Attachment 7.14

Response to Draft Decision:
Opex Partial Productivity Forecasts

A report by ACIL Allen Consulting

2016/17 to 2020/21 Access Arrangement Information Response to Draft Decision

Australian Gas Networks

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ACIL ALLEN CONSULTING

REPORT TO

AUSTRALIAN GAS NETWORKS LIMITED

1 JANUARY 2016

OPEX PARTIAL PRODUCTVITY FORECASTS

AUSTRALIAN GAS NETWORKS LIMITED

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C O N T E N T S

1 INTRODUCTION

1.1 Terms of reference

ACIL Allen Consulting (ACIL Allen) has been engaged by Australian Gas Networks Limited (AGN) to provide opex partial productivity forecasts in support of AGN's revised Access Arrangement proposal for the period 1 July 2016 to 30 June 2021.

Under the Terms of Reference for the study, ACIL Allen has been asked to provide a forecast of the operating expenditure (opex) partial factor productivity growth rate that applies to the AGN network for the period 1 July 2016 to 30 June 2021. This involves using previously estimated opex cost functions which are used to estimate an opex partial productivity growth rate forecast split into three components: technology, returns to scale and operating environment.

Opex partial productivity forecasts are provided under two separate scenarios. These are:

1. Under the AER's draft determination released on 26 November 2015 and
2. Under AGN's revised Access Arrangement proposal submitted to the AER in response to its draft determination

The methodology followed here is identical to that developed for ActewAGL by ACIL Allen as part of its Access Arrangement proposal for the 2016 to 2021 period. The methodology is detailed in a report dated 29 April 2015, 'Productivity Study: ActewAGL Distribution Gas Network' which was submitted to the AER in support of ActewAGL's Access Arrangement proposal.

1.2 Report structure

The report is structured as follows:

— section 2 presents the cost function analysis which is used as the basis for the productivity forecasts

— section 3 presents the estimates of AGN's opex productivity growth rate for the forecast period

2 OPEX COST FUNCTIONS

In this section we specify the operating cost function that characterises the operating cost structure of the nine gas distribution businesses in our sample. The estimated coefficients from the cost function model are then used in conjunction with forecasts of opex cost drivers from AGN to forecast operating cost productivity growth over the regulatory period from 2016-17 to 2020-21.

2.1 Econometric approach

An econometric approach is adopted in estimating the opex cost function. The econometric approach is a parametric approach that aims to establish a statistical relationship between operating costs and the individual cost drivers. The estimated or predicted costs are compared to a business's actual costs, with any differences attributed to inefficiency.

The main advantages of the econometric approach are that it allows for:

— statistical testing to choose between competing models
— differences in operating environment such as scale and density to be controlled for across firms, something which is not possible within many non-parametric methods.

The main disadvantages are:

— the conventional econometric method does not separate statistical noise from inefficiency
  – this is where Stochastic Frontier Analysis (SFA) deviates from the conventional econometric approach by attempting to split one from the other through the introduction of a composite error term
— the econometric method is reliant on the functional form of the model to be chosen so as to reflect the appropriate production technology of the firms in question
— it is subject to a number of data limitations and statistical problems which may bias the results.

There are a number of steps required to estimate an econometric cost function for benchmarking purposes.

First, it is necessary to identify and select the variables that will be used in the estimation process, in particular the number of outputs produced by the gas distribution businesses, the input price of opex and the choice of environmental or operating condition variables that affect operating costs. The data and variables used are discussed in section 2.2.

It is then necessary to choose a functional form for the cost function. The two functional forms considered in our previous work for ActewAGL are the Cobb-Douglas and Translog functional forms. These are discussed in greater detail in section 2.3.

Once the functional form of the cost function is selected, an estimation technique must be applied to produce estimates of the relevant parameters of the model. A large range of possible estimation techniques is possible. In our previous work for ActewAGL we considered pooled OLS, Fixed and random effects models, Feasible GLS and SFA. These are discussed in greater detail in section 2.4 and Appendix A.

In section 2.5 we discuss some of the data limitations that are present in this study. Section 2.6 presents the estimated opex cost function. Finally, section 3 presents opex partial productivity forecasts for AGN.

