Measuring productivity in the local government sector: A reply to stakeholder comments concerning DEA

Contact:

Dr Michael Kortt
Managing Director
Applied Econometrics
PO Box 6490
Tweed Heads South, NSW
e: michael.kortt@appliedeconometrics.com.au
w: www.appliedeconometrics.com.au
m: 0421 394 502

23 October 2017

Table of Contents

1. INTRODUCTION

In September 2017, the Essential Services Commission (ESC) published a Consultation Paper entitled: *Measuring Productivity in the Local Government Sector*. The purpose of this paper was to gather feedback from the Victorian local government sector on "productivity trends in the local government sector and the options identified to estimate an efficiency factor" (ESC, 2017, p. iii). ESC called for submissions on this Consultation Paper by 13 October 2017.

To estimate productivity trends for the Victorian local government sector, ESC engaged the Predictive Analytics Groups (PAG) who employed data envelopment analysis (DEA). DEA is an established and widely used non-parametric statistical technique, which has been extensively employed to measure efficiency and productivity trends in a range of public and private setting, including other Australian local government sectors (notably NSW and WA). These DEA estimates were, in turn, used to calculate a range of efficiency factors for the Victorian local government sector.

In response to the Consultation Paper, submissions from the following stakeholders raised concerns regarding the application of DEA:

- City of Casey (CoC)
- Corangamite Shire (CS)
- Municipal Association of Victoria (MAV)
- Wyndham City Council (WCC).

Moreover, Wyndham City Council also commissioned Professor Brian Dollery (2017) to prepare an independent report, which also raised concerns regarding the application of DEA. Across these submissions, concerns were raised regarding:

- DEA inputs
- DEA output
- Incorporating quality
- The influence of population density
- Differences among council sub-groups.

This Report is divided into three main parts. Section 2 provides a brief overview of DEA, the analytical strategy employed by PAG, and the principal results reported in the Consultation Paper. Section 3 will address the concerns raised by stakeholders regarding the application of DEA while Section 4 concludes the Report.

2. THE DEA RESULTS

2.1 An overview of DEA

DEA is a useful empirical technique for assessing technical efficiency. Unlike other empirical techniques DEA does not require *a priori* specification of functional form, is able to accommodate multiple inputs and outputs, and provides specific point estimates for each council. Technical efficiency (TE) is evaluated in terms of the ability of a council to convert inputs (e.g., staff and capital) into a set of outputs (e.g., number of households, number of businesses, and total length of municipal roads). The approach uses linear programming to create an efficient frontier (comprised of those councils which most efficiently convert inputs into outputs) and then estimates the relative efficiency of councils lying in the interior of the efficiency frontier according to their distance from the frontier.

The constant returns to scale (CRS) algorithm is detailed below:

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

$$
\begin{aligned}
\text{s.t.} \quad & -y_i + Y\lambda \geq 0, \\
& \theta x_i - X\lambda \geq 0, \\
& I1'\lambda = 1 \\
& \lambda \geq 0
\end{aligned}
$$

where *yi* is a vector of outputs and *xi* is a vector of inputs, θ is a scalar (the efficiency score for each council) and λ a vector of constants. The subscript *i* refers to the *ith* council and the inequalities ensure non-negative weights. The CRS specification evaluates inefficient councils against any peer on the frontier (regardless of size). The variable returns to scale (VRS) algorithm is achieved by adding the convexity constraint $I1'\lambda = 1$ so that inefficient councils are only evaluated against municipalities of a similar size.

Under both estimates, efficient councils are given a score of 1 and inefficient councils are assigned a score between 0 and 1. Scale estimates are simply the quotient of the CRS and VRS efficiency scores and a third estimate is attained by imposing the restriction $I1'\lambda \leq 1$ so that the nature of the scale inefficiency can be determined (i.e., whether councils are experiencing increasing, constant, or decreasing returns to scale). An input orientation was adopted for the DEA which "minimises inputs while satisfying at least the given output levels" (Ji and Lee, 2010, p. 268). This orientation is preferred given that councils take outputs as exogenous – that is, councils have little control over the total length of municipal roads in the short-run.

