Efficiency and Productivity Analysis of Local Government in South Australia

Report prepared for
South Australian Productivity Commission

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by

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CONTENTS

ACRONYMS

ABS	Australian Bureau of Statistics
AOV	Analysis of Variance
CPI	Consumer Price Index
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DRS	Decreasing Returns to Scale
FTE	Full Time Equivalents
IRS	Increasing Returns to Scale
KW	Kruskal Wallis test
LG	Local Government
OLS	Ordinary Least Squares
LP	Linear Program
PAG	Predictive Analytics Group
RTS	Returns to Scale
SA	South Australia
SALGGC	South Australian Local Government Grants Commission
SALGPI	South Australian Local Government Price Index
SAPC	South Australian Productivity Commission
SAVG	South Australian Valuer General
SE	Scale Efficiency
TE	Technical Efficiency
TFP	Total Factor Productivity
VESC	Victorian Essential Services Commission
VRS	Variable Returns to Scale

EXECUTIVE SUMMARY

Introduction

Economic Insights (EI) has been engaged by the South Australian Productivity Commission (SAPC) to conduct an empirical analysis of efficiency and productivity in Local Government (LG) in South Australia (SA). This report will in part inform the current SAPC *Inquiry into Local Government Costs and Efficiency*.

The SAPC have requested that we calculate global efficiency measures, which require the estimation of local government production frontiers using the Data Envelopment Analysis (DEA) method.

Regarding data, it has been proposed that 10 years (2008/09–2017/18) of annual data on 68 councils, obtained from the South Australian Local Government Grants Commission (SALGGC), be used in this exercise, along with some complementary ABS data as required.

Methodology

A number of choices can be made when estimating DEA models.

DEA models can be formulated as either input or output orientated. We have chosen an input-orientated DEA model in this study. This choice is usually made in DEA analyses of local government services because council management is generally viewed as having greater control over their various input choices (eg. labour, materials, contractors, etc.) relative to the outputs that they are required to produce (eg. services to properties, maintenance of roads, etc.).

DEA models can be formulated as either Variable Returns to Scale (VRS) or Constant Returns to Scale (CRS). Given that councils are required to service the properties and roads, etc. located within a fixed geographical area, they are clearly unable to alter the scale of their operations. We hence have chosen to estimate a VRS model so that a scale inefficient council (eg. one that might be too small or too large relative to an optimal scale) is not unfairly labelled as inefficient because of its pre-determined scale size.

However, we also estimate a CRS model so that we can separately identify the degree to which council size might be contributing to inefficiency. This is done by decomposing the CRS technical efficiency (TE) score into a VRS TE score and a scale efficiency (SE) score. All these efficiency scores vary between 0 and 1, with a score of 1 indicating full efficiency.

We also use Malmquist DEA methods to obtain measures of Total Factor Productivity (TFP) change over time – for each council over each pair of adjacent years. These indices can be decomposed into changes due to technical efficiency change (catch up to the frontier) plus technical change (shift in the frontier) and scale efficiency changes over time.

All mathematical details on the DEA methods used in this study are provided in Appendix A, along with some useful illustrations.

Outputs and Inputs

The selection of output and input variables used is a critical part of any DEA exercise. After considerable analysis and discussion our preferred DEA model is selected as follows:

Inputs:

Opex = labour expenses + materials, contracts & other expenses

Capital = depreciation expenses

Outputs:

Residential properties

Other properties

Total road length

Nominal expenses have been converted into 2018 dollar values using an appropriate price deflator. In the case of opex, the deflator used was the *South Australian Local Government Price Index* (SALGPI) for *Total Recurrent Expenditure*, while for depreciation expenses the deflator used was the SALGPI for *Total Capital Expenditure*.

Considerable discussion was devoted to the choice of depreciation as the measure of capital, relative to alternative choices such as capital expenditure. The strengths and weaknesses of the different choices were outlined before a final decision was made. An empirical analysis indicated that this choice did not have a notable effect on mean efficiency measures.

A variety of alternative output variables, such as population levels and sealed versus unsealed roads were also considered, before the final model choice was determined. Again, these choices were found to not have a substantive impact on mean efficiency measures.

Exogenous factors

Variations in measured efficiency levels across councils may be a consequence of management decisions, but may also be a result of exogenous factors which are not under the control of management. Hence in this study we identify a number of exogenous factors that may be relevant in the case of local government in South Australia, with the aim of conducting a second stage regression analysis of the efficiency and productivity scores obtained.

Using data from the Australian Bureau of Statistics (ABS) and the SALGGC we have collected data on the following 16 variables:

1. U15 = % population aged under 15
2. ABTSI = % population Aboriginal or Torres Strait Islander
3. NES = % population who speak a language other than English at home
4. PEN = % population who receive the age pension
5. UNEM = % population who receive unemployment benefits
6. MWAGE = median wage
7. GPOP = % growth in population between 2009 and 2018

8. GPROP = % growth in rateable properties between 2009 and 2018
9. DEN = Population density in persons per hectare
10. POP = Population
11. SEALRD = % sealed roads
12. BUSINC = % income from business undertakings
13. IRSED = Index of Relative Socio-economic Disadvantage
14. IRSEAD = Index of Relative Socio-economic Advantage and Disadvantage
15. IER = Index of Economic Resources
16. IEO = Index of Education and Occupation

We also investigate the degree to which the performance measures differ among groups of councils. The Australian Classification of Local Governments (ACLG) outlines 22 different categories of councils. In this study we follow the SAPC Methodology Paper suggestion that these 22 categories be aggregated into four larger groups:

- urban regional;
- rural agricultural (small and medium);
- rural agricultural (large and very large); and
- urban (including capital, development and fringe).

and assess the degree to which performance varies across these four groups.

<u>Efficiency scores</u>

Our results section commences with a discussion of the 2018 DEA model results before then summarising the DEA results for the full 10-year period.

In 2018 the sample mean values of CRSTE, VRSTE and SE are estimated to be 0.798, 0.841 and 0.946, respectively. The VRSTE mean value of 0.841 indicates that the average council could be using 15.9% fewer inputs and still produce the same bundle of outputs if it were able to emulate the performances defined by the efficient councils that define the VRS DEA frontier. The SE mean value of 0.946 indicates that the average council could save an additional 5.4% in inputs if it was to be able to increase (or decrease) its size to achieve optimal scale. This value is approximately one third of the VRS inefficiency value, indicating that scale inefficiency is not a major factor in these councils. Note also that the CRSTE scores are an aggregate of VRSTE and SE scores in the sense that: CRSTE=VRSTE×SE.

An analysis of the efficiency scores for each individual council finds that there are three councils in the data set which have low estimated VRSTE scores of below 0.5. All three of these councils are unique in certain ways and hence these low scores are explainable. However, given the anonymity requirements in this report, we do not comment further.

The above discussion relates to the DEA results obtained using the 2018 sample data. A DEA model has been estimated for each of the ten years of the 2009 to 2018 data sample. It is interesting to note that the ten-year means are quite similar to the 2018 means. That is, the ten-year means are 0.802, 0.841 and 0.950 for CRSTE, VRSTE and SE, respectively, while the corresponding mean values for 2018 were 0.798, 0.841 and 0.946, respectively.

The annual means do not vary much over the ten-year study period. For example, mean VRSTE is observed to vary from 0.836 in 2009 to 0.841 in 2018 with means in the intervening years also quite similar. One might hence be tempted to conclude that this could indicate that productivity has been quite steady over this ten-year period. However, this would only be correct if we could establish that the DEA frontier has not shifted upwards (or downwards) over time. Malmquist TFP growth measures allow us to address this issue.

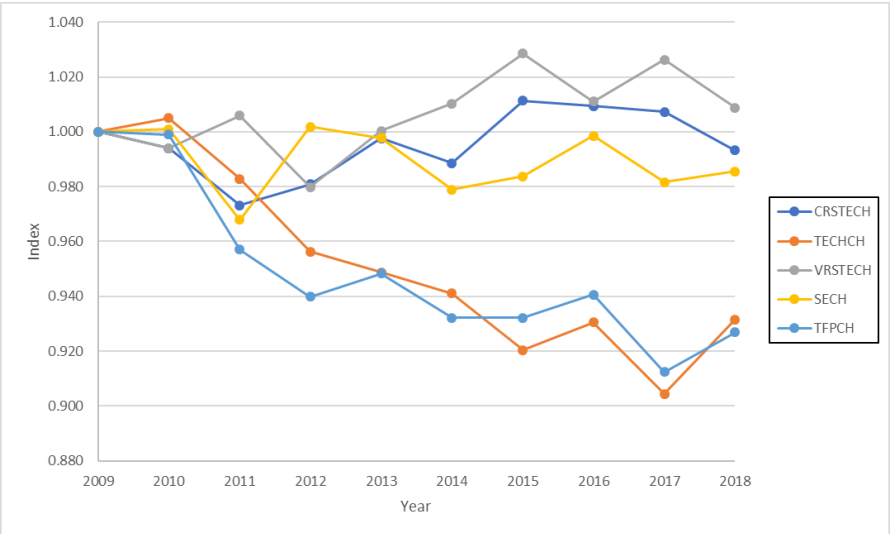
Productivity indices

We also calculate estimates of Malmquist TFP growth for the 10-year sample period. We obtain measures of TFP growth for each council between each pair of adjacent years. Thus, providing a set of 68 chained TFP indices for each of 9 periods. These TFP indices are then decomposed into that part due to frontier shift or technical change (TECHCH) and that part due to catch up or CRS technical efficiency change (CRSTECH). These latter CRSTECH measures are also then decomposed into VRS technical efficiency change (VRSTECH) and a scale efficiency change (SECH) effect.

The contributions of changes in CRSTE, VRSTE or SE over the sample period are minor. However, technical change is observed to play a major role, with an average annual decline in the frontier of 0.8% pa driving an overall decline in TFP of 0.8% pa, as illustrated in Figure 6.1 that is reproduced below.

In most sectors one would expect to observe positive technical change, as improvements in technology and knowhow cause the frontier firms to improve further and push the frontier outwards. The calculation of negative technical change (or technical regress) in this study appears to be counter-intuitive as it indicates that SA councils have collectively increased expenditure per unit of output, as measured in this study (property numbers and road length). The exact reasons for this are unclear at this stage. One possible explanation could be an increase in the volume, quality and/or range of council services that are not captured by the two output variables that are used in the DEA model. Another might be a general decline in sector performance. A third possible explanation could be measurement errors affecting the data that has been used. Testing these alternative explanations for the observed rising trend in expenditure per unit of output is a matter for further work.

Figure 6.1 **Malmquist DEA TFP change aggregate indices 2009-2018**



Measures of mean TFP change for each individual council is also calculated over the 10-year period. These range from a low of 0.940 for council #13 to a high of 1.027 for council #17. A value of 1.027 implies an annual average increase in TFP of 2.7% pa while 0.940 implies an annual average decrease in TFP of 6% pa. Additional analysis is required for one to be able to judge if these differences are due to management issues or other issues such as a unique environment or data measurement errors.

Second stage analysis

Our second stage analysis commences with an analysis of differences in mean efficiency scores and TFP indices across the four groups of councils identified above, the results of which are summarised in Table 7.1 which is reproduced below. Scale efficiency and TFP change are found to not differ significantly across the four groups, while VRSTE is found to differ significantly, with urban regional councils having the lowest mean VRSTE score. This latter group does contain some councils from remote areas and hence warrants further analysis.

Table 7.1 **Analysis of group means**

	VRSTE		CRSTE		SE		TFPCH	
Group	**mean**	**stdev**	**mean**	**stdev**	**mean**	**stdev**	**mean**	**stdev**
urban	0.866	0.033	0.827	0.034	0.953	0.016	0.993	0.003
rural ag S&M	0.871	0.033	0.835	0.034	0.959	0.016	0.993	0.003
rural ag L&XL	0.841	0.036	0.806	0.038	0.959	0.018	0.989	0.004
urban regional	0.714	0.050	0.659	0.052	0.907	0.024	0.990	0.005
Test	**prob**	**null hyp**	**prob**	**null hyp**	**prob**	**null hyp**	**prob**	**null hyp**
AOV	0.058	accept	0.039	reject	0.298	accept	0.863	accept
KW	0.025	reject	0.067	accept	0.527	accept	0.526	accept

Regression analysis was also used to see if variations in VRSTE scores and TFP indices across councils could be explained in part by the various exogenous factors outlined above. In the case of VRSTE, five of the 16 regressor variables were found to have a statistically significant influence on scores at the 5% level. Namely, ABTSI, NES, PEN, GPOP and IER. Some of these estimated coefficients (ABTSI and GPOP) had the expected signs while others were not as expected. A discussion of the possible reasons for the unexpected signs is provided, including the possibility that variables such as NES and PEN might be acting as proxies for low-socio economic demographics and hence reflect populations that demand fewer extra council services.

A regression analysis of the council-level mean TFP change indices was also conducted, where we found that all 16 regressor variables were statistically insignificant at the 5% level and that the R-squared value was only 26%. As a consequence, we conclude that none of

these 16 variables are useful in explaining variations in TFP change indices across these 68 councils.

Concluding comments

The conclusions section of this report contains a brief summary of the main empirical results of the study along with a discussion of some the possible reasons for the observed decline in productivity over the ten-year study period. Particular mention is made of the possible effects of changes in the quality and range of services provided, as well as the possible influence of enterprise bargaining agreements being more generous than other sectors in the early part of this period. The need for future analysis of these and other factors is encouraged.

It is also noted that the efficiency scores for each council that are reported in this study are estimated relative to the 68 South Australian (SA) councils included in our database. Thus, these measures are only relative to the best performers in SA. If councils from other locations, such as other States in Australia were included in our database, it is possible that these estimated efficiency scores could change. It might be a useful exercise to attempt to conduct some interstate comparisons of council performance at some stage. However, issues of data comparability and differences in services delivered across different States would need to be properly addressed for this to be a useful exercise.

Additionally, we note that the tables of council-level performance measures presented in this report have been masked so that individual councils cannot be identified. In our assessment, it may be a useful exercise for the performance measures of individual councils to be made public at some point in time. This might have the effect of encouraging councils to critique the models and data measures used and hence lead to better model structures and data quality in future analyses of local government performance in SA.

Finally, it is important to emphasise that this study, like all DEA studies, is imperfect. The input and output variables that have been chosen are the best available, but they are unable to capture all minute aspects of every individual council's activities. Hence, the council-level efficiency scores and TFP indices should be interpreted with a degree of caution. Any councils which are found to be performing particularly well or not so well should be carefully studied to see if their results are a consequence of managerial performance or alternatively a consequence of a unique environment or provision of extra services or different quality services or due to data measurement issues.

1 INTRODUCTION

Economic Insights (EI) has been engaged by the South Australian Productivity Commission (SAPC) to conduct an empirical analysis of efficiency and productivity in Local Government (LG) in South Australia (SA). This report will in part inform the current SAPC *Inquiry into Local Government Costs and Efficiency*.

The Terms of Reference of this Inquiry are available here:

https://www.sapc.sa.gov.au/inquiries/inquiries/local-government-inquiry/notice-of-inquiry

The SAPC has also written a Methodology Paper: SAPC (2017), which provides guidance on the methods to be used in this analysis.

The SAPC have requested that we calculate global efficiency measures, which require the estimation of local government production frontiers using the Data Envelopment Analysis (DEA) method.

Regarding data, it has been proposed that 10 years (2008/09–2017/18) of annual data on 68 councils, obtained from the South Australian Local Government Grants Commission (SALGGC), be used in this exercise, along with some complementary ABS data as required.

Our terms of reference ask that we undertake work on calculating relative efficiency levels in the local government sector including the following activities:

- develop the data requirements to calculate efficiency scores using DEA;
- assist SAPC staff to compile a suitable data set to calculate relative efficiency using DEA;
- for every one of the ten years calculate indicative relative efficiency levels for all councils using a single frontier for all 68 councils;
- estimate efficiency trends through the time period using an appropriate methodology;
- clearly outline details behind the methods chosen and key assumptions used;
- provide analysis and commentary on scores by sub groups as well as the total 68 councils; and
- clearly explain the factors influencing efficiency trends in the sector – either through a regression analysis of DEA outputs, or an appropriate alternative methodology.

The remainder of this report is divided into sections. In Section 2 we outline the DEA methodology used in this study. In Section 3 we discuss the selection of output and input variables, while in Section 4 we discuss exogenous factors that may influence efficiency scores across councils. In Section 5 we present and discuss our empirical estimates of efficiency, while in Section 6 we present and discuss our estimates of total factor productivity growth over time. Section 7 then contains our empirical analysis of the effects of various exogenous factors upon these estimates of efficiency and productivity, while Section 8 finishes with some concluding comments.

2 METHODOLOGY

The methodology used to estimate efficiency levels in this report will be Data Envelopment Analysis (DEA). Details of all methods used are provided in Appendix A.

Data Envelopment Analysis (DEA)

DEA models can be formulated as either input or output oriented. Given that local councils are obliged to service the residents, ratepayers, roads, etc. that are located within their jurisdiction, we have chosen an input-oriented DEA model, since it is evident that council management generally have more control over input levels relative to output levels.

DEA models can be either Variable Returns to Scale (VRS) or Constant Returns to Scale (CRS). Given that councils do not have control over the scale of their operations, we have chosen to estimate a VRS model so that a scale inefficient council (eg. one that is too small or too large relative to optimal scale) is not unfairly labelled as inefficient because of its scale size. However, we also estimate a CRS model so that we can separately identify the degree to which council size might be contributing to inefficiency. This is done by decomposing the CRS technical efficiency (TE) score into a VRS TE score and a scale efficiency (SE) score. All these scores vary between 0 and 1, with a score of 1 indicating full efficiency.

The above models are applied to all 68 councils in each of the 10 years of the 2008/09-2017/18 study period. VRS TE, CRS TE and SE scores are produced for each council in each year, providing valuable information on the evolution of efficiency over time.

Malmquist DEA

However, one must keep in mind that these efficiency scores are relative to the estimated DEA frontier in each year. If the estimated DEA frontier shifts up or down from one year to the next, these annual efficiency measures will provide a misleading indication of actual productivity changes over time.

As a consequence, we also estimate Malmquist DEA Total Factor Productivity (TFP) indices – for each council over each pair of adjacent years. These indices can be decomposed into indices of changes due to technical efficiency change (catching up to the frontier) plus technical change (shifts in the frontier) and scale efficiency changes. Thus we obtain a full comprehensive view of performance changes over time and the various factors that contribute to these changes.

Further mathematical details on the DEA methods described above are provided in Appendix A, along with some simple diagrams to help explain the various measures. For additional information please refer to Coelli et al (2005).

DEA versus partial productivity ratios

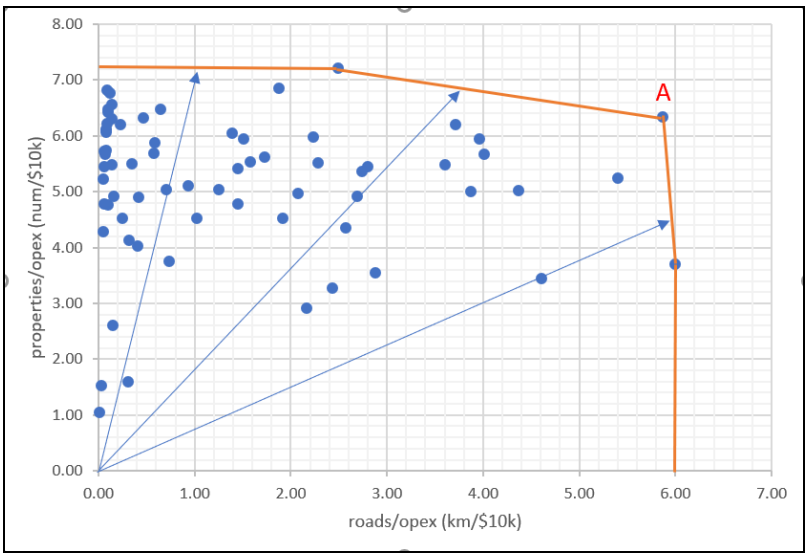
A DEA model has particular advantages over a simple ratio analysis, because it is able to accommodate multiple input and output variables in a single analysis. It might be tempting for a council to argue that DEA is a “black box” and has no value to them. But it is worth noting that if one was to consider a very simple DEA model with two outputs (properties and roads) and one input (opex) the DEA scores obtained from this model will always be equal to or larger than (ie. more flattering than) the individual partial productivity ratios of properties/opex and roads/opex for each and every council. This is because of the convex

nature of the DEA frontier and the way in which councils are only compared to similar "peer" councils, which have a similar mix of inputs and outputs and also have a similar scale size.