2.2 Data and choice of variables

2.2.1 Data sources

The cost function analysis presented in this study uses data from nine Australian gas distribution businesses serving urban populations and that are subject to full economic regulation, namely:

— ATCO Gas Australia (WA)
— Australian Gas Networks South Australia (SA) (previously Envestra)
— Australian Gas Networks Victoria (VIC) (previously Envestra)
— Multinet Gas (VIC)
— AusNet Services (VIC)
— Jemena Gas Networks (NSW)
— Australian Gas Networks Queensland (QLD) (previously Envestra)
— Allgas Energy (QLD).

The data were largely sourced from public reports including:

— gas distribution business Access Arrangement Information statements
— regulatory determinations by the AER and jurisdictional regulators
— AER performance reports
— annual and other reports published by the businesses
— consultant reports prepared as part of access arrangement review processes

The estimated models use data for nine gas distribution businesses covering the period from 2003 to 2013. The data comprises an unbalanced panel of 87 observations for the nine gas distribution businesses. While the time series component of the data ends at 2013-14, the starting point of the series differs between businesses, with the earliest observations commencing from 2003-04 for ActewAGL and Jemena.

2.2.2 Data comparability and suitability for analysis

It is our opinion that the data used in the study is robust and appropriate for indicative benchmarking analysis, particularly as the majority of the data has been subject to scrutiny by the relevant economic regulator and in many cases also by expert consultants engaged by the economic regulators.

However, there remains uncertainty about data comparability that ACIL Allen is not able to resolve. Possible differences in the comparability of cost categories and other inevitable shortcomings in the benchmarking analysis mean that the efficiency and productivity benchmarks produced should be treated as indicative, not exact. Other potential shortcomings that limit the ability of the benchmarking models in this study to represent the gas distribution businesses' true cost and production functions include:

— the limited data available for this study e.g. a richer data set with a broader range of cost inputs, outputs and operating environment factors could be used to create model specifications that better account for the variation between the gas distribution businesses
— potential data errors that have not been identified
— the limitations of the modelling techniques in terms of their ability to accurately estimate the true efficient cost and production frontiers.

2.2.3 Input, output and operating environment variables

The output, input and operating environment variables that are used in this analysis are:

Output

- customer numbers

Inputs

- capital services (constant price Regulatory Asset Base (RAB))
- opex price index (weighted price index described below)

Environmental variables

- network density (customers per km of network length)

Constant price RAB is used as a proxy for capital instead of mains length mainly to avoid significant multicollinearity issues that arise from the presence of mains length in the denominator of the network density variable.

The opex price index is the index recommended by the AER for network service providers.[1] This is a weighted opex price index formed using the following Australian Bureau of Statistics (ABS) indexes and weights:

- electricity, gas, water and waste services (EGWWS) wage price index (WPI) —62 per cent
- intermediate inputs: domestic producer price index (PPI) —19.5 per cent
- data processing, web hosting and electronic information storage PPI —8.2 per cent
- other administrative services PPI —6.3 per cent
- legal and accounting PPI —3 per cent
- market research and statistical services PPI —1 per cent.

ACIL Allen sourced these indexes from the ABS and calculated the weighted index.

Since the data set used has only one environmental control variable, the likelihood of correct model specification is limited. However, this does not invalidate the results, but rather suggests that the results need to be cautiously interpreted.

2.3 Model functional form

The functional form used to calculate the opex partial productivity forecasts for AGN is the Cobb Douglas cost function with a single output. In our earlier report for Jemena Asset Management on behalf of ActewAGL we considered both the Cobb-Douglas and the Translog functional forms with several outputs. While the Translog is an example of a flexible functional form which is considerably less restrictive than the Cobb-Douglas, we considered it unsuitable because of our small sample size which provides insufficient degrees of freedom to reliably estimate the parameters of the model.

Furthermore, there is strong multicollinearity between the explanatory variables due to numerous terms involving transformations of the same variables and interaction among variables. This problem is exacerbated when the sample size is small.

