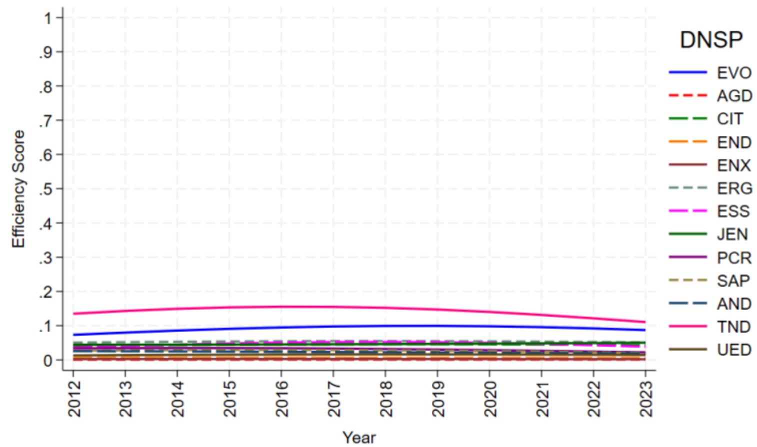

*CD Long Period*




*TLG Long Period*




*CD Short Period*




*TLG Short Period*

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