This statement can be partially illustrated by plotting these two partial productivity ratios on a scatter plot and using a ruler and pen to draw a piece-wise CRS DEA frontier over the data points and then measuring the DEA scores relative to this frontier. This is done in Figure 2.1 below. The council represented by point A provides a simple example in support of the above statement. This council is on the DEA frontier and hence has an efficiency score of 1, even though it does not have the highest properties/opex ratio nor the highest roads/opex ratio.

Furthermore, note that if we could draw the equivalent VRS DEA frontier in three dimensions (opex, roads and properties) we would also see that similar sized councils would be benchmarked with each other, producing VRS TE scores that are equal to or higher than the CRS TE scores implicit in Figure 2.1. For more on this aspect of VRS frontiers, please refer to the discussion surrounding Figure A.2 in Appendix A.

Figure 2.1 **DEA versus simple partial productivity ratios**



Additional issues

It should be noted that the DEA analysis conducted in this report adopts many of the suggestions outlined in the Methodology Paper.[1] However, a few of the suggested options have not been taken up in this report due to a combination of time constraints, data constraints and other factors. These are now discussed below.

DEA models for individual services

We have chosen to model the services provided by the entire council and have not attempted to individually estimate DEA models for individual service categories, such as transport, recreation, waste management, etc. This choice was made for a number of reasons. In particular, we were not confident that the expenses information that has been reported in each

[1] SAPC (2019).

individual service category for each council in the LGGC data is of a uniformly high quality. Our main concern here relates to the fact that different councils are likely to allocate overheads, such as admin services and office space costs, etc. in different ways. For example, if a particular council tends to allocate less overheads to transport and more to waste management, it might appear to be unusually efficient in transport and inefficient in waste management, relative to the actual situation.

In addition to this, the data on service-level output measures, such as kilometres of roads resealed and tonnes of waste collected, etc. was not available in the SALGGC data set provided to Economic Insights at the commencement of this project. Thus, additional data would need to be extracted and collated and assessed and cleaned prior to this type of analysis being feasible. This activity was deemed to be not achievable given the time constraints faced in this DEA project. However, if this data did become available at some later stage and if it was deemed to be accurate and reliable, the construction of some simple partial productivity ratios, such as operating expenses per tonne of garbage collected, could provide some service-level insights into the various aggregate council-level efficiency scores reported later in this document.

DEA models for groups and sample size issues

We have chosen to estimate our DEA frontiers using the full sample of 68 councils and have decided to not attempt the estimation of DEA frontiers for each of the four individual groups as suggested in the Methodology Paper. Those groups being:

- urban (including capital, development and fringe); and
- rural agricultural (small and medium);
- rural agricultural (large and very large);
- urban regional.

The above four groups have sample sizes of 21, 21, 17 and 9, respectively.

We are aware that the previous Victorian Essential Services Commission (VESC) analysis conducted by the Predictive Analytics Group (PAG) had estimated DEA models for five different groups of councils (of sizes 9, 19, 22, 10 and 19) from the 79 councils in Victoria.[2]

In our assessment, all of these sample sizes are too small for one to be able to obtain reliable estimates of DEA frontiers in local government, when estimating complex DEA models with multiple input and output variables. For example, the PAG analysis estimated DEA models involving a minimum of three outputs and two inputs, that are similar in nature to the models considered in our analysis here. That is, DEA models which are constructed in a five-dimensional space.

The question of what defines a suitable sample size in DEA is open to debate. In the management science literature, one sometimes sees "Nunamaker's Rule" quoted, which essentially says the sample size should be at least three times the number of inputs plus outputs in the model.[3] Hence in a five-dimensional model, this rule suggests that at least 15 observations are needed. Thus, we immediately observe that the above sample sizes of 9 and 10 would violate this rule.

[2] VESC (2017).
[3] For example, see Drew (2018).

However, most economists and econometricians (ie. statisticians) that specialise in efficiency analysis would argue that this rule is not at all adequate. Perhaps the best way to explain this is to observe that it is generally agreed that a DEA frontier is <u>considerably more flexible</u> than an econometrically estimated *translog* production frontier. A translog is a functional form that is quadratic in logs and is popular in frontier efficiency measurement studies.[4] If K is the number of inputs plus outputs in the model, then the number of parameters (P) estimated in a translog model is P=K+K(K-1)/2. Hence for K=5, we have 5+5(5-1)/2=15 parameters to be estimated.

In general, statisticians will argue that a model estimation should involve degrees of freedom of at least 30, where degrees of freedom equal the number of observations (N) minus the number of parameters to be estimated (P). Hence, one could argue that the minimum sample size one should normally consider for K=5 would be N=45, so that the implied degrees of freedom are then N-P=45-15=30.

Thus, in our case where we have 68 observations, we would argue that one should ideally not split the sample into smaller sub-groups because the implied degrees of freedom would be inadequate for one to obtain reasonable estimates of a DEA frontier.

Note that when one attempts to estimate a complex DEA model (eg. a five-dimensional model) using a small number of observations one tends to find that many of the observations (firms) are found to be "efficient by default", because they have no other similar firms located near them that have similar mixes of inputs and outputs. This issue is well illustrated by the results reported in the VESC (2017) Victorian study, where their DEA models involving the full sample had found approximately 25% of councils identified as being fully efficient (ie. located on the VRS DEA frontier) but when the smaller sub-sample DEA models were estimated this percentage increased markedly to over 50% of councils on the frontier in most cases and as high as 80% on the frontier in some cases.[5] Thus, a DEA model is unable to discriminate between the different councils when sample sizes are this small.

In addition to having many councils identified as being on the frontier, a small sample size will also have the effect of inflating the mean efficiency scores obtained. This is evident in the PAG study, where their model #1 mean VRS TE increases significantly from 0.81 in the full sample DEA model to 0.94 in their sub-sample models.

The effects of sample size on the mean efficiency scores obtained from DEA models are well known. For example, see the often-cited monte carlo simulation study by Zhang and Bartels (1998) and the large meta-analysis of 95 hospital efficiency studies reported in Nguyen and Coelli (2009). In the latter study, their Figure 10 illustrates the clear effects of sample size and number of inputs+outputs on the mean efficiency scores obtained across these 95 studies.

In addition to the sample size issue, another reason why we are comfortable with estimating a single DEA model for the full data sample is that we have carefully chosen our set of output variables and our model structure (VRS) so that the DEA model will in general identify appropriate sets of frontier "peers" for each council. That is, by using a VRS DEA model we ensure that similar sized councils are benchmarked with each other (see the discussion around Figure A.2 in Appendix A). Furthermore, rural councils (with high ratios of roads to properties) are benchmarked with similar councils and urban councils (with low ratios of

[4] See Coelli et al (2005).
[5] See Tables 1.4 to 1.8 in the PAG (2017) study.

roads to properties) are also benchmarked with similar councils. For an illustration of this, see the example benchmarking arrows drawn in Figure 2.1 above.

As a result of this, we would argue that there is no need to estimate a separate DEA model for each group as the peer sets will in essence do this work for us in a single pooled DEA model (given that an appropriate model structure and set of output variables are chosen). Furthermore, one would expect that the pooled DEA model will do a much better job of measuring efficiency scores for those councils that are located on the arbitrarily selected boundary between two groups because they will be able to make use of frontier peer information from both groups in this pooled case.

Window-DEA

The Window-DEA method of Flokou et al (2017) was suggested as one possible method that could be used to monitor efficiency changes over time. We have instead chosen to use the more widely applied Malmquist DEA method. The Malmquist DEA method does not only calculate changes in technical efficiency over time, but is able to provide comprehensive information on changes in technical efficiency, scale efficiency and frontier shifts overtime, which are collectively used to form aggregate measures of total factor productivity (TFP) change over time for each council across each pair of adjacent time periods.

Furthermore, we observe that the Window-DEA method does not appear to be widely used in the literature, relative to the Malmquist DEA method. The Malmquist DEA method was adopted by PAG in its recent analysis of efficiency and TFP change in Victorian councils for the VESC. Furthermore, the Malmquist DEA method has also been widely used in analysing changes in relative performance over time in many sectors for a number of decades. For example, refer to the recent survey of DEA applications by Emrouznejad and Yang (2018) where they analyse a database of 10,300 DEA-related journal articles over the 1978-2016 period. In a table of the 50 top keywords, the keyword “Malmquist” is ranked #14 with 359 mentions while the keyword “Window” does make it into this top 50 list.

3 OUTPUTS AND INPUTS

When estimating a DEA model, the careful selection of output and input variables is an important exercise. In this study we have considered a number of factors including: what data is available; a review of the empirical literature on local government studies;[6] the degree to which different variable sets help to identify good peer sets (eg. how the combined use of properties and roads data helps divide the data space into low and high population density councils); and degrees of freedom constraints which limit the number of variables that can be included in a DEA model without losing too much discriminating power.

In our assessment, based on the above criteria, we have looked to identify possible DEA models that involve a maximum of five or six variables (ie. dimensions). A series of scatter plots, time series plots and correlation matrices were also used in helping us identify candidate variables and models.

After considerable analysis, our preferred DEA model is as follows:

Inputs:

Opex = labour expenses + materials, contracts & other expenses

Capital = depreciation expenses

Outputs:

Residential properties

Other properties

Total road length

Please refer to Appendix B, where we provide additional discussion of our model assessment processes and provide a summary of the empirical estimates obtained from a number of different DEA models.

With regard to the selected input and output variables listed above, the following discussion provides additional detail.

<u>Price deflators</u>

Nominal expenses have been converted into 2018-dollar values using an appropriate price deflator. In the case of opex, the deflator used was the *South Australian Local Government Price Index* (SALGPI) for *Total Recurrent Expenditure*, while for depreciation expenses the deflator used was the SALGPI for *Total Capital Expenditure*. For further detail on these price indices see:

https://www.adelaide.edu.au/saces/economy/lgpi/

Note that the Consumer Price Index (CPI) was not chosen because movements in the wages and material input prices, etc. used in local government activities need not mirror movements in the prices of groceries, household goods, residential housing and other items that are normally included in the CPI basket of commodities constructed by the Australian Bureau of Statistics (ABS). For example, see the data plots provided later in this section.

[6] For example, see Drew (2018), Drew et al (2015), Fogarty and Mugera (2013), PAG (2017) and VESC (2017).

Operating expenses

In the SALGGC data provided to Economic Insights, operating expenses were reported in the following five general categories:

- Employee Costs
- Materials, Contracts and Other Expenses
- Finance Costs
- Depreciation, Amortisation and Impairment
- Share of Loss - Joint Ventures & Associates

The *Finance* expenditure category has been omitted from our analysis because this is generally viewed as being a consequence of past council decisions and not current activities.

The *Share of Loss - Joint Ventures & Associates* expenditure category has also been omitted because this relates to a small number of non-core council activities which are not directly captured on the output side of the DEA model.

Data was available on number of employees measured in full time equivalents (FTE). It was decided to not use this measure and instead use labour expenses (included as part of opex). This was for various reasons. First, the FTE data was for the entire council and was not broken up into operating and capital activities. As a result, the use of FTE would involve double counting if a capital measure (eg. capex or depreciation) was used in the model. Second, the FTE data does not reflect quality differences across employees. Those councils with a higher ratio of road lengths to properties are likely to have a higher ratio of outdoor staff compared to office staff and hence FTE measures are likely to provide an overstated measure of quality-adjusted labour for those councils. Third, it was observed that some previous DEA studies of local government had chosen to use FTE in place of the above opex input measure. In our view this could be problematic if the degree of outsourcing varies across councils, because those councils who use less outsourcing might incorrectly appear to be inefficient because they have higher FTE levels relative to those councils which do more outsourcing.

Roads data

The roads output variable used in the model is kms of total road length. A DEA model in which the total road length output variable was broken up into sealed road length and unsealed road length variables was also considered. This change was observed to have a very minimal effect on the efficiency scores obtained, with only a small number of small changes on a few scores in the third decimal place. Hence the single roads measure was adopted.[7]

A DEA model was also considered with a population output variable added into the model.[8] This also had only a small impact, with a 1% increase in mean efficiency scores. This is not surprising given that a high correlation (in excess of 99%) was observed between the population and residential properties variables.

[7] For further detail see Appendix B.
[8] For further detail see Appendix B.

Properties data

The DEA model includes properties data divided into residential and other categories. This is done to reflect the differing requirements for servicing residential versus non-residential properties. The latter would primarily be farms in rural council areas while they would be mostly commercial businesses in the case of urban councils.

The properties data that was initially provided by the SALGGC was plotted over time (along with various other data variables) so that we could study the general trends in the various data variables (see further discussion of our data plots below). The plot of the properties data series was observed to generally trend up by approximately 1% per year over the 10-year period, except for a notable drop in 2015, where it was observed that total properties data fell by 1% and "other" properties data fell by almost 20%. Given that properties are unlikely to "disappear" in aggregate, we suspected that this may be a consequence of some definitional changes in the data. After discussions with the SAPC and the SALGGC we discovered that the system used to calculate properties data did in fact change at that point in time, with the SALGGC shifting from the Land Ownership Tenure System (LOTS) to the South Australian Integrated Land Information System (SAILIS).

After a number of very useful discussions with the SAPC and the SALGGC and the SA Valuer General (SAVG), we were able to identify the main differences between these two systems, and then source some alternative data from the SAVG. We are grateful to the SALGGC and SAVG for their generous assistance with this.

We were advised that a number of changes were introduced in the new SAILIS properties system in 2015. Most changes related to moving various types of properties (eg. rural residential properties) into different classifications, the effect of which was a net decrease in the ratio of residential properties to other properties. However, the main problem we faced related to "Administrative records" being included in properties data in the early years and then being excluded post 2015. This was a logical change to make because these administrative records were generally not actual rateable properties, but were instead administrative records used by SA Water and others for billing purposes.

As a consequence, the inconsistent treatment of these administrative records across the two parts of this 10-year period had introduced an artificial decrease in the SALGGC properties data series in 2015 which then had the effect of overstating the decrease in measured productivity over time in some earlier draft versions of our DEA models.

The new properties data that we now use in this study has been supplied directly from the SAVG with the data on "Administrative records" separately identified so that we could then remove them from the 2009-2015 properties data to create a 10-year series that now uniformly excludes these "Administrative records" data.

It is important to note that the SAVG properties data (that we now use in this study) includes both rated and unrated properties in its database, while the original SALGGC properties data excluded unrated properties and also made a number of other small adjustments. However, we have observed that the differences in the total number of properties between the SAVG and SALGGC data was less than 0.7% in 2018 and hence we conclude that these factors are unlikely to have a substantive effect upon results. Furthermore, it could be argued that the inclusion of total rated and unrated properties may be a more appropriate measure to use in this instance, given that some councils would argue that they are still required to provide

services to some properties (eg. churches, hospitals, etc.) even though they do not collect rates on those particular properties.

Capital measures

The selection of depreciation as a measure of capital input was made after a significant number of issues were carefully considered. In our assessment, all available capital measures can be criticised to some degree, but on balance the depreciation measure was the best available in these data. The issue of capital measurement is discussed in some detail below.

The selection of an appropriate capital quantity measure is a complex exercise in any empirical analysis of the productive performance of a group of businesses or organisations, because capital inputs generally provide services over more than one accounting period. The case of local government is particularly complex. Hence, let us discuss a simple example first, before then tackling the case at hand.

Consider the case of a dairy farm. The capital items you might expect to see on a dairy farm (excluding land) would include the milking shed, milking equipment, tractor, ute, trailer, motor bike, plough, slasher, hay baler, irrigation pump, etc. The first thing to note is that we have listed 10 items (and there would be more if we tried). It is not feasible to include 10 capital variables in our dairy DEA model because we would quickly run out of degrees of freedom. Also, how do we distinguish between different sizes and brands of tractors, etc so as to correctly reflect the service potential of these various capital input items? Hence it is common place to construct an aggregate measure (or measures) of capital input. This requires aggregation weights, and given data availability, dollar values from the firm's accounts are normally used.

One possibility is to collect the capital values from the balance sheet for each of these items and add them together to form an aggregate measure of capital stock. This capital quantity measure would implicitly assume that a $50,000 tractor would produce 5 times the services of a $10,000 irrigation pump and so on. This might not be reasonable if the tractor has an assumed life of 10 years while the pump has an assumed life of 5 years. Hence an alternative is to use the measure of annual depreciation reported in the firm's accounts instead.

However, both of these possible measures might be sub-optimal for various reasons. First, the effects of price inflation and accounting depreciation might understate the service potential of older capital items. For example, consider the situation where two farms have near identical tractors purchased nine years apart, the old tractor has a book value of less than $5,000 versus the book value of $50,000 for the new tractor – yet both tractors produce very similar services. The farm with the new tractor might incorrectly be labelled as inefficient because it appears to be using more capital – based on a nominal written down capital stock measure. A depreciation measure will be less affected by this issue (if straight line depreciation is used) but it will still be in part affected by the effects of price inflation on the original purchase price of the older tractor.

The issue of price inflation can be addressed by doing regular revaluations of the capital stock items to reflect the current unwritten down replacement cost. In this situation, depreciation on the current unwritten down replacement cost arguably provides a good measure of the service potential of the capital item. However, this measure can still be criticised because some capital items might be more degraded because they have been used much more over the years (eg. a tractor used 30 hours per week on one farm versus 3 hours per week on another). Furthermore, current replacement cost valuations can be challenging and vary a lot across

firms – as can the depreciation assumptions used (eg. when accelerated depreciation rules offered by the tax office are used).

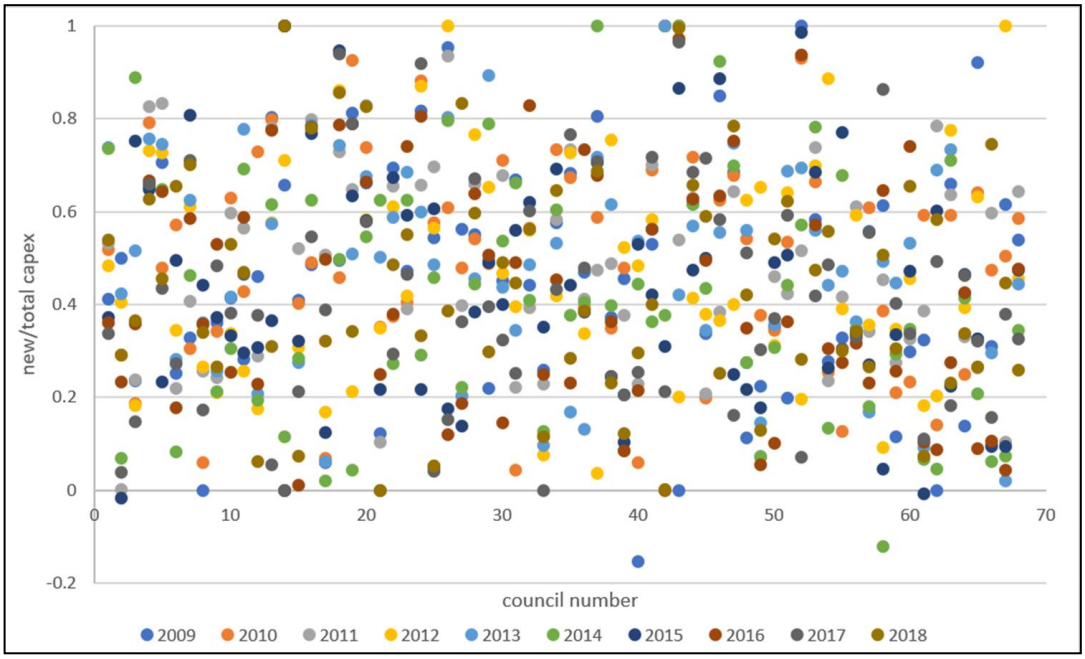
In many cases, a researcher only has access to the data reported by the dairy farm in it's annual accounts and hence only has access to capital measures based on written down historical cost based on a myriad of accounting rules. One alternative is to instead use data on reported annual capital expenditure, assuming that capital expenditure is proportional to the quantity of capital on the farm. This is obviously a brave assumption in those situations where a business is expanding or when investment in capital is lumpy from one year to the next. For example, a farm buying a large new tractor in one year will appear to be more inefficient than it actually is, relative to other farms which spend less on capital purchases that particular year. Hence, we rarely have access to good quality capital measures in this industry and many other industries for that matter.