It is our opinion that the analysis is limited in this respect and that it should remain focussed on the simpler but more restrictive Cobb-Douglas form, where the parameter estimates can be readily interpreted and are reasonably robust to changes in the estimation technique applied. Because of this necessary assumption, good statistical practice means that any results need to be further tempered.

Cobb-Douglas function

The Cobb-Douglas function assumes a log-linear functional form where the natural logarithm of opex is linear in the logarithm of the output quantities and the input price.

For a Cobb-Douglas function with:

- one output variable:
  - customer numbers (C)

1 See AER, 2013, p. 154-155.

— two input variables:
  - capital services proxied by the constant price RAB (R)
  - opex price (P)
— a single operating environment variable, customer density (CD)
— a time trend capturing technological changes

the function takes the form:

$$\ln(Opex) = a + b_1 Time + b_2 \ln(C) + b_3 \ln(P) + b_4 \ln(R) + b_5 \ln(CD)$$

To ensure homogeneity in prices, the coefficient on the opex price variable (P), b_3 is restricted to equal 1. This is dealt with in the estimation process by subtracting ln(P) from both sides of the equation so that the dependent variable in the regression becomes ln(Opex) minus ln(P) and the price variable disappears from the right hand side of the equation.

The Cobb-Douglas function imposes a constant elasticity of opex to each of the outputs regardless of the scale of the business. From the above specification, this implies that a 1 per cent increase in customer numbers (C) will result in a b_2 per cent increase in opex, regardless of whether the firm is large or small.

The magnitude of the coefficient of the output variable gives an indication of the type of returns to scale present in the sample. If the coefficients b_2 is less than 1, operating costs increase at a slower rate than the output, implying increasing returns to scale. We would expect this to be the case for gas distribution businesses.

The Cobb-Douglas functional form is useful to the extent that it reflects the underlying production technology of the gas distribution business. This functional form has been applied in a number of previous studies of gas distribution businesses.

2.4 Estimation techniques

In our earlier report for Jemena Asset Management on behalf of ActewAGL we tested the following cost function estimation techniques:

— Pooled OLS
— Fixed Effects Model
— Random Effects Model
— Feasible GLS (FGLS)
— Stochastic Frontier Analysis (SFA)

We then applied statistical tests to choose the most appropriate models. To test between OLS and a random effects model, we applied the Breusch-Pagan[2] Lagrange multiplier test. This tests the null hypothesis that variance across firms is zero and that there is no significant difference across firms. In other words, there is no panel effect. Failure to reject the null hypothesis results in the conclusion that there are no significant differences across firms and that pooled OLS can be justified. If the null hypothesis is rejected, then the random effects model is preferred to simple OLS.

The Hausman test[3] was then applied to test if the random effects estimator is unbiased. The Hausman test allows you to decide between a fixed or random effects model, where the null hypothesis supports the random effects model. The test works by testing whether the error terms are correlated with the explanatory variables, a key requirement under the random effects model. If the null hypothesis is not rejected then the random effects model is preferred over the fixed effects model.

The Breusch-Pagan LM test of random effects versus pooled OLS supports the random effects model, with a null hypothesis of no panel effects rejected at the 1 per cent significance level. The Hausman test of fixed versus random effects also failed to reject the null hypothesis of a random effects model at the 1 per cent significance level. Together, these results suggest that the businesses intercepts are different and that the random effects model is the appropriate choice.

[2] Breusch, T and A. Pagan (1980)
[3] Hausman, J. A. (1978)

Additional statistical tests were carried out to assess the presence of heteroscedasticity and autocorrelation in the model residuals. To test for heteroscedasticity, we apply a Modified Wald test for groupwise heteroscedasticity[4]. Serial correlation is tested for via the Wooldridge Lagrange Multiplier (LM)[5] test for autocorrelation in panel data.

Additional testing for group-wise heteroscedasticity rejected the null hypothesis of no heteroscedasticity at the 1 per cent significance level. The Wooldridge test of serial autocorrelation in panel data failed to reject the null hypothesis of no autocorrelation. These results provide evidence in support of group wise heteroscedasticity in the panel, but not of autocorrelation.

The FGLS model estimates a variance-covariance matrix with group-wise heteroscedasticity. For this reason, we preferred this model over the pooled OLS model which imposes an assumption of homoscedasticity on the disturbances.