2.2 The analytical strategy employed by PAG

To measure the efficiency and productivity trends in the Victorian local government sector, a three-stage analytical strategy was adopted by PAG:

- Stage 1. A conventional input-orientated DEA was undertaken to estimate the mean CRS and VRS technical efficiency scores for the Victorian local government sector using 2015/2016 financial year data. This stage was instrumental in assessing the robustness of the data sources and competing DEA specifications.

- Stage 2. A Malmquist input-orientated DEA was undertaken to estimate the TFPC (total factor productivity change) using five years of financial data (2010/11 to 2015/16). The advantage of this techniques is that it decomposes productivity into its various drivers: (i) efficiency change (i.e., councils moving closer to the frontier), and (ii) technological change (i.e., shifts in the frontier).

- Stage 3. The estimates from the above DEA were then used by PAG to calculate indicative efficiency factors.

2.3 Principal DEA findings

The principal findings and model specifications from the DEA conducted by PAG are summarised in Table 1 below.

Table 1: Principal DEA results and model specifications

Panel A – Technical efficiencies 2015/16		
Model	*Mean VRS[a]*	*Mean VRS[b]*
1	0.81	0.94
2	0.79	0.94
3	0.83	0.96
4	0.81	0.96
5	0.82	0.95
Panel B – Malmquist Index		
Model	*Mean Malmquist[a]*	*Mean Malmquist[b]*
1	0.993	0.993
2	0.994	0.994
3	0.993	0.993
4	0.984	0.985
5	0.977	0.976
Panel C – Model specifications (input orientation)		
Model	*Inputs*	*Outputs*
1	Staff ($) + Capital ($)	Households + Businesses + Road Length (km)
2	Staff (FTE) + Capital ($)	Households + Businesses + Road Length (km)
3	Staff ($) + Capital ($)	Households + Businesses + Road Length (km) + Waste Collected (tonnes)
4	Capital ($) + Operating Expenses ($) (excluding depreciation)	Households + Businesses + Road Length (km)
5	Operating Expenses $ (excluding depreciation) + Depreciation ($)	Households + Businesses + Road Length (km)

Source: PAG (2017). Notes: *a* = single group analysis; *b* = multiple group analysis.

Panel A in Table 1 reports the mean VRS technical efficiency scores for all 79 Victorian local governments for the 2015/2016 financial year. For the sector-wide (or single group analysis) VRS scores range from 0.79 to 0.83 depending on the model used. For the multiple group analysis (where like councils are clustered)[1] the mean VRS scores range from 0.94 to 0.96. The results of this analysis indicates that the majority of councils (within their assigned groups) are highly efficient.

Panel B in Table 1 presents the mean Malmquist indices for all 79 Victorian local governments over the financial years 2010/2011 to 2015/2016. For the sector-wide (or single group analysis) the mean Malmquist indices ranged from 0.977 to 0.994 depending on the model used. For the multiple group analysis (where like councils are clustered) the mean Malmquist indices ranged from 0.976 to 0.993 depending on the model used.

Finally, Panel C in Table 1 presents the alternative DEA specifications used by PAG to generate the results reported in Panels A and B. A key point to note is that application of the different DEA specifications (i.e., Models 1 to 5) makes very little difference to the overall results (although they do modify the number of fully efficiency councils that sit on the

[1] Council clusters were classified as follows: (i) interface, (ii) large rural, (iii) metropolitan, (iv) regional centre, and (v) small rural.

frontier). On this note, it is important to ensure that the selection of the preferred DEA is based on the most appropriate combination of inputs and outputs. The academic literature can help provide guidance on what combination of inputs and outputs to select conditional upon the data availability and quality.

3. RESPONSE TO CONCERNS

3.1 DEA inputs

Some stakeholders (MAV, 2017; CS, 2017) raised concerns regarding the inclusion of **capital expenditure** as a DEA input owing to its 'lumpiness' over time. Taking this into account, it would be advisable to **exclude capital expenditure** – as PAG did in Model 5 – as a DEA input.

A number of stakeholders (MAV, 2017; CS, 2017) also argued that **depreciation** should be included as a DEA input. However, there are sound reasons for excluding depreciation including:

(i) Strong evidence which suggests inconsistent depreciation practice between councils (e.g., Pilcher & Van Der Zahn, 2010; Drew & Dollery, 2015);
(ii) The Australian Accounting Standard (AASB 116) allows for an vast number of methods to estimate depreciation; and
(iii) The conflation of historical costs and fair value models in an inflationary environment results in a figure which has little relevance to the consumption of capital goods (Harris, 1999).