Now let us consider the case of measuring capital input quantity in a DEA analysis of local governments. Many of the above dairy farm comments apply equally here. However, there are a number of key differences worth noting. First, we are informed that capital stock measures are regularly revalued in most SA local councils, which is a positive. Second, we have been informed that there has been a concerted effort put into trying to make valuation methods and depreciation assumptions as uniform as possible across all SA councils over the past decade. Third, capital expenditure can vary from year to year as a result of lumpiness in grants income provided by State and Federal Governments, as is evident from the available data. Given the above three points (and the discussion above), we have chosen to use depreciation as our measure of capital input quantity in this DEA study, in preference to the use of a capital expenditure or capital stock measure.

Note that we did investigate a DEA model with capital expenditure used instead of depreciation and observed that mean VRS TE decreased by only 1%, which might have been a consequence of the greater variability in capital expenditures driven by variations in grant funding available, etc.

A few additional complications regarding capital measurement in local government need to be noted. The first relates to the fact that some councils have growing populations and hence do not only renew and replace existing assets but also invest in new and upgraded assets to accommodate this growth. These two types of capital expenditure are reported in the data base. Given that our DEA model does not include growth measures (in roads or properties) as outputs, this provides an additional argument for the use of a depreciation measure in preference to a capital expenditure measure. We did consider the possibility of using a capital expenditure measure relating to renewals and replacements only (ie. excluding expenditure on new and upgraded assets) however an investigation of the council-level data on these items suggested that the allocation of expenditures into these two sub-categories was essentially random. In Figure 3.1 we present a scatter plot of the ratios of capital expenditure on new and upgraded assets over total capital expenditure to illustrate this. We also noted that the ratios of capital expenditure on renewals and replacements over depreciation averaged 0.74 while that of total capital expenditure over depreciation averaged 1.49. The latter measure being greater than one could be explained in part by growth, but the former measure being less than 1 is hard to explain unless asset management plans for some reason systematically deviate from depreciation measures by a factor of 26% across the sector?

Figure 3.1 **Plot of new/upgrade capex over total capex**



The second issue relates to the fact that (unlike in our dairy farm example) local government assets can be divided into two categories:

1. Those which provide production services – such as plant and equipment (backhoes, trucks, etc.), depots, offices, etc., and
2. Those which provide consumer services – such as roads, drains, parks, libraries, etc.

One might argue that the correct capital input quantity variable for our DEA model relates to category 1 and not category 2. This might seem reasonable at first glance, because category 2 assets do not actually provide productive services. However, given that the expenditures recorded in our opex input measure explicitly excludes all expenditures relating to renewal and replacement of these consumer assets (ie. these latter expenses are capitalised) it is important that these expenses appear somewhere, since the provision of assets that provide consumer services (roads, drains, libraries, etc) is a significant part of council services. As a result, we conclude that expenses on category 1 and 2 assets should both be included in the input set, and since total depreciation is arguably a more reliable measure than reported annual total capital expenditures, we use total depreciation as our best (but less than perfect) measure of capital input in this study.

A third issue worth mentioning, is how well do council accounts accurately delineate between capex versus opex activities? For example, for sealed roads a resurface would be classified as capex while fixing potholes would be classified as opex. For gravel roads, regular grading would be classified as opex while a once-off reforming would be classified as capex. The various categorisations would be fairly well set out in the annual LGGC data request material, but the reality of day-to-day record keeping might be less consistent across different councils. Furthermore, if a council does more regular opex on roads, is this reflected in a longer assumed asset life and hence lower annual depreciation in the accounts? Or does this council instead appear to be more inefficient because the assumed asset life is left unchanged? We

have no immediate answer to these questions, but they are questions worth considering when comparing the estimated relative efficiencies of different councils in this study.

Data plots

It is instructive to plot the aggregate data over time to assess the degree to which the various measures are changing over the ten-year study period. This is best done using index numbers where the aggregate data for each variable in each year is converted into an index. Each variable is given an index value of one in the first year (2009) and then subsequent values reflect proportional changes relative to that base year. A number of indices are plotted in Figures 3.2 to 3.5 below. The indices themselves are also presented in a table under each plot and the annual average change in each index is listed in the final column of each table.

Consider first Figure 3.2, where a selection of input, output and prices indices are presented. The first listed index is labour in full time equivalents (FTE). This index shows that FTE labour has increased by 1% between 2009 and 2010 and then increased by 2% between 2010 and 2011 and so on. In the final year of 2018, labour FTE has increased by a total of 7% relative to 2009, with an annual average change of 0.79% pa.

We note that population has increased by 0.75% pa and properties have increased by 0.98% pa which are broadly similar to the labour FTE change. Hence one could argue that labour productivity has remained fairly constant over this period. However, given that the length of roads has only increased by 0.08% pa one might argue that labour productivity could have fallen to some extent. Furthermore, we have not taken into account non-labour inputs yet in this discussion, and if there has been a change in the degree of outsourcing over time this discussion of partial productivity measures becomes more complicated. Hence the need for an aggregate performance measure such as DEA, which can accommodate multiple inputs and outputs (more on that shortly).

Next, we observe that labour expenses have increased by 4.52% pa over this period, which is larger than the 0.79% pa increase in FTE. This difference can be in part explained by wage increases of almost 3% pa (see Figure 3.5 below). The remaining difference of approx. 1.5% could perhaps a consequence of small changes in the mix of white-collar and blue-collar workers in councils over this period, or alternatively due to some generous enterprise bargaining results in the early part of the study period. Additional investigation of these issues could be useful.

Materials Contract and Other Expenses (MCO Exp) has also increased by 4% pa, with Opex (Labour and MCO expenses) increasing in aggregate by 4.24% pa. When depreciation expenses are added to Opex we obtain our aggregate Opex2 measure, which has increased by 4.29% pa. Given that the local government price index (LGPI) has only increased by 2.48% pa over this period and the output measures (eg. properties and roads) have increased on average by 0.53% ((0.98+0.08)/2=0.53), one might argue that collectively these data point towards a productivity decline of approximately 1%. However, these calculations are very rudimentary. The Malmquist DEA calculations will provide a more accurate picture of this.

Three capital measures are reported in Figure 3.2, capital stock, depreciation and capital expenditure (capex), which increase by 5.14, 4.46 and 4.77% pa, respectively. The fact that capex growth is slightly higher than depreciation growth could be partly a consequence of investment in new and upgraded capital (in addition to renewals and replacements). The

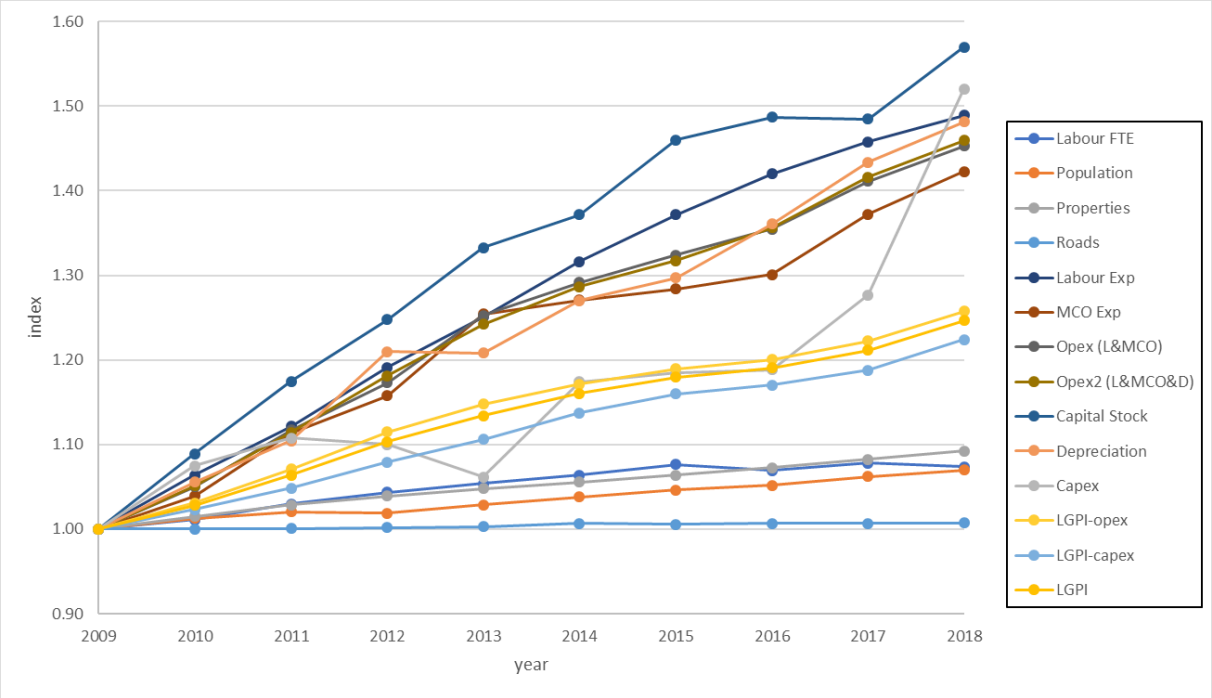
faster growth in capital stock relative to depreciation could be partly due to faster growth in long lived assets (ie. roads and bridges versus plant and equipment) increasing the average life span of capital assets.

The capex index in Figure 3.2 stands out in that it is much more stochastic than the other indices, with a notable drop in 2013 and a large increase in 2018. This is most likely a consequence of the impacts of variations in grant income from State and Federal sources over this ten-year period.

Figure 3.3 contains additional capital indices. The three main components of capital stock – buildings, structures and plant and equipment (equip) – are plotted individually. We note that plant and equipment is growing at approximately half the rate of buildings and structures, which would explain the slower growth rate in depreciation versus capital stock. We have also plotted the two main types of capital expenditure – renewals/replacements and new/upgrades – and observe that these tend to follow similar (stochastic) patterns. It is also interesting to note that the LGPI capex price index is growing at 2.27%, implying real growth in capex of 4.77-2.27=2.50% which is faster than the growth in the output measures in Figure 3.2. This could be due to a number of factors, such as lumpiness in grant income streams, improvements in capital services for ratepayers (eg. more sealed roads), declining efficiencies in capital construction projects, etc. However, further analysis is needed to know the exact reasons for the observed growth in capex.

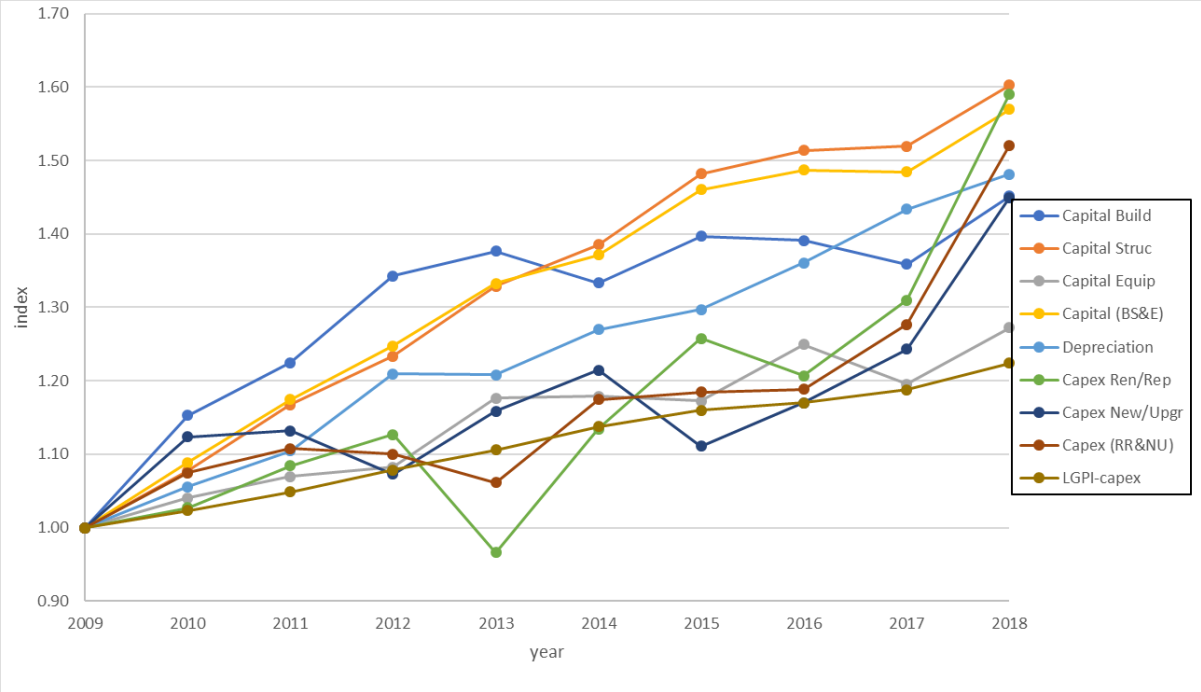
Figure 3.4 contains plots of some additional output indices. Properties are divided into residential and other categories. As discussed earlier, the introduction of the SAILIS system in 2015 resulted in a number of property types being reclassified. For example, this included moving accommodation businesses (eg. hotels, motels and hostels) from residential to commercial categories and moving “rural living” (ie. a house with primary production) from residential to primary production categories. The net effect of this on our data in 2015 was a reduction in residential properties of 2% and a corresponding increase in other properties of 12%. Although not ideal, we note that this adjustment across categories has only resulted in approximately 3% of total properties moving from the residential category to the other category and hence is unlikely to have a substantive impact on our empirical results.

Figure 3.2 **Data indices**



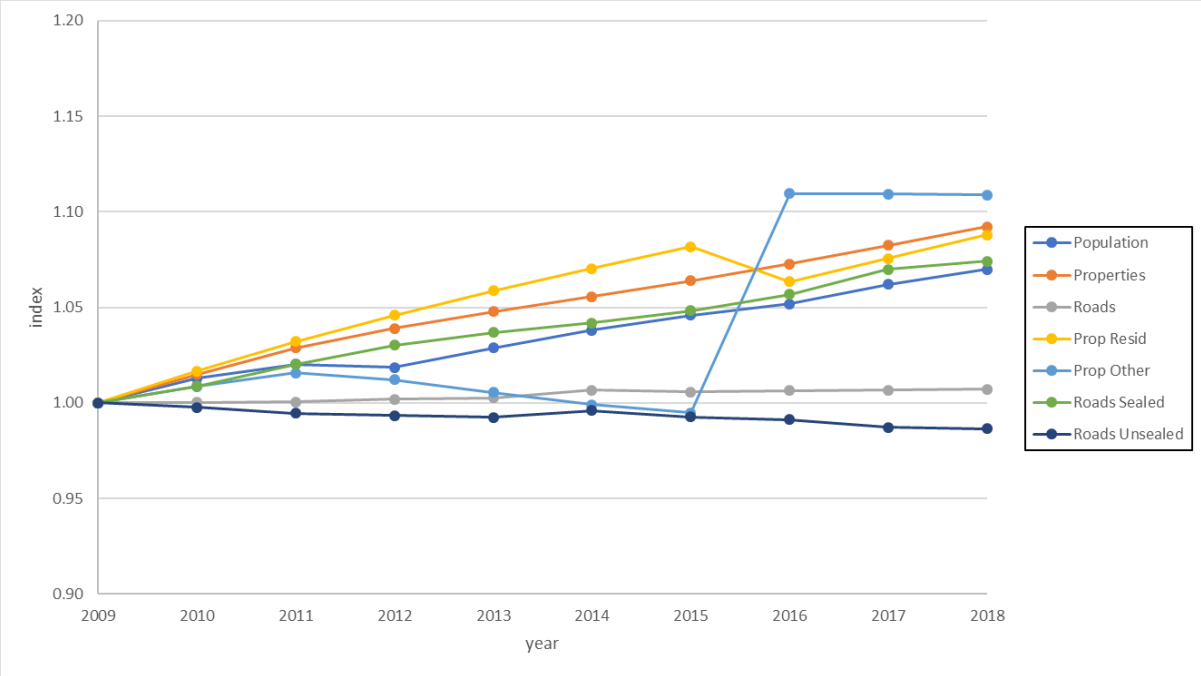
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	pa
Labour FTE	1.00	1.01	1.03	1.04	1.05	1.06	1.08	1.07	1.08	1.07	**0.79%**
Population	1.00	1.01	1.02	1.02	1.03	1.04	1.05	1.05	1.06	1.07	**0.75%**
Properties	1.00	1.02	1.03	1.04	1.05	1.06	1.06	1.07	1.08	1.09	**0.98%**
Roads	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01	**0.08%**
Labour Exp	1.00	1.06	1.12	1.19	1.25	1.32	1.37	1.42	1.46	1.49	**4.52%**
MCO Exp	1.00	1.04	1.11	1.16	1.25	1.27	1.28	1.30	1.37	1.42	**4.00%**
Opex (L&MCO)	1.00	1.05	1.12	1.17	1.25	1.29	1.32	1.35	1.41	1.45	**4.24%**
Opex2 (L&MCO&D)	1.00	1.05	1.11	1.18	1.24	1.29	1.32	1.36	1.42	1.46	**4.29%**
Capital Stock	1.00	1.09	1.17	1.25	1.33	1.37	1.46	1.49	1.48	1.57	**5.14%**
Depreciation	1.00	1.06	1.10	1.21	1.21	1.27	1.30	1.36	1.43	1.48	**4.46%**
Capex	1.00	1.07	1.11	1.10	1.06	1.17	1.18	1.19	1.28	1.52	**4.77%**
LGPI-opex	1.00	1.03	1.07	1.11	1.15	1.17	1.19	1.20	1.22	1.26	**2.58%**
LGPI-capex	1.00	1.02	1.05	1.08	1.11	1.14	1.16	1.17	1.19	1.22	**2.27%**
LGPI	1.00	1.03	1.06	1.10	1.13	1.16	1.18	1.19	1.21	1.25	**2.48%**