The analysis was therefore restricted to using estimated coefficients from the random effects, FGLS and SFA models. These estimation techniques are described in more detail in Appendix A.

2.5 Data limitations and issues

2.5.1 Small number of firms

A key limitation of this study is that the sample includes only nine firms. As a result, the results may be sensitive to the removal or addition of a single firm, and it may be difficult to accurately determine the location of the efficient frontier.

While other studies have tried to rectify this situation by significantly expanding the sample size to include firms from international jurisdictions, this is likely to exacerbate other problems such as the failure to account for operating differences between jurisdictions.

2.5.2 Multicollinearity between explanatory variables

An issue arises in the specification of econometric models when there is a high degree of multicollinearity between the explanatory variables in a regression. Multicollinearity is a phenomenon in which the predictor variables in a regression are highly correlated with each other. When this happens, it becomes difficult to measure the impact of any specific variable in the model, despite the model performing reasonably well as a whole.

A model with collinear explanatory variables will tend to be characterised by:

— imprecise coefficient estimates leading to high standard errors and statistical insignificance
— erratic shifts in the coefficients in response to small changes in the model
— the presence of theoretically inconsistent coefficients.

The presence of multicollinearity is problematic because we are attempting to estimate separate elasticities for each variable within a cost function. If these variables do not exhibit sufficient independent variation then it will not be possible to reliably disentangle the separate effects of each variable.

While multicollinearity is a significant problem in the Translog cost function specification, there is also some evidence of coliinearity in the Cobb-Douglas specification between the RAB and customer number variables, which exhibit a high degree of correlation. This suggests that the results of the Cobb-Douglas estimation should be treated with caution.

2.5.3 Different accounting treatment of opex

When benchmarking opex, different accounting practices for capitalising costs can potentially disadvantage those businesses that capitalise a smaller percentage of their expenditure. These businesses will show higher levels of opex compared to those businesses that capitalise a larger percentage of their expenditure onto their balance sheets.

4 See Greene (2000)
5 Wooldridge, J.M (2002)

2.5.4 Missing environmental variables and model mis-specification

Data limitations are such that we are only able to control for a small number of operating environment variables. Failure to control for important environmental or operational differences can potentially lead to biased results. The key operating environment variable specified in the cost functions is customer density. In previous benchmarking studies of gas distribution businesses this has been shown to be a significant explanator of differences in operating and capital costs.

Economic Insights (2014) included additional operating environment variables related to network age (proxied by the proportion of mains length not made of cast iron or unprotected steel) and service area dispersion (proxied by the number of city gates). ACIL Allen do not have the data necessary to include these additional operating environment variables. The exclusion of these, and potentially other significant operating environment variables could reduce the accuracy of the inefficiency measure that can be attributed to actions of the gas distribution businesses. However, this is not in itself a reason to discount the cost function analysis in this report. Good statistical practice requires that these limitations be considered in interpreting the results of the models.

2.6 Cost function estimates

The estimated coefficients for a Cobb Douglas function with a single output, customer numbers, for the three adopted estimation techniques are shown in **Table 2.1** below.

TABLE 2.1 ESTIMATED COBB-DOUGLAS FUNCTION: SINGLE OUTPUT

Variable	Estimation technique		
	Random effects	FGLS	SFA
Time	0.000323	-0.00413***	-0.00467***
	(0.00373)	(0.000121)	(0.000143)
Customers	0.555***	0.303***	0.518***
	(0.191)	(0.0523)	(0.0670)
RAB	0.516***	0.676***	0.606***
	(0.141)	(0.0516)	(0.0770)
Density	-0.685***	-0.254***	-0.615***
	(0.173)	(0.0579)	(0.126)
Constant	-9.471		
	(7.330)		
Observations	87	87	87
R-squared	0.9487		
Number of ID	9	9	9

Note: Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

SOURCE:

The results show that the output elasticity for customer numbers range from 0.30 in the FGLS model to 0.56 in the random effects model. This is consistent with increasing returns to scale.