Taking this into account, it would be advisable to **exclude depreciation** as a DEA input (Drew, Kortt and Dollery, 2015).

3.2 DEA outputs

Concerns were also raised regarding the suitability of using the number of households, the number of businesses, and total municipal road length as proxies for council output (CoC, CS, 2017; MAV, 2017; Wyndham, 2017). The principal concern is that such proxies represent a less than ideal measure of the diverse bundle of goods and services delivered by councils.

There are, however, a number of practical reasons why such proxies are adopted in the DEA literature and Australian DEA studies by Worthington (2000) and Fogarty and Mugera (2013) have traditionally used population, households, and the length of roads as a proxy for local government output. More recently, Drew, Kortt and Dollery (2015) have used the number of households, businesses, and road length as a proxy for local government output for the following reasons:

- Drew and Dollery (2014) have argued convincingly that the use of population as a proxy overestimates local government output and that the number of households should be used in preference;
- Businesses receive many of the same services as households (e.g., rubbish collection); and
- Maintaining municipal roads is a major function of local government.

Moreover, the use of such proxies in the academic literature is largely driven by the fact that "true measures of the aggregated multiple outputs of local authorities (such as quantity of teaching provided in schools, duration of social work visits to clients) are difficult to find" and "even if measures of the separate outputs of all services were available, it is far from obvious that they could be weighted and combined into a single index" (Andrews and Boyne 2009, p. 747). This point is also echoed by Holcombe and Williams (2009, p. 419) who note that "government output is multidimensional, so even if one could define a unit of police services, or a unit of sewer services, if some communities produce more police services and others produce more sewer service they cannot be added up to create a homogeneous measure of government output".

For the above reasons, such proxies represent a practical measure of local government output, which has been extensively employed in the academic literature (e.g., Da Cruz and Marques, 2014). Adhering to this academic convention will: (i) ensure that the results are consistent with the published literature, and (ii) facilitate comparisons will similar Australian studies (e.g., Drew, Kortt, and Dollery, 2015).

Taking this into account, it would be advisable to **retain the number of households, the number businesses, and total road length** as proxies for local government output.

3.3 Incorporating quality

A number of stakeholders (CS, 2017; CoC, 2017) raised the point that DEA does not take into account quality considerations. While this is the case, accounting for and finding suitable measures of quality – especially in the context of local government – is inherently difficult. One possible option would be to investigate whether the scores from Victoria's local government annual community satisfaction survey could be incorporated into a subsequent DEA. Drew, Dollery and Kortt (2015) have previously examined the association between population size and community satisfaction for Victorian councils. The key findings from this study provided evidence of an inverted 'U-shape' relationship, which predicts low community satisfactions scores at very large *and* very small population sizes.

3.4 The influence of population density

The submissions from Wyndham City Council (2017) and Dollery (2017) attempted to cast doubt on the findings by arguing that the "highly implausible DEA results . . . can be ascribed in part to model miss-specification in general and the neglect of population density in particular" (Dollery, 2017, p. 20). To account for environment factors like population density, a second-stage regression analysis of DEA score is typically undertaken.

While the second-stage regressions were not included in the Consultation Paper, this analysis was, in fact, undertaken by PAG. In essence, the estimated efficiency scores from DEA Model 1 were regressed on a range of putative determinants within a conventional Tobit and OLS regression framework:

$$\mathbf{ES} = \alpha + \beta\mathbf{X} + \mu$$

where, **ES** is the CRS efficiency and VRS efficiency scores estimated using DEA Model 1, **X** is a vector of exogenous variables (population, population density, proportion of the population under 15, proportion of the population over 65, percentage of Aboriginal and Torres Strait Islander (ATSI) population, percentage of non-English speaking background

(NESB) population, unemployment rate, median annual wage rate, total liabilities, total infrastructure value, total grants, annual depreciation, length of roads) and **μ** is an independent identically distributed random error term.