Figure 3.3 **Data indices - capital**



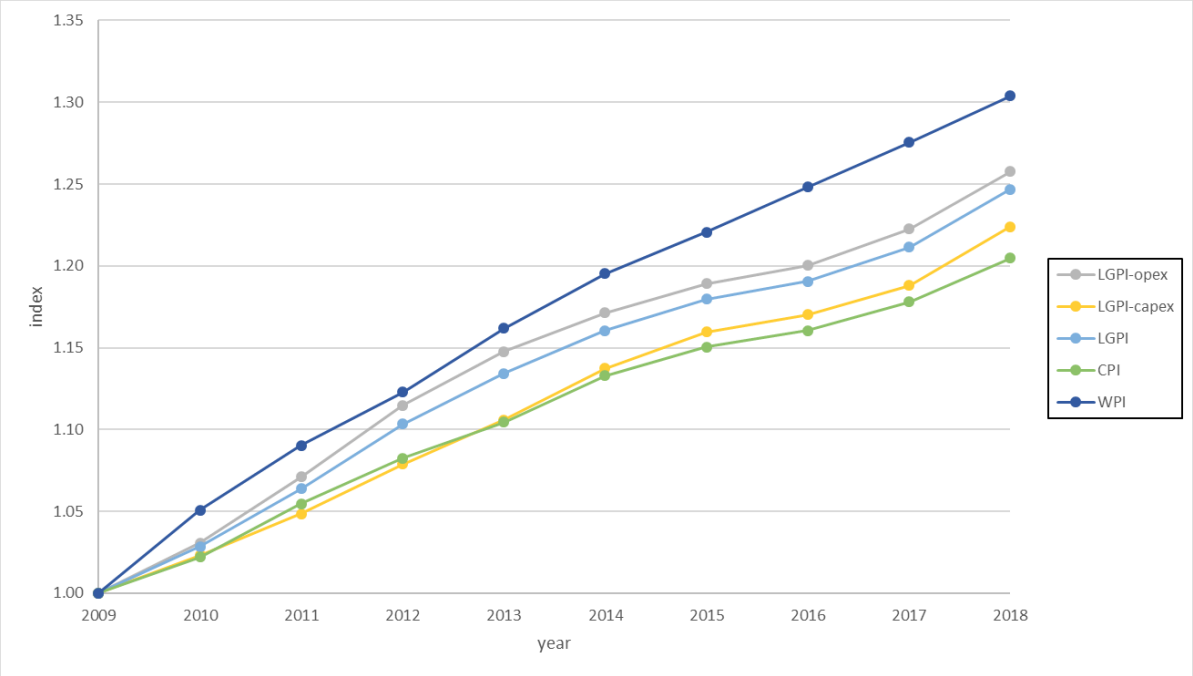
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	pa
Capital Build	1.00	1.15	1.22	1.34	1.38	1.33	1.40	1.39	1.36	1.45	**4.22%**
Capital Struc	1.00	1.08	1.17	1.23	1.33	1.39	1.48	1.51	1.52	1.60	**5.38%**
Capital Equip	1.00	1.04	1.07	1.08	1.18	1.18	1.17	1.25	1.20	1.27	**2.71%**
Capital (BS&E)	1.00	1.09	1.17	1.25	1.33	1.37	1.46	1.49	1.48	1.57	**5.14%**
Depreciation	1.00	1.06	1.10	1.21	1.21	1.27	1.30	1.36	1.43	1.48	**4.46%**
Capex Ren/Rep	1.00	1.03	1.08	1.13	0.97	1.13	1.26	1.21	1.31	1.59	**5.29%**
Capex New/Upgr	1.00	1.12	1.13	1.07	1.16	1.21	1.11	1.17	1.24	1.45	**4.21%**
Capex (RR&NU)	1.00	1.07	1.11	1.10	1.06	1.17	1.18	1.19	1.28	1.52	**4.77%**
LGPI-capex	1.00	1.02	1.05	1.08	1.11	1.14	1.16	1.17	1.19	1.22	**2.27%**

Figure 3.4 **Data indices - outputs**



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	pa
Population	1.00	1.01	1.02	1.02	1.03	1.04	1.05	1.05	1.06	1.07	**0.75%**
Properties	1.00	1.02	1.03	1.04	1.05	1.06	1.06	1.07	1.08	1.09	**0.98%**
Roads	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.01	1.01	**0.08%**
Prop Resid	1.00	1.02	1.03	1.05	1.06	1.07	1.08	1.06	1.08	1.09	**0.94%**
Prop Other	1.00	1.01	1.02	1.01	1.01	1.00	0.99	1.11	1.11	1.11	**1.15%**
Roads Sealed	1.00	1.01	1.02	1.03	1.04	1.04	1.05	1.06	1.07	1.07	**0.80%**
Roads Unsealed	1.00	1.00	0.99	0.99	0.99	1.00	0.99	0.99	0.99	0.99	**-0.15%**

Figure 3.5 **Data indices - prices**



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	pa
LGPI-opex	1.00	1.03	1.07	1.11	1.15	1.17	1.19	1.20	1.22	1.26	**2.58%**
LGPI-capex	1.00	1.02	1.05	1.08	1.11	1.14	1.16	1.17	1.19	1.22	**2.27%**
LGPI	1.00	1.03	1.06	1.10	1.13	1.16	1.18	1.19	1.21	1.25	**2.48%**
CPI	1.00	1.02	1.05	1.08	1.10	1.13	1.15	1.16	1.18	1.20	**2.09%**
WPI	1.00	1.05	1.09	1.12	1.16	1.20	1.22	1.25	1.28	1.30	**2.99%**

4 EXOGENOUS FACTORS

The input and output variables included in the DEA model are designed to capture the main activities of local government service provision. It is tempting to then attempt to interpret the efficiency scores obtained from the resulting DEA models as reflecting the degree of managerial competence or otherwise of the individual councils. A degree of inefficiency may be in part explained by managerial factors, but may also be a consequence of exogenous factors relating to demography, topography, etc. that may make service provision more resource intensive in some cases.

As a consequence, we attempt to identify those exogenous factors which could conceptually influence service provision and then investigate the degree to which the variations in DEA efficiency scores across different councils can in part be explained by these exogenous factors.

In our analysis in Section 7 we use the following 16 variables in a series of second stage regressions:

1. U15 = % population aged under 15
2. ABTSI = % population Aboriginal or Torres Strait Islander
3. NES = % population who speak a language other than English at home
4. PEN = % population who receive the age pension
5. UNEM = % population who receive unemployment benefits
6. MWAGE = median wage
7. GPOP = % growth in population between 2009 and 2018
8. GPROP = % growth in rateable properties between 2009 and 2018
9. DEN = Population density in persons per hectare
10. POP = Population
11. SEALRD = % sealed roads
12. BUSINC = % income from business undertakings
13. IRSED = Index of Relative Socio-economic Disadvantage
14. IRSEAD = Index of Relative Socio-economic Advantage and Disadvantage
15. IER = Index of Economic Resources
16. IEO = Index of Education and Occupation

Variables 1 to 6 are taken from:

1410.0 - Data by Region, 2013-18

LATEST ISSUE Released at 11:30 AM (CANBERRA TIME) 17/05/2019

https://www.abs.gov.au/ausstats/abs@.nsf/mf/1410.0

Variables 7 to 12 are derived from the SALGGC database.[9]

Variables 13 to 16 are taken from:

> 2033.0.55.001 - Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), Australia, 2016
>
> LATEST ISSUE Released at 11:30 AM (CANBERRA TIME) 27/03/2018
>
> https://www.abs.gov.au/ausstats/abs@.nsf/mf/2033.0.55.001

Data on variables 1-6 and 13-16 are mostly only collected in census years and hence are only available for the years of 2011 and 2016 in our 10-year sample. As a consequence, we have decided to use the 2016 data as the regressor variables in our second stage regressions. We therefore use the 10-year means of the efficiency scores and the TFP indices for each council as the dependent variables in these regressions.

Ordinary Least Squares (OLS) regression methods are used to investigate the influence of these factors on the TFP growth indices. However, given that the DEA efficiency scores are censored at 1, we follow the usual practice and use the Tobit regression method for those scores. As a check, we also apply OLS regression and find that there are few differences between the Tobit and OLS results.

Other factors

A number of factors have not been accounted for in the above list either because of data and time constraints or because we judged them to be of minor importance. Some of these are outlined below:

1. climatic factors – such as higher rainfall might influence efficiency through increasing maintenance requirements on roads and bridges due to water damage;
2. soil types – such as reactive clays versus more stable gravels and loams might affect road maintenance costs;
3. topographic differences – such as hilly versus flat terrain might also influence maintenance costs of roads and parks to some degree;
4. coastal versus inland setting – humid salty air might imply extra maintenance needed on buildings plus there might be more parks, jetties and wharves to maintain in coastal areas;
5. multiple towns/service delivery centres – might reduce efficiency because a duplication of services such as libraries may be required;
6. tourism – extra seasonal population might put extra pressure on parks and waste facilities;
7. quality of services – some councils might deliver higher quality services because they are demanded by their residents. This factor might be in part captured by the median wage variable, but survey data on resident satisfaction might be useful as well.

Recent discussions with stakeholders suggest that the first four factors listed above are likely to be of minor importance, while the latter three could be worthy of further investigation if suitable data can be identified.

[9] With the exception of the growth in properties variable which is now derived from SAVG properties data.

The issue of quality of services is one that has been regularly discussed. We make a few observations here. First, attitudinal surveys of ratepayer satisfaction levels with regard to council services might capture differences in service quality across councils but might also capture differences in expectations due to differing socio-economic conditions across different council areas. Second, if residents in a higher socio-economic area demand higher quality services (eg. more libraries and art galleries and manicured parks) then one could argue that the efficiency analysis in this report might identify their council as being "inefficient" to some extent. The council might then choose to cost out the extra services that they are providing so that they could then make a case to their ratepayers that the measured level of inefficiency can in fact be explained by the cost of the additional services provided. It could then be up to the ratepayers to decide if their "willingness to pay" equates to the extra expenses involved.

Grouping councils

In the SAPC Methodology Paper it has been suggested that councils be grouped in some manner so that comparisons can be made among similar councils. The Australian Classification of Local Governments (ACLG) outlines 22 different categories of councils. The SAPC Methodology Paper suggests that these 22 categories be aggregated into four larger groups:

- urban (including capital, development and fringe);
- rural agricultural (small and medium);
- rural agricultural (large and very large); and
- urban regional.

Applying their suggested groupings, we obtain the list of councils as outlined in Table 4.1 below.

In our second stage analysis we obtain sample means of efficiency scores and TFP indices for these four groups and also conduct *Analysis of Variance* (AOV) tests to see if there is a significant difference in the mean scores among these four groups. Given that these indices and scores are arguably not derived from an independent normal distribution, we also run the non-parametric Kruskal-Wallis (KW) test to confirm the results of our AOV tests.

Table 4.1 **Grouping of councils**

Urban	Rural Agricultural S/M	Rural Agricultural L/XL	Urban Regional
Adelaide	Barunga West	Adelaide Plains	Coober Pedy
Adelaide Hills	Ceduna	Berri Barmera	Mount Barker
Alexandrina	Cleve	Clare & Gilbert Valleys	Mount Gambier
Barossa	Elliston	Coorong	Murray Bridge
Burnside	Flinders Ranges	Copper Coast	Port Augusta
Campbelltown	Franklin Harbour	Grant	Port Lincoln
Charles Sturt	Goyder	Light	Roxby Downs
Gawler	Kangaroo Island	Lower Eyre Peninsula	Victor Harbor
Holdfast Bay	Karoonda East Murray	Loxton Waikerie	Whyalla
Marion	Kimba	Mid Murray	
Mitcham	Kingston	Naracoorte Lucindale	
Norwood, P & SP	Mount Remarkable	Port Pirie	
Onkaparinga	Northern Areas	Renmark Paringa	
Playford	Orroroo Carrieton	Tatiara	
Port Adelaide Enfield	Peterborough	Wakefield	
Prospect	Robe	Wattle Range	
Salisbury	Southern Mallee	Yorke Peninsula	
Tea Tree Gully	Streaky Bay		
Unley	Tumby Bay		
Walkerville	Wudinna		
West Torrens	Yankalilla		

5 EFFICIENCY SCORES

Our preferred DEA model is one with three outputs and two inputs. That is:

Inputs:

Opex = labour expenses + materials, contracts & other expenses

Capital = depreciation expenses

Outputs:

Residential properties

Other properties

Total road length

This DEA model has been estimated using data on the 68 councils in each of the 10 years of the sample data. The results obtained from the final year (2018) are reported in Table 5.1 below. The councils have been numbered from 1 to 68 (in non-alphabetical order) with the identity of each council not disclosed in this report – as was requested by the SAPC.

The second column of Table 5.1 contains CRS TE scores. The mean value is 0.798. This indicates that the average council could produce its current bundle of outputs with 20.2% fewer inputs, if it was to be able to equal the performance defined by the CRS DEA frontier.

However, councils are generally unable to alter their scale of operation. Hence, we argue that the VRS frontier is a more appropriate benchmark. The third column of Table 5.1 contains VRS TE scores. The mean value is 0.841. This indicates that the average council could produce its current bundle of outputs with 15.9% fewer inputs, if it was to equal the performance defined by the VRS DEA frontier.

The fourth column of Table 5.1 contains SE scores, which are calculated as the ratio of VRS TE over CRS TE. The mean value is 0.946. This is a measure of the additional input savings possible if the average council was to be able to increase (or decrease) its size to achieve optimal scale. In this case it is 5.4%, which is approximately one quarter of the overall CRS TE, indicating that scale inefficiency is not a major factor in these data.

The final column in Table 5.1 provides returns to scale (RTS) information, which indicates if a council is operating at a point of increasing returns to scale (IRS), suggesting it is too small, or is operating at a point of decreasing returns to scale (DRS), suggesting it is too large. If the CRS TE score and VRS TE scores are identical for a particular council, the SE score equals one and the council is observed to operating at optimal scale. Overall, we observe that there are 7 councils operating at optimal scale, 30 at DRS and 31 at IRS. Hence there is no clear pattern of councils being generally too large or too small in these data.

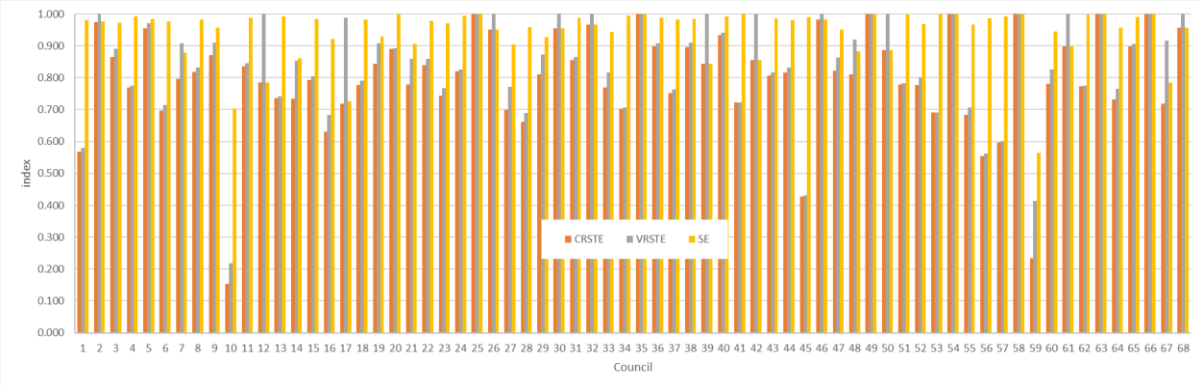
Table 5.1 **DEA results using 2018 sample data**

Council	CRSTE	VRSTE	SE	RTS
1	0.568	0.579	0.980	drs
2	0.975	0.999	0.976	irs
3	0.865	0.890	0.972	irs
4	0.770	0.776	0.993	irs
5	0.955	0.971	0.984	irs
6	0.697	0.714	0.977	drs
7	0.797	0.908	0.878	drs
8	0.819	0.832	0.983	drs
9	0.870	0.910	0.956	drs
10	0.154	0.219	0.702	drs
11	0.836	0.846	0.988	irs
12	0.784	1.000	0.784	irs
13	0.736	0.741	0.993	irs
14	0.735	0.854	0.861	irs
15	0.792	0.804	0.985	drs
16	0.630	0.684	0.921	drs
17	0.719	0.988	0.727	irs
18	0.777	0.790	0.983	irs
19	0.844	0.908	0.929	drs
20	0.891	0.892	0.999	irs
21	0.779	0.859	0.907	drs
22	0.839	0.859	0.978	drs
23	0.744	0.767	0.971	drs
24	0.820	0.825	0.994	drs
25	1.000	1.000	1.000	-
26	0.951	1.000	0.951	irs
27	0.698	0.771	0.905	drs
28	0.661	0.689	0.959	irs
29	0.810	0.873	0.928	drs
30	0.954	1.000	0.954	drs
31	0.856	0.866	0.988	irs
32	0.966	1.000	0.966	drs
33	0.770	0.817	0.944	drs
34	0.703	0.707	0.995	irs
35	1.000	1.000	1.000	-
36	0.898	0.909	0.988	irs
37	0.751	0.764	0.982	drs
38	0.896	0.910	0.984	irs
39	0.843	1.000	0.843	drs
40	0.934	0.941	0.992	irs
41	0.722	0.723	0.999	drs
42	0.855	1.000	0.855	irs
43	0.806	0.817	0.987	drs
44	0.816	0.831	0.981	irs
45	0.427	0.431	0.990	irs
46	0.983	1.000	0.983	drs
47	0.822	0.864	0.952	drs
48	0.811	0.919	0.883	irs
49	1.000	1.000	1.000	-
50	0.886	1.000	0.886	drs
51	0.780	0.783	0.997	drs
52	0.777	0.801	0.969	irs
53	0.691	0.692	0.999	irs
54	1.000	1.000	1.000	-
55	0.683	0.707	0.966	drs
56	0.555	0.563	0.986	drs
57	0.597	0.601	0.993	irs
58	1.000	1.000	1.000	-
59	0.233	0.413	0.565	irs
60	0.781	0.825	0.946	irs
61	0.898	1.000	0.898	drs
62	0.773	0.775	0.998	irs
63	1.000	1.000	1.000	-
64	0.732	0.766	0.956	irs
65	0.899	0.907	0.991	irs
66	1.000	1.000	1.000	-
67	0.718	0.916	0.784	irs
68	0.956	1.000	0.956	drs
mean	**0.798**	**0.841**	**0.946**	

These various efficiency scores can be better understood by looking at the results for a single council. For example, consider council number 40 in Table 5.1. It has CRSTE=0.934, VRSTE=0.941, SE=0.992 and RTS=IRS. The VRSTE score of 0.941 indicates that this council could produce its same output bundle with 5.9% fewer inputs. The SE score of 0.992 indicates that it could save a further 0.8% of inputs (per unit output) if it could adjust its scale of operations to some extent. The RTS=IRS label indicates that this firm is located on the increasing returns to scale portion of the VRS DEA frontier and hence is "too small" to some extent. Furthermore, note that these scores are multiplicatively related in that we can show that CRSTE=VRSTE*SE=0.941*0.992=0.934. [10]

Finally, the various CRSTE, VRSTE and SE scores from Table 5.1 are also reproduced in a bar graph in Figure 5.1 below. This graph shows that there are three councils with VRSTE scores below 0.5. All three of these councils are unique in certain ways and hence these low scores are explainable. However, given the anonymity requirements in this report, we will not comment further.

Figure 5.1 **DEA results using 2018 sample data**



Peers

Now we consider the information on DEA peers presented in Table 5.2. As described in Appendix A, a DEA model involves running a series of linear programs (LPs) where each data point in the sample (ie. one for each council) is projected onto an estimated frontier. The frontier can be visualised as a series of interconnecting planes where each plane is defined (supported) by a number of efficient councils. These efficient councils are known as "peers" in DEA.[11]

Consider for example council #1 in Table 5.2. It is an inefficient council, which has been projected onto that part of the DEA frontier which is held up by the four efficient peer councils: 58, 63, 30, and 49, which have weights of 0.02, 0.16, 0.06, and 0.77, respectively. The higher weight for the latter peer indicates that it might be "more similar" to council #1 than the other three peers, in terms of input and output mixes.

[10] For more on scale efficiency see the discussion surrounding Figure A.2 in Appendix A, where examples of increasing, constant and decreasing returns to scale firms are plotted.
[11] See the discussion surrounding Figure A.1 in Appendix A for further explanation of peers.

It is a useful exercise for each inefficient council to identify its set of peers. These may be councils which are similar to it in many ways, but are doing a few things a bit better. Or alternatively, one or more of the peer firms might have particular characteristics that are not captured by the DEA model and hence the peer information may not be as valuable.

Another thing we can note from Table 5.2 is that there are 16 councils which are peers for themselves with a weight of 1. This indicates that they are on the VRS frontier and hence are technically efficient. The final column of Table 5.2 provides a "peer count" summary. This indicates the number of times each frontier council acts as a peer for other councils in the sample. Councils 49 and 58 have the highest counts, with 26 and 39, respectively. It will be of interest to study those councils which have higher peer counts. Do they have very good management practices? – or are they unique in some manner? – or has there been an error made in recording some of their input and output values?