3 OPEX PRODUCTIVITY GROWTH FORECASTS

In this section we take the parameter estimates from the preferred cost function models (i.e. the random effects, FGLS and SFA cost models) and combine them with AGN's forecasts of customer numbers, RAB, and pipeline length over the next regulatory control period to obtain forecasts of AGN's opex partial productivity. Forecasts are generated under two separate scenarios:

— with growth drivers from the AER's draft decision, released on 26 November 2016 and
— with growth drivers from AGN's revised Access Arrangement proposal submitted in response to the AERs draft decision.

3.1 Inputs to calculating opex partial productivity

The parameter estimates from the models are shown in **Table 3.1** below.

TABLE 3.1 SINGLE OUTPUT OPEX COST FUNCTION REGRESSION ESTIMATE

Coefficients	Estimation technique		
	Random effects	FGLS	SFA
Time	0.000323	-0.00413	-0.00467
Customers	0.555	0.303	0.518
RAB	0.516	0.676	0.606
Customer density	-0.685	-0.254	-0.615

SOURCE: ACIL ALLEN

Table 3.2 shows AGN's forecast growth drivers of opex over the period 2016-17 to 2020-21 under the AER's draft decision. Average customer number growth is expected to be 0.94 per cent per annum, while the RAB and customer density are projected to grow at an annual average rate of 1.99 per cent and 0.39 per cent respectively.

TABLE 3.2 AER DRAFT DECISION: FORECAST CHANGES IN GROWTH DRIVERS

Year	Customers	RAB	Customer density
2016-17	0.24%	2.68%	-0.32%
2017-18	0.67%	2.57%	0.14%
2018-19	1.22%	1.92%	0.68%
2019-20	1.29%	1.33%	0.72%
2020-21	1.31%	1.45%	0.73%

Year	Customers	RAB	Customer density
Average	**0.94%**	**1.99%**	**0.39%**

SOURCE: AGN

Table 3.3 shows AGN's forecasts of the growth drivers of opex over the period from 2016-17 to 2020-21 under its revised Access Arrangement proposal.

The growth in customer density is derived from forecast customer numbers and line length.

Over the next regulatory period average customer number growth is expected to be 0.95 per cent per annum, while the RAB and customer density are projected to grow at an annual average rate of 4.67 per cent and 0.39 per cent respectively.

TABLE 3.3 AGN REVISED PROPOSAL: FORECAST CHANGES IN GROWTH DRIVERS

Year	Customers	RAB	Customer density
2016-17	0.24%	5.48%	-0.32%
2017-18	0.67%	5.74%	0.14%
2018-19	1.22%	4.32%	0.68%
2019-20	1.29%	5.14%	0.72%
2020-21	1.32%	2.66%	0.74%
Average	**0.95%**	**4.67%**	**0.39%**

SOURCE: AGN

3.2 Calculating opex partial productivity

Following Economic Insights (2014), ACIL Allen calculate the partial opex partial productivity growth rate and its three components, namely:

— technical change
— returns to scale
— changes in operating environment.

Technical change is represented by the time trend in the regression. It has a negative coefficient and represents the percentage decrease in opex every year as a result of technological change. This may be due to actual technology, but also encompasses improvements in work practices and methods that lead to lower opex over time.

The productivity gains associated with technical change (A) is estimated as:

$$Technology\ (A) = -Time\ coeffcient$$

Returns to scale are productivity gains that arise as a result of increasing business size over time. The productivity gains from returns to scale (B) are calculated as:

$$Returns\ to\ scale\ (B) = (1 - Customer\ elasticity) \times (Percentage\ \ change\ in\ customers)$$

Operating environment partial productivity is calculated as the RAB and customer density coefficients multiplied by each of their respective changes in each year. The total operating environment contribution to opex partial productivity is the negative of the sum of the RAB and customer density contributions.

$$Operating\ environment\ factors\ (C) = (RAB\ elasticity \times \%\Delta\ in\ RAB) + (Customer\ density\ elasticity \times \%\Delta\ in\ Customer\ density)$$

The opex partial factor productivity growth rate is estimated from these three elements, using the formula:

$$\textit{Opex partial productivity growth rate} = A\,(\textit{Technology}) + B\,(\textit{Returns to scale}) - C\,(\textit{Operating environment factors})$$

3.2.1 Opex partial productivity forecasts under AER draft decision

In this section we calculate opex partial productivity forecasts using growth drivers from the AER's draft determination.