The key results from the second-stage regression of DEA scores are reported in Table 2 below. The main finding across all regression models is that population density **is not** statistically significant. In other words, population density has little, if any, bearing on municipal performance in Victoria. While this findings differs from the NSW study conducted by Drew, Kortt and Dollery (2015) it is broadly consistent with the WA study by Fogarty and Mugera (2013, p. 308) who find that "population density does not appear to be something that is able to explain the observed variation in efficiency scores".

Table 2: Second-stage regression of DEA scores for Model 1 (n = 79)

	Tobit		**OLS**	
Variable	**VRS efficiency score (ln)**	**VRS efficiency score**	**VRS efficiency score (ln)**	**VRS efficiency score**
Population (ln)	0.443**	0.339**	0.375**	0.287**
	-0.139	-0.110	-0.114	-0.09
Population Density (ln)	-0.088	-0.067	-0.068	-0.052
	-0.045	-0.036	-0.038	-0.030

Notes: ** $p < 0.05$. All regression control for the proportion of the population under 15, proportion of the population over 65, percentage of Aboriginal and Torres Strait Islander (ATSI) population, percentage of non-English speaking background (NESB) population, unemployment rate, median annual wage rate, total liabilities, total infrastructure value, total grants, annual depreciation, length of roads.

To test the robustness of these results the following alternative **input-orientated** DEA model was estimated:

- Operational Expenditure ($) + Staffing ($) = Businesses + Households + Roads.[2]

The VRS efficiency scores from this alternative DEA specification were then used in a second-stage regression analysis. The results from this analysis are reported in Table 3 below.

Table 3: Second-stage regression of efficiency scores using an alternative DEA specification (n = 79)

	Tobit		**OLS**	
Variable	**VRS efficiency score (ln)**	**VRS efficiency score**	**VRS efficiency score (ln)**	**VRS efficiency score**
Population (ln)	0.280*	0.208**	0.245**	0.182**
	(0.125)	(0.099)	(0.111)	(0.088)
Population Density (ln)	-0.049	-0.036	-0.033	-0.023
	(0.041)	(0.033)	(0.037)	(0.029)

Notes: * $p < 0.10$ ** $p < 0.05$. All regression control for the proportion of the population under 15, proportion of the population over 65, percentage of Aboriginal and Torres Strait Islander (ATSI) population, percentage of non-English speaking background (NESB) population, unemployment rate, median annual wage rate, total liabilities, total infrastructure value, total grants, annual depreciation, length of roads.

Once again, the results clearly demonstrate the population density **is not** statistically significant. This confirms that population density has little, if any, influence on municipal performance in Victoria. It also demonstrates that the findings from the second-stage regression is robust to a range of competing DEA specifications.

[2] This alternative DEA specification most closely aligns with the preferred model in Drew, Kortt and Dollery (2015). In this specification, operational expenditure ($) **does not** include staffing dollars.

Taking this into account, the concerns raised by Wyndham City Council (2017) and the claim by Dollery (2017) that the results are being influenced by model specification and population density **is not supported** by the empirical evidence.[3]

Several other concerns raised by Dollery (2017) are worthy of clarification. First, Dollery (2017) states "that it is far from clear which of these generic [DEA] approaches [input-orientated or output-orientated] is being advocated in *Measuring Productivity in Local Government*." While it is not mentioned in the Consultation Paper, an "input oriented DEA" was, in fact, used as noted in the report by PAG (2017) because "local government has a large degree of control over its inputs and takes outputs to be exogenous" (PAG, 2017, p. 10). Moreover, this is consistent with "research into the efficiency of local governments" (PAG, 2017, p. 10) (see, for example, Worthington and Dollery, 2001). Secondly, Dollery (2017, p. 16) states that the results in Table 2.2 of the Consultation Paper:

> ". . . must have come as something of a surprise to both the Predictive Analytics Group and the Essential Services Commission since all five models yield a decline in the average TFPC score. In essence, this means that all five models estimate that productivity over the period 2010/11 to 2016/17 fell."

Given that the DEA results are not being influenced by model specification or population density it is unclear why the PAG or ESC would be surprised by these results (i.e., a decline in TFP). The explanation offered by the Essential Services Commission – that gains in technological efficiency are more than outweighed by a fall in technological change – is entirely plausible. Similar results have been found in other studies that have examined the Australian Water Supply Industry (Coelli and Walding, 2005) and Urban Water Utilities in regional NSW and Victoria (Brynes et al., 2010).