Results for 2009-2018

The above discussion has focussed on the DEA results obtained using the 2018 sample data. A DEA model has been estimated for each of the 10 years of the 2009 to 2018 data sample. The efficiency scores obtained from these 10 DEA models are summarised in Tables 5.3 to 5.5 below. It is interesting to note that the 10-year means are quite similar to the 2018 means. That is, the 10-year means are 0.802, 0.841 and 0.950 for CRS TE, VRS TE and SE, respectively, while the corresponding mean values for 2018 were 0.798, 0.841 and 0.946, respectively.

The annual means do not vary much over the ten-year study period. For example, mean VRS TE is observed to vary from 0.836 in 2009 to 0.841 in 2018 with means in the intervening years also quite similar. One might hence be tempted to conclude that this could indicate that productivity has been quite steady over this 10-year period. However, this would only be correct if we could establish that the DEA frontier has not shifted upwards (or downwards) over time. The next section on Malmquist TFP growth allows us to address this issue.

Table 5.2 DEA VRS frontier peers using 2018 sample data

Council	Peers				Peer Weights				Peer Count
1	58	63	30	49	0.02	0.16	0.06	0.77	0
2	58	12			0.38	0.62			0
3	58	12			0.35	0.66			0
4	66	54	35	49	0.08	0.08	0.32	0.52	0
5	54	35	66	49	0.03	0.03	0.01	0.93	0
6	58	54	66	35	0.10	0.02	0.45	0.43	0
7	50	61	58	39	0.06	0.15	0.07	0.72	0
8	35	58	49	30	0.01	0.04	0.59	0.36	0
9	58	54	66		0.15	0.03	0.82		0
10	61	50			0.94	0.06			0
11	49	54	58	12	0.61	0.22	0.01	0.16	0
12	12				1.00				22
13	58	35	49	54	0.00	0.05	0.94	0.01	0
14	54	49	12		0.00	0.61	0.39		0
15	58	30	32		0.13	0.69	0.19		0
16	58	35	30	39	0.00	0.75	0.08	0.17	0
17	12	49	54		0.89	0.10	0.02		0
18	58	12	49	63	0.01	0.09	0.89	0.02	0
19	30	58	39	35	0.79	0.02	0.16	0.02	0
20	58	12			0.93	0.08			0
21	35	58	30	39	0.06	0.03	0.59	0.33	0
22	58	32	49	30	0.02	0.18	0.50	0.31	0
23	58	30	39	35	0.06	0.80	0.02	0.13	0
24	32	30	49	58	0.02	0.06	0.90	0.02	0
25	25				1.00				0
26	26				1.00				0
27	39	30	58	35	0.21	0.33	0.01	0.46	0
28	54	42	12		0.37	0.32	0.31		0
29	30	39	58	35	0.60	0.12	0.01	0.27	0
30	30				1.00				18
31	49	58	12	54	0.38	0.25	0.32	0.06	0
32	32				1.00				6
33	30	61	46		0.89	0.10	0.01		0
34	54	66	49		0.14	0.51	0.35		0
35	35				1.00				15
36	58	12	49		0.21	0.40	0.40		0
37	58	54	66	35	0.07	0.13	0.64	0.16	0
38	58	12			0.48	0.52			0
39	39				1.00				7
40	12	58	54		0.27	0.62	0.11		0
41	49	58	30	35	0.47	0.05	0.00	0.48	0
42	42				1.00				2
43	30	49	35	58	0.54	0.27	0.07	0.12	0
44	49	54	66		0.80	0.15	0.05		0
45	49	12	54	58	0.80	0.07	0.08	0.05	0
46	46				1.00				2
47	66	50	58		0.41	0.04	0.55		0
48	54	49	12		0.01	0.53	0.46		0
49	49				1.00				26
50	50				1.00				3
51	32	49	30	58	0.22	0.62	0.01	0.15	0
52	54	12	58		0.35	0.61	0.04		0
53	12	58	49		0.01	0.02	0.98		0
54	54				1.00				19
55	58	30	49	32	0.02	0.71	0.22	0.05	0
56	58	32	49	30	0.01	0.03	0.83	0.14	0
57	12	49	58		0.03	0.96	0.01		0
58	58				1.00				39
59	12	42			0.87	0.13			0
60	49	12	58		0.64	0.34	0.02		0
61	61				1.00				4
62	49	66	54	35	0.15	0.03	0.06	0.77	0
63	63				1.00				2
64	12	58			0.81	0.19			0
65	58	12			0.46	0.54			0
66	66				1.00				9
67	54	58	12		0.03	0.03	0.94		0
68	30	61	46		0.97	0.02	0.02		0

Table 5.3 **CRSTE DEA results using 2009-2018 sample data**

Council	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	mean
1	0.567	0.551	0.544	0.542	0.534	0.597	0.592	0.544	0.590	0.568	**0.563**
2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.997	0.975	**0.997**
3	0.920	0.850	0.853	0.839	0.909	0.827	0.860	0.867	0.899	0.865	**0.869**
4	0.661	0.607	0.678	0.699	0.749	0.740	0.801	0.762	0.832	0.770	**0.730**
5	0.878	0.944	0.809	0.931	0.952	0.974	0.909	0.928	0.989	0.955	**0.927**
6	0.724	0.717	0.684	0.704	0.686	0.680	0.679	0.716	0.744	0.697	**0.703**
7	0.818	0.906	0.868	0.842	0.890	0.843	0.859	0.840	0.848	0.797	**0.851**
8	0.951	0.886	0.947	0.907	0.962	0.976	0.944	0.853	0.830	0.819	**0.908**
9	0.803	0.814	0.826	0.823	0.855	0.859	0.874	0.896	0.900	0.870	**0.852**
10	0.164	0.154	0.188	0.153	0.151	0.167	0.171	0.169	0.172	0.154	**0.164**
11	0.843	0.707	0.727	0.767	0.837	0.684	0.989	0.838	0.837	0.836	**0.807**
12	0.984	0.944	0.854	0.795	0.802	0.773	0.764	0.864	0.726	0.784	**0.829**
13	1.000	1.000	1.000	1.000	1.000	0.967	0.930	0.883	0.767	0.736	**0.928**
14	0.759	0.877	0.843	0.848	0.768	0.815	0.860	0.736	0.771	0.735	**0.801**
15	0.976	0.927	0.938	0.943	0.931	0.693	0.918	0.928	0.922	0.792	**0.897**
16	0.710	0.728	0.708	0.656	0.666	0.634	0.674	0.650	0.678	0.630	**0.673**
17	0.435	0.455	0.439	0.423	0.471	0.516	0.582	0.523	0.715	0.719	**0.528**
18	0.937	0.925	0.919	0.857	0.970	0.962	0.935	0.959	0.937	0.777	**0.918**
19	0.785	0.851	0.705	0.708	0.839	0.857	0.880	0.917	0.783	0.844	**0.817**
20	0.907	0.906	0.905	0.917	0.890	0.844	0.849	0.876	0.911	0.891	**0.890**
21	0.801	0.814	0.763	0.924	0.827	0.783	0.778	0.739	0.770	0.779	**0.798**
22	0.856	0.828	1.000	0.902	0.767	0.786	0.821	0.840	0.836	0.839	**0.848**
23	0.522	0.573	0.675	0.728	0.713	0.760	0.785	0.785	0.762	0.744	**0.705**
24	0.901	0.993	1.000	0.992	0.972	1.000	0.998	0.933	0.799	0.820	**0.941**
25	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
26	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.900	0.951	**0.985**
27	0.626	0.736	0.590	0.669	0.655	0.669	0.697	0.698	0.678	0.698	**0.672**
28	0.725	0.650	0.640	0.625	0.635	0.610	0.630	0.625	0.662	0.661	**0.646**
29	0.719	0.667	0.693	0.706	0.754	0.761	0.752	0.798	0.787	0.810	**0.745**
30	0.984	0.956	0.853	0.912	1.000	0.966	0.896	1.000	1.000	0.954	**0.952**
31	0.833	0.859	0.882	0.858	0.887	0.864	0.887	0.883	0.899	0.856	**0.871**
32	0.815	0.761	0.806	0.973	0.906	0.905	0.866	0.855	0.906	0.966	**0.876**
33	0.670	0.744	0.611	0.683	0.771	0.744	0.719	0.806	0.739	0.770	**0.726**
34	0.626	0.582	0.623	0.581	0.612	0.658	0.698	0.728	0.728	0.703	**0.654**
35	1.000	0.906	0.868	0.953	1.000	1.000	1.000	1.000	0.954	1.000	**0.968**
36	0.955	0.995	0.930	0.892	0.951	0.900	0.901	0.904	0.904	0.898	**0.923**
37	0.659	0.669	0.665	0.687	0.694	0.695	0.704	0.735	0.755	0.751	**0.701**
38	0.895	0.963	1.000	0.907	0.912	0.860	0.886	0.903	0.954	0.896	**0.918**
39	1.000	1.000	0.956	1.000	1.000	1.000	0.971	0.917	0.857	0.843	**0.954**
40	1.000	0.934	0.970	0.991	0.983	0.948	0.991	1.000	1.000	0.934	**0.975**
41	0.794	0.800	0.798	0.846	0.823	0.835	0.844	0.794	0.791	0.722	**0.805**
42	1.000	0.834	0.859	0.765	0.811	0.828	0.811	0.801	0.813	0.855	**0.838**
43	0.898	0.777	0.821	0.737	0.801	0.825	0.798	0.813	0.821	0.806	**0.810**
44	0.924	0.931	1.000	0.798	0.914	0.909	0.865	0.803	0.817	0.816	**0.878**
45	0.651	0.568	0.354	0.352	0.434	0.397	0.447	0.474	0.368	0.427	**0.447**
46	0.835	0.906	0.901	0.881	0.872	0.878	0.958	0.918	0.991	0.983	**0.912**
47	0.827	0.814	0.820	0.808	0.798	0.794	0.807	0.815	0.864	0.822	**0.817**
48	0.754	0.824	0.688	0.757	0.750	0.850	0.898	0.772	0.760	0.811	**0.786**
49	1.000	0.975	0.805	0.992	1.000	1.000	1.000	1.000	1.000	1.000	**0.977**
50	1.000	0.987	1.000	0.995	0.997	0.935	0.939	0.941	0.942	0.886	**0.962**
51	0.796	0.900	0.802	0.870	0.853	0.833	0.842	0.803	0.801	0.780	**0.828**
52	0.828	0.795	0.776	0.790	0.808	0.771	0.802	0.795	0.808	0.777	**0.795**
53	0.805	0.808	0.713	0.651	0.722	0.728	0.749	0.687	0.768	0.691	**0.732**
54	0.950	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**0.995**
55	0.675	0.663	0.693	0.662	0.593	0.637	0.712	0.684	0.669	0.683	**0.667**
56	0.608	0.554	0.590	0.674	0.636	0.718	0.661	0.652	0.598	0.555	**0.625**
57	0.517	0.503	0.558	0.547	0.525	0.584	0.518	0.568	0.593	0.597	**0.551**
58	0.944	0.933	0.973	0.948	0.966	0.913	0.932	0.987	1.000	1.000	**0.960**
59	0.250	0.232	0.228	0.224	0.229	0.235	0.240	0.248	0.250	0.233	**0.237**
60	0.694	0.755	0.752	0.764	0.696	0.709	0.696	0.706	0.712	0.781	**0.727**
61	0.758	0.822	0.778	0.940	0.943	0.897	0.904	0.926	0.893	0.898	**0.876**
62	0.779	0.873	0.749	0.776	0.804	0.778	0.800	0.760	0.833	0.773	**0.793**
63	1.000	1.000	0.958	1.000	1.000	1.000	1.000	1.000	0.879	1.000	**0.984**
64	0.788	0.735	0.727	0.764	0.749	0.701	0.698	0.743	0.755	0.732	**0.739**
65	0.886	0.851	0.861	0.856	0.869	0.836	0.845	0.926	0.962	0.899	**0.879**
66	0.744	0.764	0.768	0.780	0.895	0.942	1.000	0.990	1.000	1.000	**0.888**
67	0.775	0.714	0.612	0.566	0.603	0.631	0.636	0.723	0.712	0.718	**0.669**
68	0.841	0.830	0.856	0.923	0.859	0.661	0.830	0.916	0.847	0.956	**0.852**
mean	**0.805**	**0.802**	**0.785**	**0.794**	**0.807**	**0.796**	**0.813**	**0.811**	**0.809**	**0.798**	**0.802**

Table 5.4 VRSTE DEA results using 2009-2018 sample data

Council	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	mean
1	0.595	0.560	0.568	0.553	0.537	0.606	0.603	0.564	0.609	0.579	**0.577**
2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	**1.000**
3	0.925	0.855	0.863	0.849	0.932	0.844	0.882	0.890	0.924	0.890	**0.885**
4	0.663	0.613	0.679	0.700	0.757	0.754	0.825	0.765	0.833	0.776	**0.737**
5	0.941	0.984	0.819	0.958	1.000	1.000	0.958	0.948	0.994	0.971	**0.957**
6	0.728	0.721	0.703	0.704	0.689	0.683	0.684	0.748	0.775	0.714	**0.715**
7	0.969	0.981	0.989	0.874	0.916	0.905	0.889	0.918	0.947	0.908	**0.930**
8	0.970	0.902	0.949	0.910	0.971	1.000	0.951	0.855	0.872	0.832	**0.921**
9	0.806	0.815	0.835	0.823	0.856	0.860	0.880	0.924	0.931	0.910	**0.864**
10	0.198	0.159	0.212	0.153	0.172	0.167	0.173	0.229	0.253	0.219	**0.194**
11	0.844	0.727	0.762	0.805	0.875	0.687	1.000	0.842	0.843	0.846	**0.823**
12	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
13	1.000	1.000	1.000	1.000	1.000	1.000	0.992	0.891	0.783	0.741	**0.941**
14	0.771	0.922	0.926	0.932	0.871	0.949	0.979	0.871	0.885	0.854	**0.896**
15	0.979	0.930	0.998	0.944	0.932	0.734	0.990	0.961	0.923	0.804	**0.920**
16	0.733	0.758	0.774	0.662	0.666	0.658	0.680	0.670	0.732	0.684	**0.702**
17	0.584	0.701	0.708	0.669	0.721	0.794	0.799	0.600	0.987	0.988	**0.755**
18	0.952	0.940	0.925	0.859	1.000	1.000	0.958	0.961	0.958	0.790	**0.934**
19	0.846	0.865	0.827	0.709	0.841	0.909	0.922	0.976	0.873	0.908	**0.868**
20	0.986	0.975	0.963	0.949	0.913	0.962	0.923	0.907	0.911	0.892	**0.938**
21	0.803	0.819	0.867	0.924	0.828	0.882	0.856	0.788	0.865	0.859	**0.849**
22	0.873	0.830	1.000	0.904	0.779	0.800	0.837	0.841	0.838	0.859	**0.856**
23	0.534	0.579	0.746	0.730	0.715	0.814	0.812	0.824	0.825	0.767	**0.735**
24	0.955	1.000	1.000	1.000	0.993	1.000	1.000	0.941	0.814	0.825	**0.953**
25	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
26	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.980	1.000	**0.998**
27	0.655	0.777	0.739	0.702	0.672	0.693	0.728	0.736	0.758	0.771	**0.723**
28	0.727	0.665	0.661	0.646	0.671	0.650	0.664	0.642	0.689	0.689	**0.670**
29	0.743	0.679	0.747	0.709	0.757	0.809	0.813	0.830	0.860	0.873	**0.782**
30	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
31	0.846	0.862	0.882	0.858	0.889	0.866	0.888	0.883	0.900	0.866	**0.874**
32	0.841	0.821	0.965	1.000	0.908	0.960	0.967	0.864	0.908	1.000	**0.923**
33	0.686	0.779	0.768	0.695	0.772	0.843	0.809	0.829	0.764	0.817	**0.776**
34	0.657	0.585	0.644	0.581	0.615	0.662	0.704	0.731	0.741	0.707	**0.663**
35	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
36	0.960	1.000	0.932	0.893	0.955	0.910	0.911	0.905	0.911	0.909	**0.929**
37	0.661	0.672	0.672	0.688	0.696	0.697	0.707	0.763	0.786	0.764	**0.711**
38	0.953	0.964	1.000	0.914	0.923	0.882	0.923	0.904	0.963	0.910	**0.934**
39	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
40	1.000	0.934	0.971	1.000	0.992	0.977	1.000	1.000	1.000	0.941	**0.982**
41	0.829	0.820	0.825	0.851	0.839	0.853	0.846	0.797	0.818	0.723	**0.820**
42	1.000	0.921	0.963	0.861	0.920	0.950	0.951	0.907	0.957	1.000	**0.943**
43	0.960	0.781	0.903	0.737	0.804	0.835	0.805	0.832	0.824	0.817	**0.830**
44	0.935	0.949	1.000	0.808	0.925	0.937	0.878	0.806	0.821	0.831	**0.889**
45	0.654	0.580	0.358	0.354	0.439	0.421	0.462	0.476	0.368	0.431	**0.454**
46	0.898	0.967	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**0.987**
47	0.833	0.823	0.846	0.820	0.806	0.843	0.830	0.859	0.916	0.864	**0.844**
48	0.757	0.832	0.695	0.794	0.822	0.953	1.000	0.897	0.854	0.919	**0.852**
49	1.000	1.000	0.912	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**0.991**
50	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
51	0.807	0.907	0.808	0.871	0.858	0.838	0.843	0.803	0.807	0.783	**0.833**
52	0.840	0.810	0.797	0.808	0.832	0.793	0.833	0.819	0.827	0.801	**0.816**
53	0.837	0.840	0.728	0.681	0.761	0.793	0.822	0.698	0.773	0.692	**0.763**
54	0.973	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**0.997**
55	0.710	0.705	0.766	0.700	0.598	0.698	0.771	0.684	0.687	0.707	**0.703**
56	0.632	0.573	0.637	0.699	0.637	0.726	0.661	0.653	0.599	0.563	**0.638**
57	0.520	0.505	0.561	0.548	0.536	0.587	0.540	0.572	0.606	0.601	**0.558**
58	0.963	0.967	1.000	0.992	1.000	1.000	1.000	1.000	1.000	1.000	**0.992**
59	0.388	0.398	0.425	0.397	0.446	0.512	0.474	0.399	0.476	0.413	**0.433**
60	0.772	0.806	0.829	0.809	0.779	0.811	0.752	0.743	0.774	0.825	**0.790**
61	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
62	0.811	0.892	0.787	0.785	0.807	0.816	0.800	0.760	0.867	0.775	**0.810**
63	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.890	1.000	**0.989**
64	0.804	0.747	0.731	0.769	0.759	0.721	0.715	0.760	0.791	0.766	**0.756**
65	0.895	0.851	0.861	0.856	0.869	0.843	0.847	0.928	0.967	0.907	**0.882**
66	0.768	0.791	0.812	0.780	0.990	0.947	1.000	1.000	1.000	1.000	**0.909**
67	1.000	0.952	0.854	0.809	0.870	0.883	0.952	0.968	0.918	0.916	**0.912**
68	0.867	0.867	1.000	0.955	0.861	0.703	0.908	0.931	0.855	1.000	**0.895**
mean	**0.836**	**0.833**	**0.841**	**0.823**	**0.838**	**0.844**	**0.859**	**0.843**	**0.853**	**0.841**	**0.841**