Table 3.4 shows the annual opex partial productivity forecasts for the period from 2016-17 to 2020-21 from the random effects model. This model predicts average partial productivity to decline by 0.37 per cent per annum over the forecast period.

TABLE 3.4 ANNUAL OPEX PARTIAL PRODUCTIVITY FORECASTS, RANDOM EFFECTS MODEL

Year	Technology (A)	Returns to scale (B)	Operating environment factors (C)	PP Opex growth rate (A+B-C)
2016-17	-0.03%	0.10%	1.60%	-1.53%
2017-18	-0.03%	0.30%	1.23%	-0.97%
2018-19	-0.03%	0.54%	0.52%	-0.01%
2019-20	-0.03%	0.57%	0.19%	0.35%
2020-21	-0.03%	0.58%	0.25%	0.30%
Average	**-0.03%**	**0.42%**	**0.76%**	**-0.37%**

SOURCE: ACIL ALLEN

The FGLS model predicts a slower decline (relative to the random effects model) in the average rate of partial productivity of 0.18 per cent per annum over the period 2016-17 to 2020-21 (see **Table 3.5**).

TABLE 3.5 ANNUAL OPEX PARTIAL PRODUCTIVITY FORECASTS, FGLS MODEL

Year	Technology (A)	Returns to scale (B)	Operating environment factors (C)	PP Opex growth rate (A+B-C)
2016-17	0.41%	0.16%	1.89%	-1.31%
2017-18	0.41%	0.46%	1.70%	-0.83%
2018-19	0.41%	0.85%	1.12%	0.14%
2019-20	0.41%	0.90%	0.72%	0.60%
2020-21	0.41%	0.91%	0.80%	0.53%
Average	**0.41%**	**0.66%**	**1.25%**	**-0.18%**

SOURCE: ACIL ALLEN

Table 3.6 shows that the SFA cost model projects average partial productivity to decline over the period 2016-17 to 2020-21 by 0.04 per cent per annum.

TABLE 3.6 ANNUAL OPEX PARTIAL PRODUCTIVITY FORECASTS, SFA MODEL

Year	Technology (A)	Returns to scale (B)	Operating environment factors (C)	PP Opex growth rate (A+B-C)
2016-17	0.47%	0.11%	1.82%	-1.24%
2017-18	0.47%	0.32%	1.47%	-0.68%
2018-19	0.47%	0.59%	0.74%	0.31%
2019-20	0.47%	0.62%	0.36%	0.73%

Year	Technology (A)	Returns to scale (B)	Operating environment factors (C)	PP Opex growth rate (A+B-C)
2020-21	0.47%	0.63%	0.43%	0.66%
Average	**0.47%**	**0.45%**	**0.97%**	**-0.04%**

SOURCE: ACIL ALLEN

If we apply the same methodology as the previous section where we took an average of all three estimation techniques, the average forecast opex partial productivity growth rate is **–0.20 per cent per annum.**

3.2.2 Opex partial productivity forecasts under AGN revised Access Arrangement proposal

In this section we calculate opex partial productivity forecasts using growth drivers from AGN's revised Access Arrangement proposal.

Table 3.7 shows the annual opex partial productivity forecasts for the period from 2016-17 to 2020-21 from the random effects model. This model predicts average partial productivity to decline by 1.75 per cent per annum over the forecast period.

TABLE 3.7 ANNUAL OPEX PARTIAL PRODUCTIVITY FORECASTS, RANDOM EFFECTS MODEL

Year	Technology (A)	Returns to scale (B)	Operating environment factors (C)	PP Opex growth rate (A+B-C)
2016-17	-0.03%	0.10%	3.05%	-2.98%
2017-18	-0.03%	0.30%	2.86%	-2.60%
2018-19	-0.03%	0.54%	1.76%	-1.25%
2019-20	-0.03%	0.57%	2.16%	-1.62%
2020-21	-0.03%	0.59%	0.87%	-0.32%
Average	**-0.03%**	**0.42%**	**2.14%**	**-1.75%**

SOURCE: ACIL ALLEN

As shown in **Table 3.8**, the FGLS model predicts a higher average rate of partial productivity decline of 1.98 per cent per annum over the period 2016-17 to 2020-21.