3.5 Differences in council sub-groups

The submissions from Corangamite Shire (2017) and Dollery (2017) raised concerns regarding placing different council sub-groups (i.e., interface, large rural, metropolitan, regional centre, and small rural) into a single group (or sector-wide analysis). While a sector-wide (or single group) analysis was undertaken it is important to stress that a DEA – clustered by council sub-group – was also undertaken (in the Consultation Paper, this is referred to as the multiple group analysis). Thus, the analysis explicitly accounted for different council sub-groups. These council sub-groups were, in turn, compared to the overarching meta-frontier to allow for the technical gap ratio (TGR) to be calculated between the sub-group frontiers and the overarching meta-frontier. However, it is important to note that this analysis was not included as part of the Consultation Paper (ESC, 2017) or the report by PAG (2017). Taking this into account, it may be worth considering whether the results from this analysis should be incorporated into any future reports.

On a related note, Dollery (2017, p. 22) also raised concerns that the relatively small number of observations for 'interface' and 'regional' sub-group councils may "lead to a reduction in the discriminatory power of the DEA models". In support of this, Dollery (2017, p. 22) –

[3] Dollery (2017) is, however, correct that the Consultation Paper (ESC, 2017, p. 27) mistakenly claims that Drew, Kortt and Dollery (2015) find that "population levels had a positive effect on a council's technical efficiency." This minor oversight should be corrected as it was population density in the case of NSW council's that influenced efficiency. However, for Victorian councils, the analysis by PAG suggests that population size – not population density – influences efficiency scores.

citing Banker, Charnes, and Cooper (1984) – states that "the number of observations and number of inputs and outputs used in a given DEA should follow a fundamental rule of thumb: $(p + q) \leq (n/3)$, where n = the number of DMUs, p = number of inputs and q = number of outputs. This means that that the number of observations in each group should at least be 15".

In response, the following points are worth noting. In the first place, it appears that it was Banker et al. (1989) and not Banker, Charnes, and Cooper (1984) who suggested this rough rule of thumb. Secondly, the literature is not in agreement regarding minimum number of decision making units (DMUs) required for a DEA model. For instance, Boussofiane et al. (1991) have stated that to get good discriminatory power out of a DEA model, the lower bound on the number of decision making unit (councils) should be the multiple of the number of inputs and outputs. Thus, the required lower bound for the DEA models clustered by council sub-group is 6 (i.e., 2 inputs multiplied by 3 outputs) for discriminatory power to exist. Thus the DEA models clustered by council sub-group meet the lower bound number of DMUs as suggested by Boussofiane et al. (1991). Finally, it is important to remain cognisant of the fact that these are guiding principles and that the strength of a DEA model will ultimately be judged on the basis of its results (and its discriminatory power). In the estimation of the DEA models by PAG, no problems were encountered in discriminating between different councils sub-groups. Put differently, the DEA models were able to successfully discriminate between different council sub-groups.

4. CONCLUSION

In summary, the DEA approach undertaken by PAG was practical and in keeping with accepted academic practice. More importantly, concerns relating to model specification, population density, and differences in councils sub-groups were not borne out in the empirical analysis. On the contrary, the DEA results were robust to a range of alternative specifications. Having said that, however, it is recommended that further consideration be given to:

(i) Excluding capital expenditure ($) and depreciation ($) as DEA inputs;
(ii) Refining the DEA specification to comprise of: Operational Expenditure ($) + Staffing ($) = Businesses + Households + Roads[4];
(iii) Investigating the role, if any, quality (as measured by community satisfaction surveys) may play influencing local government efficiency; and
(iv) Potentially bootstrapping the DEA scores to generate confidence intervals for efficiency scores.

Finally, a number of the stakeholders mentioned that the Consultation Paper was somewhat 'heavy' on statistical presentation. Taking this into account, consideration should be given to streamlining the presentation of the statistical material. For example, perhaps the 'final' DEA model should take centre stage with the alternative specifications relegated to an appendix.