Table 5.5 Scale efficiency DEA results using 2009-2018 sample data

Council	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	mean
1	0.953	0.984	0.958	0.980	0.994	0.985	0.982	0.965	0.969	0.981	**0.975**
2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.997	0.976	**0.997**
3	0.995	0.994	0.988	0.988	0.975	0.980	0.975	0.974	0.973	0.972	**0.981**
4	0.997	0.990	0.999	0.999	0.989	0.981	0.971	0.996	0.999	0.992	**0.991**
5	0.933	0.959	0.988	0.972	0.952	0.974	0.949	0.979	0.995	0.984	**0.968**
6	0.995	0.994	0.973	1.000	0.996	0.996	0.993	0.957	0.960	0.976	**0.984**
7	0.844	0.924	0.878	0.963	0.972	0.931	0.966	0.915	0.895	0.878	**0.917**
8	0.980	0.982	0.998	0.997	0.991	0.976	0.993	0.998	0.952	0.984	**0.985**
9	0.996	0.999	0.989	1.000	0.999	0.999	0.993	0.970	0.967	0.956	**0.987**
10	0.828	0.969	0.887	1.000	0.878	1.000	0.988	0.738	0.680	0.703	**0.867**
11	0.999	0.972	0.954	0.953	0.957	0.996	0.989	0.995	0.993	0.988	**0.980**
12	0.984	0.944	0.854	0.795	0.802	0.773	0.764	0.864	0.726	0.784	**0.829**
13	1.000	1.000	1.000	1.000	1.000	0.967	0.938	0.991	0.980	0.993	**0.987**
14	0.984	0.951	0.910	0.910	0.882	0.859	0.878	0.845	0.871	0.861	**0.895**
15	0.997	0.997	0.940	0.999	0.999	0.944	0.927	0.966	0.999	0.985	**0.975**
16	0.969	0.960	0.915	0.991	1.000	0.964	0.991	0.970	0.926	0.921	**0.961**
17	0.745	0.649	0.620	0.632	0.653	0.650	0.728	0.872	0.724	0.728	**0.700**
18	0.984	0.984	0.994	0.998	0.970	0.962	0.976	0.998	0.978	0.984	**0.983**
19	0.928	0.984	0.852	0.999	0.998	0.943	0.954	0.940	0.897	0.930	**0.942**
20	0.920	0.929	0.940	0.966	0.975	0.877	0.920	0.966	1.000	0.999	**0.949**
21	0.998	0.994	0.880	1.000	0.999	0.888	0.909	0.938	0.890	0.907	**0.940**
22	0.981	0.998	1.000	0.998	0.985	0.983	0.981	0.999	0.998	0.977	**0.990**
23	0.978	0.990	0.905	0.997	0.997	0.934	0.967	0.953	0.924	0.970	**0.961**
24	0.943	0.993	1.000	0.992	0.979	1.000	0.998	0.991	0.982	0.994	**0.987**
25	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
26	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.918	0.951	**0.987**
27	0.956	0.947	0.798	0.953	0.975	0.965	0.957	0.948	0.894	0.905	**0.930**
28	0.997	0.977	0.968	0.967	0.946	0.938	0.949	0.974	0.961	0.959	**0.964**
29	0.968	0.982	0.928	0.996	0.996	0.941	0.925	0.961	0.915	0.928	**0.954**
30	0.984	0.956	0.853	0.912	1.000	0.966	0.896	1.000	1.000	0.954	**0.952**
31	0.985	0.997	1.000	1.000	0.998	0.998	0.999	1.000	0.999	0.988	**0.996**
32	0.969	0.927	0.835	0.973	0.998	0.943	0.896	0.990	0.998	0.966	**0.949**
33	0.977	0.955	0.796	0.983	0.999	0.883	0.889	0.972	0.967	0.942	**0.936**
34	0.953	0.995	0.967	1.000	0.995	0.994	0.991	0.996	0.982	0.994	**0.987**
35	1.000	0.906	0.868	0.953	1.000	1.000	1.000	1.000	0.954	1.000	**0.968**
36	0.995	0.995	0.998	0.999	0.996	0.989	0.989	0.999	0.992	0.988	**0.994**
37	0.997	0.996	0.990	0.999	0.997	0.997	0.996	0.963	0.961	0.983	**0.988**
38	0.939	0.999	1.000	0.992	0.988	0.975	0.960	0.999	0.991	0.985	**0.983**
39	1.000	1.000	0.956	1.000	1.000	1.000	0.971	0.917	0.857	0.843	**0.954**
40	1.000	1.000	0.999	0.991	0.991	0.970	0.991	1.000	1.000	0.993	**0.993**
41	0.958	0.976	0.967	0.994	0.981	0.979	0.998	0.996	0.967	0.999	**0.981**
42	1.000	0.906	0.892	0.889	0.882	0.872	0.853	0.883	0.850	0.855	**0.888**
43	0.935	0.995	0.909	1.000	0.996	0.988	0.991	0.977	0.996	0.987	**0.978**
44	0.988	0.981	1.000	0.988	0.988	0.970	0.985	0.996	0.995	0.982	**0.987**
45	0.995	0.979	0.989	0.994	0.989	0.943	0.968	0.996	1.000	0.991	**0.984**
46	0.930	0.937	0.901	0.881	0.872	0.878	0.958	0.918	0.991	0.983	**0.925**
47	0.993	0.989	0.969	0.985	0.990	0.942	0.972	0.949	0.943	0.951	**0.968**
48	0.996	0.990	0.990	0.953	0.912	0.892	0.898	0.861	0.890	0.882	**0.927**
49	1.000	0.975	0.883	0.992	1.000	1.000	1.000	1.000	1.000	1.000	**0.985**
50	1.000	0.987	1.000	0.995	0.997	0.935	0.939	0.941	0.942	0.886	**0.962**
51	0.986	0.992	0.993	0.999	0.994	0.994	0.999	1.000	0.993	0.996	**0.995**
52	0.986	0.981	0.974	0.978	0.971	0.972	0.963	0.971	0.977	0.970	**0.974**
53	0.962	0.962	0.979	0.956	0.949	0.918	0.911	0.984	0.994	0.999	**0.961**
54	0.976	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**0.998**
55	0.951	0.940	0.905	0.946	0.992	0.913	0.923	1.000	0.974	0.966	**0.951**
56	0.962	0.967	0.926	0.964	0.998	0.989	1.000	0.998	0.998	0.986	**0.979**
57	0.994	0.996	0.995	0.998	0.979	0.995	0.959	0.993	0.979	0.993	**0.988**
58	0.980	0.965	0.973	0.956	0.966	0.913	0.932	0.987	1.000	1.000	**0.967**
59	0.644	0.583	0.536	0.564	0.513	0.459	0.506	0.622	0.525	0.564	**0.552**
60	0.899	0.937	0.907	0.944	0.893	0.874	0.926	0.950	0.920	0.947	**0.920**
61	0.758	0.822	0.778	0.940	0.943	0.897	0.904	0.926	0.893	0.898	**0.876**
62	0.961	0.979	0.952	0.989	0.996	0.953	1.000	1.000	0.961	0.997	**0.979**
63	1.000	1.000	0.958	1.000	1.000	1.000	1.000	1.000	0.988	1.000	**0.995**
64	0.980	0.984	0.995	0.993	0.987	0.972	0.976	0.978	0.954	0.956	**0.978**
65	0.990	1.000	1.000	1.000	1.000	0.992	0.998	0.998	0.995	0.991	**0.996**
66	0.969	0.966	0.946	1.000	0.904	0.995	1.000	0.990	1.000	1.000	**0.977**
67	0.775	0.750	0.717	0.700	0.693	0.715	0.668	0.747	0.776	0.784	**0.732**
68	0.970	0.957	0.856	0.966	0.998	0.940	0.914	0.984	0.991	0.956	**0.953**
mean	**0.959**	**0.960**	**0.930**	**0.962**	**0.959**	**0.941**	**0.945**	**0.958**	**0.943**	**0.946**	**0.950**

6 PRODUCTIVITY INDICES

In this section we report our estimates of Malmquist TFP growth for the ten-year sample period of 2009-2018. We obtain measures of TFP growth for each council between each pair of adjacent years. Thus, providing a set of 68 chained TFP indices for each of 9 periods. These TFP indices are then decomposed into that part due to frontier shift or technical change (TECHCH) and that part due to catch up or CRS technical efficiency change (CRSTECH). These latter CRSTECH measures are also then decomposed into VRS technical efficiency change (VRSTECH) and a scale efficiency change (SECH) effect.[12]

Summary information on these various indices are presented in Figures 6.1 and 6.2 and Tables 6.1 and 6.2 below. First, consider the bottom row of Table 6.2, where estimates of the annual average mean changes in each of the above indices are provided for the ten-year period. Mean TFPCH is 0.992, indicating that TFP has fallen by an average of 0.8% per year over this period. This decline in productivity is primarily due to TECHCH which similarly falls by an average of 0.8% per year over this period. There are also some very small contributions from technical efficiency and scale efficiency (of approx. 0.1%) but these tend to be minor compared to the larger effect of TECHCH.

These various changes are best illustrated using Figure 6.1 where the plots of these chained indices clearly illustrate that TECHCH is the main driver of the decline in TFP over this period, while CRSTECH, VRSTECH and SECH all follow a fairly flat trend over this period. The small contribution of these latter three measures should not be a surprise given that CRSTE, VRSTE and SE were all observed to be fairly stable (in aggregate) in the latter three tables in Section 5.

The average annual technical change (TECHCH) measure of negative 0.8% implies an average decline in the frontier of 0.8% per year over this ten-year period. In most sectors one would expect to observe positive technical change, as improvements in technology and knowhow cause the frontier firms to improve further and push the frontier outwards. The calculation of negative technical change (or technical regress) in this study appears to be counter-intuitive as it indicates that SA councils have collectively increased expenditure per unit of output, as measured in this study (property numbers and road length). The exact reasons for this are unclear at this stage. One possible explanation could be an increase in the volume, quality and/or range of council services that the model is not picking up in the output variables that are used. Another might be a general decline in sector performance. A third possible explanation could be measurement errors affecting the data that has been used. Testing these alternative explanations for the observed rising trend in expenditure per unit of output is a matter for further work.

Figure 6.2 and Table 6.2 contains information on mean TFP change for each council over the 10-year period. These range from a low of 0.940 for council #13 to a high of 1.027 for council #17. A value of 1.027 implies an annual average increase in TFP of 2.7% pa while 0.940 implies an annual average decrease in TFP of 6% pa. Once again, additional analysis is required for one to be able to judge if these council-level differences are due to management issues or other issues such as a unique environment or data measurement errors.

[12] For further details on these Malmquist DEA methods and measures please refer to Appendix A.

Figure 6.1 **Malmquist DEA TFP change aggregate indices 2009-2018**

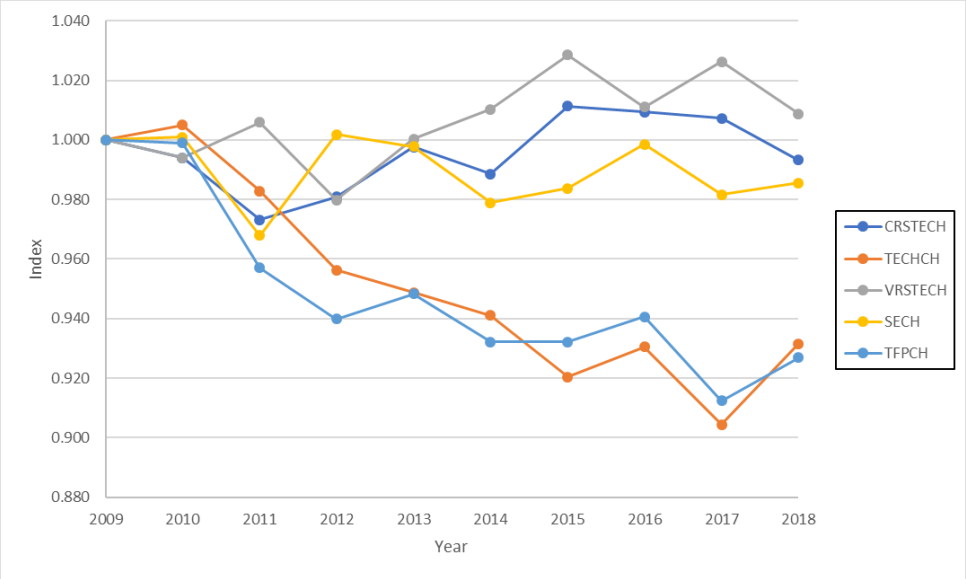


Table 6.1 **Malmquist DEA TFP change aggregate indices 2009-2018**

Year	CRSTECH	TECHCH	VRSTECH	SECH	TFPCH
2009	1.000	1.000	1.000	1.000	1.000
2010	0.994	1.005	0.994	1.001	0.999
2011	0.973	0.983	1.006	0.968	0.957
2012	0.981	0.956	0.980	1.002	0.940
2013	0.998	0.949	1.000	0.998	0.948
2014	0.989	0.941	1.010	0.979	0.932
2015	1.011	0.920	1.029	0.984	0.932
2016	1.009	0.931	1.011	0.999	0.941
2017	1.007	0.904	1.026	0.982	0.912
2018	0.993	0.932	1.009	0.985	0.927

Figure 6.2 **Malmquist DEA TFP change means for each council 2009-2018**

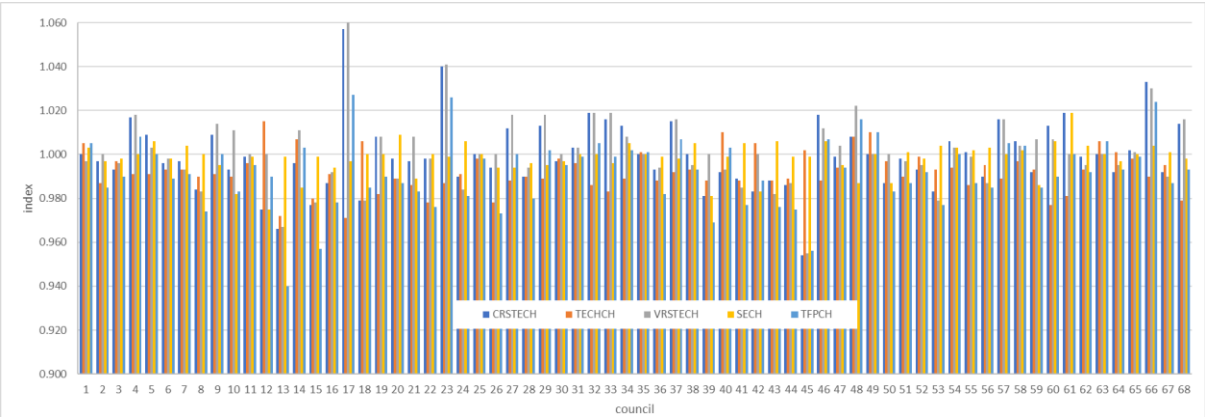


Table 6.2 **Malmquist DEA TFP change means for each council 2009-2018**

Council	CRSTECH	TECHCH	VRSTECH	SECH	TFPCH
1	1.000	1.005	0.997	1.003	1.005
2	0.997	0.987	1.000	0.997	0.985
3	0.993	0.997	0.996	0.998	0.990
4	1.017	0.991	1.018	1.000	1.008
5	1.009	0.991	1.003	1.006	1.000
6	0.996	0.993	0.998	0.998	0.989
7	0.997	0.993	0.993	1.004	0.991
8	0.984	0.990	0.983	1.000	0.974
9	1.009	0.991	1.014	0.995	1.000
10	0.993	0.990	1.011	0.982	0.983
11	0.999	0.996	1.000	0.999	0.995
12	0.975	1.015	1.000	0.975	0.990
13	0.966	0.972	0.967	0.999	0.940
14	0.996	1.007	1.011	0.985	1.003
15	0.977	0.980	0.978	0.999	0.957
16	0.987	0.991	0.992	0.994	0.978
17	1.057	0.971	1.060	0.997	1.027
18	0.979	1.006	0.979	1.000	0.985
19	1.008	0.982	1.008	1.000	0.990
20	0.998	0.989	0.989	1.009	0.987
21	0.997	0.986	1.008	0.989	0.983
22	0.998	0.978	0.998	1.000	0.976
23	1.040	0.987	1.041	0.999	1.026
24	0.990	0.991	0.984	1.006	0.981
25	1.000	0.998	1.000	1.000	0.998
26	0.994	0.978	1.000	0.994	0.973
27	1.012	0.988	1.018	0.994	1.000
28	0.990	0.990	0.994	0.996	0.980
29	1.013	0.989	1.018	0.995	1.002
30	0.997	0.998	1.000	0.997	0.995
31	1.003	0.996	1.003	1.000	0.999
32	1.019	0.986	1.019	1.000	1.005
33	1.016	0.983	1.019	0.996	0.999
34	1.013	0.989	1.008	1.005	1.002
35	1.000	1.001	1.000	1.000	1.001
36	0.993	0.988	0.994	0.999	0.982
37	1.015	0.992	1.016	0.998	1.007
38	1.000	0.993	0.995	1.005	0.993
39	0.981	0.988	1.000	0.981	0.969
40	0.992	1.010	0.993	0.999	1.003
41	0.989	0.988	0.985	1.005	0.977
42	0.983	1.005	1.000	0.983	0.988
43	0.988	0.988	0.982	1.006	0.976
44	0.986	0.989	0.987	0.999	0.975
45	0.954	1.002	0.955	0.999	0.956
46	1.018	0.988	1.012	1.006	1.007
47	0.999	0.994	1.004	0.995	0.994
48	1.008	1.008	1.022	0.987	1.016
49	1.000	1.010	1.000	1.000	1.010
50	0.987	0.997	1.000	0.987	0.983
51	0.998	0.990	0.997	1.001	0.987
52	0.993	0.999	0.995	0.998	0.992
53	0.983	0.993	0.979	1.004	0.977
54	1.006	0.994	1.003	1.003	1.000
55	1.001	0.986	0.999	1.002	0.987
56	0.990	0.995	0.987	1.003	0.985
57	1.016	0.989	1.016	1.000	1.005
58	1.006	0.997	1.004	1.002	1.004
59	0.992	0.993	1.007	0.986	0.985
60	1.013	0.977	1.007	1.006	0.990
61	1.019	0.981	1.000	1.019	1.000
62	0.999	0.993	0.995	1.004	0.992
63	1.000	1.006	1.000	1.000	1.006
64	0.992	1.001	0.995	0.997	0.993
65	1.002	0.998	1.001	1.000	0.999
66	1.033	0.990	1.030	1.004	1.024
67	0.992	0.995	0.990	1.001	0.987
68	1.014	0.979	1.016	0.998	0.993
mean	**0.999**	**0.992**	**1.001**	**0.998**	**0.992**

7 SECOND STAGE ANALYSIS

In this section we look at a number of factors that might potentially help explain observed variations in efficiency measures and TFP change indices across different councils.

Council groups

First, we investigate if efficiency levels and TFP indices differ according to the four council groupings described earlier in this report. Namely:

- urban (including capital, development and fringe);
- rural agricultural (small and medium);
- rural agricultural (large and very large); and
- urban regional.

To address this issue, we have estimated the group means of CRS TE, VRS TE, SE and TFP change for each of these groups, which are reported in Table 7.1 below. We have also reported their standard deviations and then tested the null hypothesis that the four means are the same, using a traditional analysis of variance (AOV) test.

We have furthermore noted that these various scores and indices are unlikely to be normally and/or independently distributed and hence have also estimated the non-parametric Kruskal-Wallis ranks test, which is a test of the null hypothesis that these four samples are drawn from populations with identical probability distributions.

The mean VRS TE score varies across the four groups, with rural agricultural (small & medium) having the highest mean at 0.871 and urban regional having the lowest mean of 0.714. The urban regional group is a small group with a few members that are quite unique, which could partly explain this result. The AOV test of the null hypothesis of the equality of these four means produces a probability of 0.058 hence we do not reject the null hypothesis at the 0.05 (5%) level and conclude that the VRS TE means do not differ across these four groups. However, the KW test has a probability of 0.025 which leads us to the opposite conclusion. Given the non-normal nature of these data we place greater weight on this KW test result.

The means of the CRS TE scores follow a similar pattern, but with slightly lower means as one would expect. The AOV test rejects the null of equal means at the 5% level while the KW test indicates the null would not be rejected on this metric. Once again, given the non-normal nature of these data we place greater weight on the KW result.