TABLE 3.8 ANNUAL OPEX PARTIAL PRODUCTIVITY FORECASTS, FGLS MODEL

Year	Technology (A)	Returns to scale (B)	Operating environment factors (C)	PP Opex growth rate (A+B-C)
2016-17	0.41%	0.16%	3.79%	-3.21%
2017-18	0.41%	0.46%	3.84%	-2.96%
2018-19	0.41%	0.85%	2.75%	-1.48%
2019-20	0.41%	0.90%	3.29%	-1.98%
2020-21	0.41%	0.92%	1.61%	-0.28%
Average	**0.41%**	**0.66%**	**3.06%**	**-1.98%**

SOURCE: ACIL ALLEN

Table 3.9 shows that the SFA cost model also projects average partial productivity to decline over the period 2016-17 to 2020-21 by 1.66 per cent per annum.

TABLE 3.9 ANNUAL OPEX PARTIAL PRODUCTIVITY FORECASTS, SFA MODEL

Year	Technology (A)	Returns to scale (B)	Operating environment factors (C)	PP Opex growth rate (A+B-C)
2016-17	0.47%	0.11%	3.52%	-2.94%
2017-18	0.47%	0.32%	3.39%	-2.60%
2018-19	0.47%	0.59%	2.20%	-1.14%
2019-20	0.47%	0.62%	2.67%	-1.58%
2020-21	0.47%	0.63%	1.16%	-0.06%
Average	**0.47%**	**0.46%**	**2.59%**	**-1.66%**

SOURCE: ACIL ALLEN

In choosing between the alternative estimates from the three separate specifications, we apply the same methodology used for ActewAGL, where we adopt the advice of Armstrong (2001) which suggests that combining forecasts derived from methods that differ substantially can improve forecast accuracy[6].

Armstrong (2001) suggests equal weights as a starting point where there is no additional knowledge about which method is the most accurate. If we follow this advice, then a simple average of the three separate average partial productivity measures should be considered. This would result in an average forecast opex partial productivity growth rate of **-1.80 per cent per annum.**

3.3 AER's draft decision on productivity change for AGN

On November 26 2015, the AER released its draft decision on Australian Gas Networks' Access Arrangement for the period 1 July 2016 to 30 June 2021. In its decision, the AER noted that AGN provided an opex partial productivity forecast of zero in its proposal while the other service providers, ActewAGL and Jemena Gas Networks (JGN), both provided forecasts of improving gas distribution productivity.

In the absence of a positive productivity factor for AGN, the AER decided to substitute the productivity forecast of 0.5% per annum developed by ACIL Allen for ActewAGL. It is our opinion that this is inappropriate given that fact that AGN's growth drivers are significantly different from those of ActewAGL, and we would expect the partial productivity forecasts to differ as a result.

6 See Armstrong J. S (2001), p. 417-439.

A

ESTIMATION TECHNIQUES

A.1 Random effects models

The panel nature of our dataset has a number of attractive features which can be captured through the application of random effects models. These are:

— panel data can be used to deal with heterogeneity across firms. There are a large number of unmeasured explanatory variables that will affect the behaviour of each firm. Failure to account for these can lead to bias in estimation.

— by combining both cross section and time series, panel data provides more variation in data which can help to alleviate multicollinearity problems and lead to more efficient estimates.

In the standard fixed effects specification, the unobserved variables that drive the heterogeneity across firms is accounted for by different intercepts for each firm in the estimation. The main drawback of the fixed effects model is the loss of significant degrees of freedom through the implicit inclusion of dummy variables to account for the different intercepts across firms. This leads to less efficient estimates of the common slopes.

The random effects model adopts an alternative way of allowing for different intercepts across firms, which aims to overcome the loss of efficiency that arises in the fixed effect specification.