[4] In this specification, operational expenditure ($) **does not** include staffing dollars.

5. REFERENCES

Andrews R, Boyne GA. (2009). Size, structure and administrative overheads: An empirical analysis of English local authorities. *Urban Studies*, 46(4): 739-759.

Banker, R.D., Charnes, A. and Cooper, W.W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science*, 30(9): 1078–1092.

Banker, R. D., A. Charnes, W. W. Cooper, J. Swarts and D. Thomas (1989). An introduction to data envelopment analysis with some of its models and their uses. *Research in Governmental and Nonprofit Accounting*, 5: 125–163.

Boussofiane, A., Dyson, R.G., and Thanassoulis, E. (1991). Applied Data Envelopment Analysis. *European Journal of Operational Research*, 52: 1-15.

Byrnes, J., et al. (2010). The relative economic efficiency of urban water utilities in regional New South Wales and Victoria. *Resource and Energy Economics*, 32(3): 439-455.

COC [City of Casey] (2017). Submission to Essential Services Commission, *Measuring productivity in the local government sector consultation paper*, October, Victoria.

Coelli, T and Shannon W. (2005). Performance Measurement in the Australian Water Supply Industry, Centre for Efficiency and Productivity Analysis, Working Paper Series No. 01/2005, University of Queensland.

CS [Corangamite Shire] (2017). Submission to Essential Services Commission, *Measuring productivity in the local government sector consultation paper*, October, Victoria.

Da Cruz, N. and Marques, R. (2014). Revisiting the Determinants of Local Government Performance. *Omega*, 44: 91–103.

Drew, J. and Dollery, B. (2014). Keeping It In-House: Households versus Population as Alternative Proxies for Local Government Output. *Australian Journal of Public Administration*, 73(2): 235-246.

Drew, J. and Dollery, B. (2015). Inconsistent Depreciation Practice and Public Policymaking: local Government Reform in New South Wales, *Australian Accounting Review*, 25(1): 28–37.

Drew J, Dollery B, Kortt MA (2016). Can't get no satisfaction? The association between community satisfaction and population size for Victoria. *Australian Journal of Public Administration*, 75(1): 65-77.

Drew, J, Kortt M. and Dollery, B (2015). What determines efficiency in local government? A DEA analysis of NSW local government. *Economic Papers: A journal of applied economics and policy*: 34(4): 243-256.

Dollery B (2017). Submission to Essential Services Commission *Measuring productivity in the local government sector consultation paper*, September: NSW.

ESC [Essential Services Commission] (2017). *Measuring productivity in the local government sector consultation paper*, September: Victoria.

Fogarty, J. and Mugera, A. (2013). Local Government Efficiency: evidence from Western Australia. *Australian Economic Review*, 46(3), 300–11.

Harris, J. (1999). Capitalization and Depreciation of Infrastructure by State and Local Government Entities. *Public Budgeting & Finance*, Winter: 35–47.

Holcombe RG, Williams DW (2009). Are there economies of scale in municipal government expenditures? *Public Finance and Management*, 9(3): 416-438.

Ji, Y. and Lee, C. (2010). Data Envelopment Analysis. *The Stata Journal*, 10(2): 267-280.

MAV [Municipal Association of Victoria] (2017). Submission to Essential Services Commission, *Measuring productivity in the local government sector consultation paper*, October, Victoria.

PAG [Predictive Analytics Group] (2017). *Local Government: Measuring productivity using a direct method*, Predictive Analytics Group, Melbourne.

Pilcher, R. and Van Der Zahn, M. (2010). Local Governments Unexpected Depreciation and Financial Performance Adjustment. *Financial Accountability & Management*, 26(3): 299–323.

WCC [Wyndham City Council] (2017). Submission to Essential Services Commission, *Measuring productivity in the local government sector consultation paper*, October, Victoria.

Worthington, A. (2000). Cost Efficiency in Australian Local Government: A Comparative Analysis of Mathematical Programming and Econometric Approaches. *Financial Accountability & Management*, 16(3), 201–23.

Worthington, Andrew C., and Brian E. Dollery. (2001) Measuring efficiency in local government: an analysis of New South Wales municipalities' domestic waste management function. *Policy Studies Journal*, 29(2): 232-249.