The mean SE scores generally show less variation among the four groups. The two rural groups have slightly higher levels of SE relative to the two urban groups. However, we note that the null hypothesis of equal SE means is not rejected by either the AOV or KW tests at the 5% level and hence these differences are not significant.

Finally, the mean TFP change indices for these four groups are also reported in Table 7.1. These are quite similar across the four groups, with rural agricultural (large and very large) being marginally lower than the other three groups. However, these differences are not significant at the 5% level by either the AOV or KW tests.

Table 7.1 **Analysis of group means**

	VRSTE		CRSTE		SE		TFPCH	
Group	**mean**	**stdev**	**mean**	**stdev**	**mean**	**stdev**	**mean**	**stdev**
urban	0.866	0.033	0.827	0.034	0.953	0.016	0.993	0.003
rural ag S&M	0.871	0.033	0.835	0.034	0.959	0.016	0.993	0.003
rural ag L&XL	0.841	0.036	0.806	0.038	0.959	0.018	0.989	0.004
urban regional	0.714	0.050	0.659	0.052	0.907	0.024	0.990	0.005
Test	**prob**	**null hyp**	**prob**	**null hyp**	**prob**	**null hyp**	**prob**	**null hyp**
AOV	0.058	accept	0.039	reject	0.298	accept	0.863	accept
KW	0.025	reject	0.067	accept	0.527	accept	0.526	accept

Regressions

Differences in efficiency scores and TFP indices are also investigated using second stage regression methods. The mean council-level efficiency scores and TFP change indices are regressed on the following 16 variables:

1. U15 = % population aged under 15
2. ABTSI = % population Aboriginal or Torres Strait Islander
3. NES = % population who speak a language other than English at home
4. PEN = % population who receive the age pension
5. UNEM = % population who receive unemployment benefits
6. MWAGE = median wage ($'000)
7. DEN = Population density in persons per hectare
8. GPOP = % growth in population between 2009 and 2018
9. GPROP = % growth in rateable properties between 2009 and 2018
10. POP = Population ('000)
11. SEALRD = % sealed roads
12. BUSINC = % income from business undertakings
13. IRSED = Index of Relative Socio-economic Disadvantage
14. IRSEAD = Index of Relative Socio-economic Advantage and Disadvantage
15. IER = Index of Economic Resources
16. IEO = Index of Education and Occupation

We first present a matrix of correlation coefficients in Table 7.2 below to see if some of these indicators are highly correlated and hence could be reduced in number. We observe that many of the correlations are well below 0.5 with only a few of the SEIFA indices having values greater than 0.8.

The regression results for the VRS TE scores are presented in Tables 7.3 and 7.4 below.[13] Ordinary Least Squares (OLS) regression results are in Table 7.3 while Tobit regression results are reported in Table 7.4. We note that the two sets of results are quite similar, but will focus on the Tobit results since this method is able to better accommodate the censored nature of the efficiency scores (ie. they are censored from above at 100). Note that in this section the efficiency scores and TFP indices are scaled by 100 so that the regression coefficients are easier to interpret as percentages.

From the Tobit results in Table 7.4 we observe that five of the 16 regressor variables are statistically significant at the 5% level. These are ABTSI, NES, PEN, GPOP and IER. Each of these regressor variables has a p-value which is less than 0.05 in the final column of the table. We now discuss each of these five variables in turn.

For ABTSI the estimated coefficient value is negative 1.309 and indicates that a 1 unit increase in the % of ABTSI people in a council area is associated with a 1.309 reduction in the VRS TE score. This could perhaps be a consequence of the extra services that are provided to ABTSI people in some council areas, or alternatively ABTSI could be acting as an indirect proxy for remoteness and hence picking up the effect of the extra costs associated with servicing remote areas.

For NES the estimated coefficient value is 0.863 and indicates that a 1 unit increase in the % of NES people in a council area is associated with a 0.863 increase in the VRS TE score. Initially it was expected that this variable might have a negative effect on efficiency because NES residents might require extra language assistance with some services. However, one possible explanation for this positive effect could be that councils with high NES levels might also have a mix of lower socio-economic residents who would not be demanding the level of services that are sought in some wealthier council areas. That is, this variable might be estimating a statistical *association* rather than a *causation*.

For PEN the estimated coefficient value is 1.636 and indicates that a 1 unit increase in the % of pensioners in a council area is associated with a 1.636 increase in the VRS TE score. Once again, it was initially expected that this variable might have a negative effect on efficiency because pensioners might require extra assistance with some services. However, the explanation provided above for the case of NES might also explain this result as well, given that one would expect to find more pensioners in lower socio-economic council areas.

For GPOP the estimated coefficient value is negative 0.518 and indicates that a 1 unit increase in population growth in a council area is associated with a 0.518 reduction in the VRS TE score. The direction of this effect is as expected, with councils in high growth areas (eg. the urban fringe) having to deal with the extra logistical challenges of growing as well as maintaining services.

Finally, for IER the estimated coefficient value is 0.300 and indicates that a 1 unit increase in the Index of Economic Resources in a council area is associated with a 0.300 increase in the

[13] As noted in Section 4, due to data constraints, these exogenous variables are mostly defined for the year 2016, while the VRS TE scores and TFP change indices are the averages across the 10-year period.

VRS TE score. The direction of this effect is not as expected if one follows the above argument that residents in richer council areas are likely to demand more services and hence have lower measured efficiency levels. However, this index might be picking up the effects of higher wealth rather than higher disposable income which perhaps could have a different impact here. Further analysis is required to better disentangle and understand these factors.

The other variables in Table 7.4 are not significant at the 5% level, but we do note that most of the signs on the estimated coefficients do accord with our expectations.

A regression analysis of the council-level mean TFP change indices is provided in Table 7.5. OLS regression is appropriate to use here because the indices are not censored like the efficiency scores were. We observe that all 16 regressor variables are statistically insignificant at the 5% level and that the R-squared value is only 26%. As a consequence, we conclude that none of these variables are useful in explaining variations in TFP change indices across these 68 councils.

Table 7.2 **Correlation matrix for second stage variables**

	U15	ABTSI	NES	PEN	UNEM	MWAGE	DEN	GPOP
U15	1.000							
ABTSI	0.120	1.000						
NES	-0.328	-0.061	1.000					
PEN	-0.403	0.044	-0.367	1.000				
UNEM	-0.115	0.566	-0.014	0.388	1.000			
MWAGE	0.213	-0.016	0.436	-0.568	-0.260	1.000		
DEN	-0.365	-0.258	0.786	-0.312	-0.289	0.477	1.000	
GPOP	-0.254	-0.286	0.332	-0.088	-0.043	0.162	0.254	1.000
GPROP	-0.023	-0.023	0.216	-0.265	-0.024	0.237	0.141	0.670
POP	-0.010	-0.183	0.551	-0.198	-0.005	0.373	0.458	0.358
SEALRD	-0.137	-0.238	0.733	-0.368	-0.157	0.657	0.764	0.416
BUSINC	-0.009	0.314	0.034	-0.119	0.217	0.126	-0.232	-0.064
IRSED	-0.005	-0.469	0.194	-0.463	-0.900	0.381	0.443	0.124
IRSEAD	-0.129	-0.437	0.361	-0.494	-0.825	0.421	0.584	0.149
IER	0.262	-0.456	-0.241	-0.231	-0.805	0.108	0.017	-0.028
IEO	-0.347	-0.345	0.477	-0.375	-0.637	0.323	0.676	0.141
	GPROP	**POP**	**SEALRD**	**BUSINC**	**IRSED**	**IRSEAD**	**IER**	**IEO**
GPROP	1.000							
POP	0.229	1.000						
SEALRD	0.333	0.680	1.000					
BUSINC	0.061	-0.302	-0.217	1.000				
IRSED	0.036	0.086	0.270	-0.036	1.000			
IRSEAD	0.069	0.131	0.374	-0.031	0.969	1.000		
IER	-0.152	-0.071	-0.118	-0.143	0.810	0.686	1.000	
IEO	0.068	0.135	0.393	-0.013	0.835	0.936	0.464	1.000

Table 7.3 **Regression analysis of VRSTE**

Variable	Coefficient	Std. Error	t-ratio	p-value
U15	1.234	0.832	1.480	0.144
ABTSI	-1.199	0.497	-2.420	0.019
NES	0.689	0.351	1.960	0.055
PEN	1.435	0.580	2.470	0.017
UNEM	1.630	2.749	0.590	0.556
MWAGE	0.163	0.305	0.530	0.596
DEN	0.535	0.412	1.300	0.200
GPOP	-0.417	0.264	-1.580	0.119
GPROP	0.226	0.372	0.610	0.547
POP	0.090	0.066	1.360	0.180
SEALRD	-0.078	0.094	-0.830	0.412
BUSINC	-0.249	0.185	-1.350	0.183
IRSED	0.288	0.283	1.020	0.314
IRSEAD	-0.749	0.464	-1.610	0.113
IER	0.304	0.119	2.540	0.014
IEO	0.279	0.181	1.540	0.129
Constant	-101.263	93.959	-1.080	0.286
R-squared	0.660			

Table 7.4 **Tobit Regression analysis of VRSTE**

Variable	Coefficient	Std. Error	t-ratio	p-value
U15	1.223	0.809	1.510	0.137
ABTSI	-1.309	0.468	-2.790	0.007
NES	0.863	0.375	2.300	0.025
PEN	1.636	0.560	2.920	0.005
UNEM	1.864	2.598	0.720	0.476
MWAGE	0.220	0.293	0.750	0.456
DEN	0.533	0.387	1.380	0.174
GPOP	-0.518	0.253	-2.050	0.045
GPROP	0.344	0.356	0.960	0.339
POP	0.099	0.069	1.430	0.160
SEALRD	-0.106	0.089	-1.190	0.240
BUSINC	-0.281	0.176	-1.600	0.115
IRSED	0.393	0.277	1.420	0.162
IRSEAD	-0.854	0.461	-1.850	0.070
IER	0.300	0.116	2.580	0.013
IEO	0.292	0.176	1.660	0.103
Constant	-117.528	88.856	-1.320	0.192
R-squared	NA			

Table 7.5 **Regression analysis of TFP change indices**

Variable	Coefficient	Std. Error	t-ratio	p-value
U15	0.130	0.121	1.070	0.287
ABTSI	-0.121	0.072	-1.680	0.100
NES	0.053	0.051	1.030	0.306
PEN	-0.054	0.084	-0.640	0.522
UNEM	0.152	0.400	0.380	0.706
MWAGE	-0.028	0.044	-0.620	0.536
DEN	-0.017	0.060	-0.290	0.774
GPOP	-0.018	0.038	-0.460	0.647
GPROP	-0.011	0.054	-0.200	0.840
POP	0.006	0.010	0.650	0.521
SEALRD	-0.002	0.014	-0.170	0.862
BUSINC	0.034	0.027	1.270	0.209
IRSED	-0.001	0.041	-0.030	0.979
IRSEAD	-0.032	0.067	-0.470	0.637
IER	0.017	0.017	0.980	0.330
IEO	0.023	0.026	0.860	0.391
Constant	91.089	13.662	6.670	0.000
R-squared	0.261			

8 CONCLUSIONS

Our key empirical results are as follows:

- We estimate mean CRS TE of 0.798, mean VRS TE of 0.841, mean SE of 0.950. The SE scores are approximately one third of the size of the VRS TE scores, indicating that scale inefficiency plays a lesser role compared to technical efficiency.
- We obtain a mean annual TFP change estimate of 0.992, which indicates that productivity has been declining at an average annual rate of 0.8% per year.

Our empirical results also indicate that the estimated decline in TFP is primarily due to technical regress. That is, due to the estimated DEA frontier shifting backwards over time. The reasons for this measured reduction in productivity over time are unclear. Some possible explanations include: a general decline in performance across the sector; an increase in the volume, quality and/or range of council services provided (that are not reflected in the output variables used in our model); measurement errors affecting the data that has been used; and so on. The empirical results draw attention to the value of further work to test the veracity of these alternative explanations.

Additional research will hopefully shed light of the relative importance of these alternative explanations. For example, if there has been an apparent increase in service levels in a particular area, such as provision of additional waste recycling collections, it might be useful to estimate the aggregate costs of these additional recycling services and then compare these cost measures to the scale of cost increases implied by the estimated TFP decline.

We also note that some observers have also commented that measured productivity declines could be in part explained by generous enterprise bargaining agreements in the first half of the study period that appear to be larger than the wages price indices utilised in the SALGPI calculations. One might then be tempted to argue that we should adjust these input price deflators to reflect these higher rates of council wage increases. We would caution against this, since this might reduce incentives for managers to bargain for acceptable wage increases in the future. In other jurisdictions, regulators have observed that public sector managers will tend to take the "path of least resistance" if they believe they can "pass through" generous wage increases and not be judged in a negative manner by regulatory authorities.

It is important to emphasise that the efficiency scores for each council that are reported in this study are estimated relative to the 68 South Australian (SA) councils included in our database. Thus, these measures are only relative to the best performers in SA. If councils from other locations, such as other States in Australia were included in our database, it is possible that these estimated efficiency scores could change. It might be a useful exercise to attempt to conduct some interstate comparisons of council performance if possible. However, issues of data comparability and differences in services delivered across different States would need to be properly addressed for this to be a useful exercise.

Additionally, we note that the tables of council-level performance measures presented in this report have been masked so that individual councils cannot be identified. In our assessment, it may be a useful exercise for the performance measures of individual councils to be made public at some stage. This might have the effect of encouraging councils to critique the models and data measures used and hence lead to better model structures and data quality in

future analyses of local government performance in SA. It might also encourage those councils which are perhaps providing extra "non-standard" services (and hence might be identified as "inefficient councils") to outline these extra services and their associated costs so that their ratepayers can then assess whether they are receiving the services they desire in a cost-effective manner.

Finally, it is important to conclude with the observation that this study, like all DEA studies, is imperfect. The input and output variables that have been chosen are the best available, but they are unable to capture all minute aspects of every individual council's activities. Hence, the council-level efficiency scores and TFP indices should be interpreted with a degree of caution. Any councils which are found to be performing particularly well or not so well should be carefully studied to see if their results are a consequence of managerial performance or alternatively a consequence of a unique environment or provision of extra services or different quality services or a data measurement issue.

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APPENDIX A DETAILED METHODOLOGY

In this appendix we provide technical detail on the methods used to calculate efficiency and productivity in this report. We describe two methods:

- Efficiency measurement using data envelopment analysis (DEA)
- Productivity measurement using Malmquist DEA TFP methods

The discussion draws upon that presented in Coelli et al (2005).

Note that the DEA software used to calculate these models is described in Coelli (1996).

Efficiency measurement using data envelopment analysis (DEA)

Data envelopment analysis (DEA) is a non-parametric mathematical programming approach that is used for estimating production frontiers and measuring efficiency. DEA involves the use of linear programming methods to construct a non-parametric piece-wise surface (or frontier) over the data. Efficiency measures are then calculated relative to this surface.

Various DEA models are estimated in this study. First, we define the constant returns to scale (CRS) DEA model.

Assume there are data on K inputs and M outputs for each of N firms. For the i-th firm these are represented by the column vectors x_i and y_i, respectively. The K×N input matrix, X, and the M×N output matrix, Y, represent the data for all N firms.

An input-orientated CRS DEA model is defined as:

$$\begin{aligned} &\min_{\theta,\lambda} \theta, \\ &\text{st} \quad -y_i + Y\lambda \geq 0, \\ &\qquad \theta x_i - X\lambda \geq 0, \\ &\qquad \lambda \geq 0, \end{aligned} \tag{1}$$

where θ is a scalar and λ is a N×1 vector of constants. The value of θ obtained will be the efficiency score for the i-th firm. It will satisfy: $\theta \leq 1$, with a value of 1 indicating a point on the frontier and hence a technically efficient firm. Note that the linear programming problem must be solved N times, once for each firm in the sample. A value of θ is then obtained for each firm.

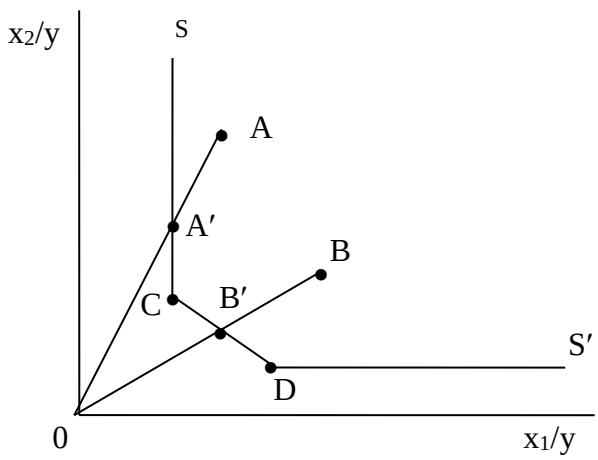
The DEA problem in equation 1 has an intuitive interpretation. Essentially, the problem takes the i-th firm and then seeks to radially contract the input vector, x_i, as much as possible, while still remaining within the feasible production set. The inner-boundary of this set is a piece-wise linear isoquant determined by the observed data points (i.e., all the firms in the sample). The radial contraction of the input vector, x_i, produces a projected point, (Xλ,Yλ), on the surface of this technology. This projected point is a linear combination of these observed data points. The constraints in equation 1 ensure that this projected point cannot lie outside the feasible set.

This may be illustrated using the simple two-input one-output example that is drawn in Figure A.1, where we have four firms denoted by the points A, B, C and D. The frontier isoquant

(denoted by SS′) is determined by firms C and D. Firms A and B are inefficient. Their projected points are denoted by A′ and B′, respectively.

Note that the efficient projected point for firm B is B′, where B′ is a linear combination of points C and D. In DEA terminology we state that firms C and D are the "peers" for firm B, because they define that part of the efficient frontier that defines the best practice point for firm B.[14]

Figure A.1 **Efficiency measurement**



Next we define the variable returns to scale (VRS) DEA model.

The CRS assumption is only appropriate when all firms are operating at an optimal scale. The use of the CRS specification when not all firms are operating at the optimal scale, results in measures of TE that are confounded by *scale efficiencies* (SE). The use of the VRS specification permits the calculation of TE devoid of these SE effects.

The CRS linear programming problem can be easily modified to account for VRS by adding the convexity constraint: $N1'\lambda=1$ to equation 1 to provide:

$$\min_{\theta,\lambda} \theta,$$

$$\begin{aligned} \text{st} \quad & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & N1'\lambda=1 \\ & \lambda \geq 0, \end{aligned} \qquad (2)$$

where N1 is an N×1 vector of ones.

This approach forms a convex hull of intersecting planes which envelope the data points more tightly than the CRS conical hull and thus provides technical efficiency scores, which are

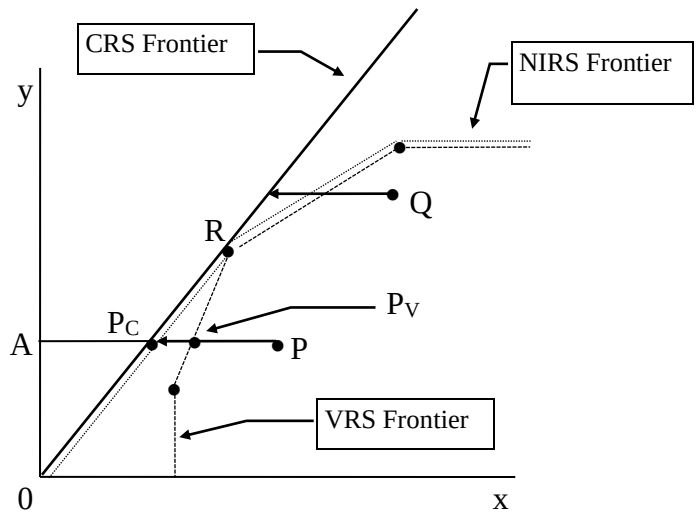
[14] When the DEA model involves more input and/or output variables the model involves more dimensions and hence the peer set for a firm will often involve more than just two peers, as is drawn here in two dimensions.

greater than, or equal to those obtained using the CRS model. Note that the convexity constraint ($N1'\lambda=1$), essentially ensures that an inefficient firm is only "benchmarked" against firms of a similar size. That is, the projected point (for that firm) on the DEA frontier will be a *convex* combination of observed firms. This convexity restriction is not imposed in the CRS case. Hence, in a CRS DEA, a firm may be benchmarked against firms that are substantially larger (smaller) than it. In this instance the λ-weights will sum to a value less than (greater than) one.