The random effects model views the different intercepts across firms as having been drawn from a random pool of possible intercepts. The random effects model therefore has a single overall intercept, a set of explanatory variables and a composite error term. The composite error term has two components:

— the random intercept term which measures the extent to which the individual firms intercept differs from the overall intercept

— the conventional error term, which indicates the random disturbance for a given firm in each time period.

The random intercept term is the same for each firm across all time periods.

The random effects estimator saves on degrees of freedom and consequently produces more efficient estimates of the slope coefficients than the fixed effects model. This suggests that the random effects estimator is superior to the fixed effects model. Unfortunately, this is only true if the individual firms' intercepts are not correlated with any of the explanatory variables. If they are, then the estimated slope coefficients will be biased. This is not a problem with the fixed effects estimator because the different intercepts are recognised explicitly.

A.2 Feasible GLS (FGLS)

An alternative estimation method to that of OLS is Feasible Generalised Least Squares (FGLS).

OLS estimates are only efficient under the assumption of homoscedasticity and no serial correlation in the residuals. When these assumptions are violated, the OLS estimates are inefficient, although they remain unbiased. By inefficient we mean that the estimator no longer has the minimum variance among the class of linear unbiased estimators.

In this circumstance, the usual formula of the variance-covariance matrix is incorrect and the estimated variance-covariance matrix will be biased. In this context, interval estimation and hypothesis testing can no longer be trusted.

An estimator which explicitly recognises the non-constant variance and autocorrelation of the disturbances is FGLS, which can produce a linear unbiased estimator with smaller variances than OLS. While OLS estimation minimises the sum of squared residuals, FGLS minimises an appropriately weighted sum of squared residuals, which gives lower weights to those residuals that are expected to be large because their variance is large or those residuals that are expected to be large because other residuals are large.

This approach results in a more efficient estimator than that obtained through OLS regression under heteroscedasticity or serial correlation. Under the classical OLS assumptions of spherical disturbances, the OLS estimator is the most efficient.

A.3 Stochastic Frontier Analysis (SFA)

The standard econometric approach is typically interpreted as all deviations from the predicted values of the model are due to inefficiency. This interpretation is an assumption, whereas in truth, the error term (i.e. 'deviation') is due to three causes: measurement error and other statistical noise, firm heterogeneity outside of management control, and managerial inefficiency.

Just like the standard econometric approach, SFA aims to model the relationship between operating costs, outputs and environmental variables. However, SFA separates the error term into two components:

- an inefficiency term, and
- a random error component.

This split attempts to remove the influence of random noise from the estimate of firm inefficiency. However, these two terms can only be interpreted as such if all firm heterogeneity outside of management control is accounted for within the model. If such factors are not taken into account within the model, then this firm heterogeneity will enter, most likely, both terms as well as affect estimates of the other parameters.

SFA uses maximum likelihood estimation to model the relationship between opex and its drivers. The model takes the form:

$$\ln(C_{it}) = \beta_0 + \sum \beta_j \ln(x_{jit}) + v_{it} + u_{it}$$

where, in the ideal case:

- C_{it} is the opex for firm i at time t
- x_{jit} refers to all output and environmental drivers of opex j for firm i at time t
- v_{it} captures the effect of random factors such as unusual weather conditions for firm i at time t
- u_{it} captures the inefficiency for firm i at time t.

The statistical noise term is assumed to follow a normal distribution with mean zero and variance σ^2:

$$v_{it} \sim N(0, \sigma_v^2)$$

The inefficiency term is assumed to follow a one-sided non-negative truncated normal distribution with mean μ and variance equal to σ^2:

$$u_{it} = N^{+}(\mu, \sigma_u^2)$$

It is logical for the inefficiency term to remain positive because a business cannot reduce costs below the minimum possible level for a given set of outputs at a given set of input prices.

Just as in the standard econometric approach, SFA requires additional assumptions about the functional form of the cost function. If the underlying production technology of the industry is not reflected in the choice of cost function, there is a risk that this mis-specification could lead to biased estimates.

Because of the separation of the error term into two separate components, estimation of SFA cost models are more computationally demanding than conventional econometric methods. Moreover, separating the random and inefficiency components of the error term requires a large number of data points. This is a significant drawback in our case, where we have data on only nine firms and a panel with 87 observations.

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