The VRS and CRS DEA models can be used to calculate scale efficiencies. This is done by estimating both a CRS and a VRS DEA. The TE scores obtained from the CRS DEA are then decomposed into two components, one due to scale inefficiency and one due to "pure" technical inefficiency (the VRS score). If there is a difference in the CRS and VRS TE scores for a particular firm, then this indicates that the firm has scale inefficiency, and that the scale inefficiency can be calculated from the difference between the VRS and CRS TE scores.

In Figure A.2 we illustrate scale inefficiency using a one-input, one-output example. The CRS and VRS DEA frontiers are indicated in the figure. Under CRS, the input-orientated technical inefficiency of the point P is the distance PP_C. However, under VRS, the technical inefficiency would only be PP_V. The difference between these two TE measures, P_CP_V, is due to scale inefficiency.

Figure A.2 **Calculation of scale efficiency**



These concepts can be expressed in ratio efficiency measures as:

$$TE_{CRS} = AP_C/AP$$

$$TE_{VRS} = AP_V/AP$$

$$SE = AP_C/AP_V$$

where all of these measures are bounded by zero and one. We also note that

$$TE_{CRS} = TE_{VRS} \times SE$$

because

$$AP_C/AP = (AP_V/AP) \times (AP_C/AP_V).$$

Thus, the CRS technical efficiency measure is decomposed into "pure" (VRS) technical efficiency and scale efficiency. This scale efficiency measure can be roughly interpreted as the ratio of the average product of a firm operating at the point P_V to the average product of the point operating at a point of (technically) optimal scale (point R).

The diagram in Figure A.2 also provides a simple illustration of returns to scale (RTS) concepts. The three firms denoted by the points P, R and Q denote firms that are operating at increasing returns to scale (IRS), constant returns to scale (CRS) and decreasing returns to scale (DRS), respectively. That is, if the firm P was to expand its scale of production it would approach the optimal scale point, R, while if firm Q was to contract its scale of production it would also approach this optimal scale point, R (where productivity is maximised on the VRS frontier).

One shortcoming of this measure of scale efficiency is that the value does not indicate whether the firm is operating in an area of increasing or decreasing returns to scale. This latter issue can be determined by running an additional DEA problem with non-increasing returns to scale (NIRS) imposed. This is done by altering the DEA model in equation 2 by substituting the $N1'\lambda = 1$ restriction with $N1'\lambda \leq 1$, to provide:

$$\begin{aligned} &\min_{\theta,\lambda} \theta, \\ &\text{st} \quad -y_i + Y\lambda \geq 0, \\ &\qquad \theta x_i - X\lambda \geq 0, \\ &\qquad N1'\lambda \leq 1 \\ &\qquad \lambda \geq 0. \end{aligned} \tag{3}$$

The NIRS DEA frontier is also plotted in Figure 2.A. The nature of the scale inefficiencies (i.e., due to increasing or decreasing returns to scale) for a particular firm can be determined by seeing whether the NIRS TE score is equal to the VRS TE score. If they are unequal (as is the case for the point P) then increasing returns to scale exist for that firm. If they are equal (as is the case for point Q) then decreasing returns to scale apply. Finally, we note that if $TE_{CRS}=TE_{VRS}$, then by definition, the firm is operating under CRS.

<u>Productivity measurement using Malmquist DEA TFP methods</u>

This section provides a brief description of the Malmquist DEA TFP index methodology that is used to estimate TFP change for SA local councils in this study. We illustrate how, with access to suitable panel data, DEA frontier construction methods can be used to obtain estimates of TFP growth and its decomposition into various useful components:

- technical change (frontier-shift),
- technical efficiency change (catch-up), and

- scale efficiency change.

The Malmquist TFP index measures the TFP change between two data points by calculating the ratio of the distances of each data point relative to a common technology.[15] The Malmquist (input-orientated) TFP change index between period s (the base period) and period t is given by

$$M_i(y_s, x_s, y_t, x_t) = \left[\frac{d_i^s(y_t, x_t)}{d_i^s(y_s, x_s)} \times \frac{d_i^t(y_t, x_t)}{d_i^t(y_s, x_s)} \right]^{1/2}, \qquad (4)$$

where the notation $d_i^s(x_t, y_t)$ represents the distance from the period t observation to the period s technology. A value of M_i greater than one will indicate positive TFP growth from period s to period t while a value less than one indicates a TFP decline. Note that equation 4 is, in fact, the geometric mean of two TFP indices. The first is evaluated with respect to period s technology and the second with respect to period t technology.

An equivalent way of writing this productivity index is

$$M_i(y_s, x_s, y_t, x_t) = \frac{d_i^t(y_t, x_t)}{d_i^s(y_s, x_s)} \left[\frac{d_i^s(y_t, x_t)}{d_i^t(y_t, x_t)} \times \frac{d_i^s(y_s, x_s)}{d_i^t(y_s, x_s)} \right]^{1/2}, \qquad (5)$$

where the ratio outside the square brackets measures the change in the input-oriented measure of Farrell technical efficiency between periods s and t. That is, the efficiency change is equivalent to the ratio of the Farrell technical efficiency in period t to the Farrell technical efficiency in period s. The remaining part of the index in equation 5 is a measure of technical change. It is the geometric mean of the shift in technology between the two periods, evaluated at x_t and also at x_s. Thus the two terms in equation 6 are:

$$\text{Efficiency change} = \frac{d_i^t(y_t, x_t)}{d_i^s(y_s, x_s)} \qquad (6)$$

and

$$\text{Technical change} = \left[\frac{d_i^s(y_t, x_t)}{d_i^t(y_t, x_t)} \times \frac{d_i^s(y_s, x_s)}{d_i^t(y_s, x_s)} \right]^{1/2} \qquad (7)$$

This decomposition is illustrated in Figure A3 which depicts a constant returns to scale technology involving a single input and a single output.

The firm produces at the points D and E in periods s and t, respectively. In each period the firm is operating below the technology for that period. Hence, there is technical inefficiency in both periods. Using equations 6 and 7 we obtain:

$$\text{Efficiency change} = \frac{x_c / x_t}{x_b / x_s} \qquad (8)$$

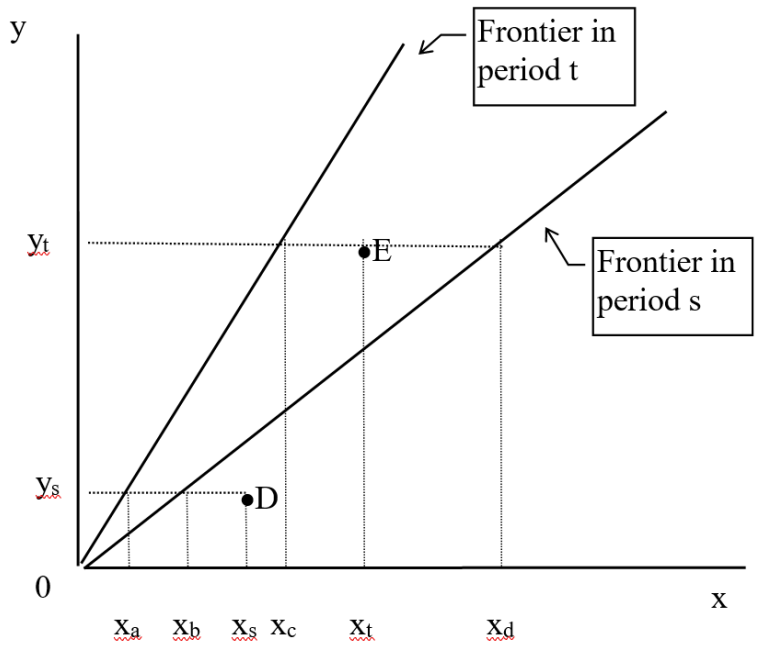
[15] Note that these distance measures are essentially equivalent to the efficiency measures defined above. The only difference is that in some cases "efficiency" is measured across different time periods. For example, comparing data on a firm in period t with the frontier from period s, etc.

$$\text{Technical change} = \left[\frac{x_d / x_t}{x_c / x_t} \times \frac{x_b / x_s}{x_a / x_s} \right]^{1/2} \qquad (9)$$

In an empirical application the four distance measures which appear in equation 4 must be calculated for each firm in each pair of adjacent time periods. This can be done using DEA mathematical programming techniques. These methods are discussed below.

There are a number of different methods that could be used to measure the distance functions that make up the Malmquist TFP index. To date, the most popular method has been DEA-like linear programming methods. For the i-th firm, we must calculate four distance functions to measure the TFP change between two periods. This requires the solving of four linear programming (LP) problems.

Figure A.3 **Malmquist productivity indices**



The required LPs are:

$$d_i^t(y_t, x_t) = \min_{\theta,\lambda} \theta,$$

$$\text{st} \quad -y_{it} + Y_t\lambda \geq 0,$$

$$\theta x_{it} - X_t\lambda \geq 0,$$

$$\lambda \geq 0, \qquad (10)$$

$$d_i^s(y_s, x_s) = \min_{\theta,\lambda} \theta,$$

$$\text{st} \quad -y_{is} + Y_s\lambda \geq 0,$$

$$\theta x_{is} - X_s\lambda \geq 0,$$
$$\lambda \geq 0, \qquad (11)$$

$$d_i^t(y_s, x_s) = \min_{\theta,\lambda} \theta,$$
$$\text{st} \quad -y_{is} + Y_t\lambda \geq 0,$$
$$\theta x_{is} - X_t\lambda \geq 0,$$
$$\lambda \geq 0, \qquad (12)$$

and

$$d_i^s(y_t, x_t) = \min_{\theta,\lambda} \theta,$$
$$\text{st} \quad -y_{it} + Y_s\lambda \geq 0,$$
$$\theta x_{it} - X_s\lambda \geq 0,$$
$$\lambda \geq 0, \qquad (13)$$

Note that in LP's 12 and 13, where production points are compared to technologies from different time periods, the θ parameter need not be less than or equal to one, as it must be when calculating Farrell input-orientated technical efficiencies. The data point could lie above the feasible production set. This will most likely occur in LP 13 where a production point from period t is compared to technology in an earlier period, s. If technical progress has occurred, then a value of θ>1 is possible. Note that it could also possibly occur in LP 12 if technical regress has occurred, but this is less likely in most sectors.

Some points to keep in mind are that the θ's and λ's are likely to take different values in the above four LP's. Furthermore, note that the above four LP's must be solved for each firm in the sample. Thus, if there are 20 firms and 2 time periods, 80 LP's must be solved. Note also that as extra time periods are added, one must solve an extra three LP's for each firm (to construct a chained index). If there are T time periods, then (3T-2) LP's must be solved for each firm in the sample. Hence, if there are N firms, N×(3T-2) LP's need to be solved. For example, with N=20 firms and T=10 time periods, this would involve 20×(3×10-2) = 560 LP's.

The above approach can be extended to measure the effects of scale efficiency upon productivity growth. This is done in this study by decomposing the CRS technical efficiency change into scale efficiency and "pure" VRS technical efficiency components. This requires the solution of two additional LPs (when comparing two production points). These would involve repeating LPs 10 and 11 with the convexity restriction (N1′λ=1) added to each. That is, these two distance functions would be calculated relative to a variable returns to scale (VRS), instead of a CRS, technology. The CRS and VRS values are used to calculate the scale efficiency measures residually. For the case of N firms and T time periods, this would increase the number of LPs from N×(3T-2) to N×(4T-2).

APPENDIX B ALTERNATIVE MODELS

Empirical assessment of alternative DEA models

As mentioned in Section 3, a number of additional models were also estimated in order to assess the effect our variable choices might have upon the results obtained. Some summary information on eight different models is provided in Table B.1 below, with the preferred model listed as model #1. The main variations considered included: splitting the roads output variable up into sealed and unsealed roads output variables; adding population in as an extra variable; replacing the depreciation variable with a capex measure; aggregating opex and depreciation together to form a single aggregate input variable (opex2), and so on.

The mean CRS TE, VRS TE and SE scores obtained from these eight models (using 2018 data) are reported in Table B.1. Our observations are as follows.

Model #2 shows that replacing depreciation with capex has only a small negative effect on efficiency scores. Given the observed stochastic nature of capex and the conceptual issues discussed in Section 3, model #2 is not preferred.

Model #3 considers dropping depreciation and having only one input variable (opex). This has a large negative impact on efficiency scores and shows that an assumption that opex might be closely correlated with capital activity is not warranted. Model #3 is not preferred.

Model #4 splits the roads output variable up into sealed and unsealed variables. This has no effect on aggregate efficiency scores and in fact on closer inspection we find that only a small number of the individual efficiency scores change by only a small amount (in the 3rd decimal place only). Hence model #1 is preferred on the basis of parsimony.

Model #5 combines the changes in models #3 and #4 and has a predicable result.

Models #6 and #7 re-consider models #1 and #4 with opex and depreciation aggregated into a single input variable (opex2). They both result in some decrease in efficiency scores, as one would expect from decreasing the total number of variables in a DEA model. In our assessment the models with two input variables help identify better peer sets because capital intensive councils are compared with similar councils. Hence this proposed input aggregation is not used.

Finally, Model #8 includes population as an extra input variable. We find that this has only a small effect on efficiency scores, which is not surprising given that population and residential property numbers have a correlation in excess of 99% in these data. Hence, we once again prefer model #1 on the basis of parsimony.

In addition to reporting mean TE scores for 2018 in Table B.1, we have also reported mean Malmquist TFP change (TFPCH) for the 2009-2018 period in the final column of the Table. Model #1 has a mean TFPCH of 0.992, implying an average annual decline in TFP of 0.8%. The remaining seven models have very similar mean TFPCH measures. All are within 0.1% of the Model #1 value of 0.8%, with the exception of Model #2, which is 0.3% higher at 0.5%. This larger variation for Model #2 is not surprising given the stochastic nature of the capex series that has been noted in the discussion of the data plots in Section 3.

Table B.1 **DEA models investigated**

Model	Outputs:						Inputs:				Results:			
	Resid Prop	Other Prop	Roads	Sealed Roads	Unsealed Roads	Popln	OPEX	CAPEX	Depn	OPEX2	CRSTE	VRSTE	SE	TFPCH
1	X	X	X				X		X		0.798	0.841	0.946	0.992
2	X	X	X				X	X			0.800	0.832	0.961	0.995
3	X	X	X				X				0.754	0.788	0.954	0.992
4	X	X		X	X		X		X		0.799	0.841	0.946	0.992
5	X	X		X	X		X				0.754	0.788	0.954	0.992
6	X	X		X	X					X	0.784	0.817	0.954	0.993
7	X	X	X							X	0.738	0.787	0.936	0.992
8	X	X	X			X	X		X		0.813	0.854	0.948	0.991

Comparison with VESC-PAG model results

Here we make some observations regarding the results obtained by PAG in their DEA analysis of Victorian councils for the VESC. They considered five different DEA models, as outlined in Table B.2 below, which is a copy of Tables 2.1, 2.2 and 2.4 taken from pages 8, 10 and 15 of the VESC (2017) report.

First, we consider the input and output variables considered by PAG. At face value, PAG have used similar variables to those used in past literature and also in the current study. However, some key points should be made. First, in terms of output variables, their data on numbers of households and businesses is taken from the ABS and not from the councils themselves or the Grants Commission or Valuer General's Office. This is most likely because they faced similar data challenges to us. However, it should be noted that there could be some double counting here in this ABS data, with some businesses operating out of a residential address and in some cases multiple businesses operating out of the one address.

Second, in terms of input variables chosen, we have concerns with the use of either a staff expenses variable or a staff FTE variable when a non-staff operating expenses variable is not also included in the models. From our assessment of council-level data in Queensland and South Australia, we observe some variation in outsourcing activities across councils. For example, with some councils outsourcing waste collection to contractors while others choose do it in-house with their own labour force, etc. Hence, in our assessment, PAG models #1, #2 & #3 might in some cases produce inaccurate efficiency scores for some councils if outsourcing rates vary across these data on Victorian councils in a similar manner to data from other States.

Thus, it is interesting to note that in our study we have chosen the equivalent of their Model #5 as our preferred model while they have chosen their Model #1 as their preferred model. However, this different choice may well be a consequence of some other issues in the Victorian data that we are unaware of.

Having said all this, we note that the first three PAG models in Table B.2 produce mean TFC change indices which are very similar to the -0.8% value we have obtained in our study. However, their Models #4 and #5 produce much greater TFP declines, being -1.6% and -2.3%, respectively.

The fact that their Model #5 is almost identical to our Model #1 is noteworthy. Why have they estimated TFPCH of -2.3% for their data while we have estimated -0.8% for our data? Any answers to this question would be pure speculation without further information on the exact data they have used. However, some possibilities include:

- the selection of price deflators for expenses that are different to our price deflators (e.g. they might have chosen a CPI measure);
- or perhaps there may have been some changes in the way in which depreciation has been measured in these Victorian councils during this five-year period;
- or some actual differences in council performance over time;
- or it could simply be a consequence of the fact that their analysis is done over the six-year period of 2011-2016 while ours is over the ten-year period 2009-2018. Shorter time periods tend to provide more variable measures of TFPCH due to the fact that one "unusual" year can have a big impact on the mean TFPCH measure.

Finally, it is interesting to note that the PAG mean VRS TE scores are similar but slightly smaller than ours. For example, their Model #5 produces a mean VRS TE score of 0.82 while our Model #1 has a mean VRS TE score of 0.84.[16] This difference could be due in part to the fact that they have 79 observations versus our 68 observations. Sample size can have a notable impact on the mean efficiency scores obtained in DEA models, as is evident from the PAG single-group versus multi-group comparison at the bottom of Table B.2.

[16] We also note that the Nguyen and Coelli (2009) meta-analysis of hospital efficiency studies observed a mean efficiency of 84% across the 95 empirical studies included in their analysis. Hence the mean efficiency scores obtained in our study appear to be similar in nature to other studies.

Table B.2 **PAG VESC DEA Analysis of Victorian Councils**

Table 2.1 Model specifications for data envelopment analysis

Model Number	Inputs	Outputs
1	council staff ($) capital ($)	households, businesses, length of roads (km)
2	council staff (FTE) capital ($)	households, businesses, length of roads (km)
3	council staff ($) capital ($)	households, businesses, length of roads (km), waste collected (tonnes)
4	capital ($) operating expenses (excl. depreciation) ($)	households, businesses, length of roads (km)
5	operating expenses (excl. depreciation) ($) + depreciation ($)	households, businesses, length of roads (km)

Source: Predictive Analytics Group

Table 2.2 Summary of Malmquist index and total factor productivity change (TFPC) 2010–11 to 2015–16

Model	Average Malmquist index Single group analysis	Average TFPC Single group analysis (%)	Average Malmquist index Single group analysis	AverageTFPC Multiple group Analysis (%)
1	0.993	-0.7	0.993	-0.7
2	0.994	-0.6	0.994	-0.6
3	0.993	-0.7	0.993	-0.7
4	0.984	-1.6	0.985	-1.5.
5	0.977	-2.3	0.976	-2.4

Source: Predictive Analytics Group. The Malmquist index is calculated by multiplying technical efficiency change and technological change together.

Table 2.4 Technical efficiencies — 2015–16

Model number	Single group mean technical efficiency (VRS)	Multiple group mean technical efficiency (VRS)
1	0.81	0.94
2	0.79	0.94
3	0.83	0.96
4	0.81	0.96
5	0.82	0.96

Source: Predictive Analytics Group

Note: TFPC=TFPCH in this Table.

APPENDIX C DETAILED RESULTS AND CALCULATIONS

All input, output and data files used in the calculations in this report are provided in electronic form in a zip file.