Two dimensional efficiency measurements in Australian TAFE Institutes

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Abstract

Technical and Further Education (TAFE) institutes provide for the majority of Australian government funded courses in vocational education. In this study we used institutional financial, educational, demographic and employed stochastic frontier analysis to develop two distinct efficiency measures. The first model examined institutional efficiency in the transformation of financial resources into teaching loads. The second model evaluated efficiency in the transformation of institutional resources into post-study employment outcomes. In both models we found significant inefficiencies in the Australian TAFE system. We then assessed the relationship between both efficiency measures. While there was no direct linear relationship, a distinct pattern was detectable. K-means cluster analysis was used to establish groupings of similar institutes and subsequent canonical discriminant analysis to develop a typology of these clusters. We conclude that, based on the measures developed in this study, there are inefficiencies in the Australian TAFE system for which an underlying typology exists.

I. Introduction

Finite resources and the demand for greater accountability in areas that are fully or partially publically funded have in recent decades led to government's efforts toward improved outcomes and an increase of productivity of public institutions. Such efforts to assess and improve efficiency of public institutions have predominantly been aimed at areas with the largest share of public expenditure such as health care, social welfare and education. In Australia, the vocational education sector accounts for approximately A$ 8 billion of public funding of which about A$ 6.6 billion is spend on government providers including Technical and Further Education (TAFE) institutes and the remainder is allocated to private providers for the delivery of vocational education (NCVER Financial Information, 2014).

In the face of mounting strain on the public purse expenditure of this magnitude has given rise to increasing scrutiny and the entire TAFE sector has come under pressure to improve outcomes with the available funding. Improvement of efficiency of TAFE institutes is thus of great interest to policy makers, regulators, consumers, and to the institutions

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themselves. Knowledge about institutional efficiency may aid government agencies in allocating funds and in assessing the impact of funding decisions. Furthermore, institutions themselves may use information about their own efficiency to benchmark themselves against other institutions and to make adjustments to their own resource allocation.

The contemporary approach to analyse the productivity of public institutions is based on the initial work done by Farrell (1957). In his seminal paper, he argued that the measurement of efficiency is necessary to ascertain whether additional inputs are needed to increase desired outputs or if such outputs can be increased by raising efficiency alone. Farrell also developed a generalisable production function which enabled the computation of efficiency measurements under multiple input scenarios. Two distinctly different methodologies the determine production frontier have emerged since the 1970s. The first followed from Aigner, Lovell, and Schmitt's (1977) work who formulated the stochastic frontier model, a parametric maximum likelihood technique. This method overcame the previous limitations of frontier estimation by introducing a new approach to the specification of the error term, namely its separation into a normal 'noise' term and a one sided inefficiency term. Almost at the same time, Charnes, Cooper, and Rhodes (1978) published their work on a non-parametric linear programming method, Data Envelopment Analysis (DEA). This method focuses on the scalar measure of the efficiency of each unit under consideration which is obtained after the determination of weights for the observed data for inputs and outputs. The main application of both methods has been the efficiency analysis of public institutions and government owned entities where inputs and outputs can often difficult to capture through traditional accounting methods. The spectrum of sectors analysed has varied across a wide field of institutional units, ranging from hospitals, public transport, public utilities, and prisons, to numerous applications of educational contexts.

In this study we will define two different types of efficiencies in the Australian TAFE sector and employ parametric Stochastic Frontier Analysis (SFA) to determine the respective efficiencies of individual institutes. The first empirical model is designed to estimate efficiency in the transformation of financial resources into teaching hours (from here on termed 'teaching load model'). The second model estimates the efficiency of the transformation of teaching resources into post study outcomes, namely the employment rate of TAFE graduates (from here on termed 'employment outcome model'). Once both institutional efficiencies for each institute have been established we will analyse whether there is a relationship between both types of efficiencies, and whether a typology of efficient institutes can be developed. We will proceed in the following manner: First, we will review the theoretical underpinnings of the technique used and identify and describe the appropriate variables and data that are going to be used in the analysis. Then, we will operationalise the models, discuss the resulting estimates, and establish groups that share similar patterns of efficiency. A canonical discriminant analysis will follow to determine which variables are related to membership in different groups of efficiency. Finally we will consider what practical relevance the research results have and whether concrete policy implications could emerge from our findings.

II. Review of Literature

Efficiency analysis utilising SFA or DEA has been applied frequently in educational contexts. However, despite the popularity of econometric frontier analysis overseas, the existing published research utilising SFA or DEA in Australian education is somewhat limited. Most of the existing published research has focussed on universities. Avkiran (2001) applied DEA and used 1995 data of Australian universities to determine universities' productivity in respect to the delivery of educational services and fee paying enrolments. Other DEA studies examining cross-sectional university performance were performed by Abbott and Doucouliagos (2003), Carrington, Coelli, & Rao (2005), and Worthington and Lee (2008). Horne and Hu (2008) and Abbott and Doucouliagos (2009) published SFA research of Australian and New Zealand and Australian universities. Finally, only a small number of studies involving Australian TAFEs could be identified. These were notably the research by Abbott and Doucouliagos (1998 and 2002) that performed DEA applications utilising data from Victorian institutes only and one nationwide DEA study by Fieger (2010). There has been no previous published efficiency analysis of the Australian TAFE sector which utilised the stochastic frontier approach.

III. Method of Analysis

We will be estimating 'teaching hours' efficiency and 'employment outcome' efficiency based of the stochastic frontier methodology developed by Aigner, Lovell, and Schmidt (1977). Their main contribution was the introduction of a new approach to the specification of the error term, namely its separation into a normal 'noise' term and a one sided inefficiency term. Stochastic frontier production functions are an extension to the classic Cobb-Douglas (1928) function which can generally be expressed in this form:

$$Y = e^{\beta_0} X_1^{\beta_1} X_2^{\beta_2} \ldots X_n^{\beta_n} e^{\varepsilon} \quad (1)$$

This model can then be transformed by taking the log of both sides and the error term ε then be disaggregated into the statistical noise portion v, and the non-negative technical efficiency component u which is distributed independently from v. The technical efficiency TE_i of individual DMUs of u_i can then be determined by

$$TE_i = e^{-u_i} \quad (2)$$

Once we have estimated the institutional technical efficiencies for 'teaching hours' and 'employment outcome' we will analyse the potential relationship between both efficiencies. This will include the graphing of both efficiency components and a cluster analysis to determine 'efficiency clusters'. Finally, we will employ canonical discriminant analysis with the aim of developing a typology of efficient institutions.

IV. Data characteristics and preparation

One of the aims of this study is to ascertain the efficiency of Australian TAFE institutes via SFA and to determine which exogenous variables drive the calculated efficiencies. When deciding on an approach to undertake efficiency frontier analysis of TAFE institutes one has to take into account some specific circumstances that are unique to the VET sector. Similar efficiency frontier analyses involving universities or secondary schools can often rely on data such as the number of full time staff, staff qualifications, number of graduates, test scores, grades, research outputs such as publications and conference presentations, successful grant applications, and others. Data comparable to the aforementioned are difficult to obtain for TAFE institutes. There is obviously a scarcity of research and research related inputs and outputs that relate to TAFEs. Many TAFEs employ a large percentage of part time lecturers, and this proportion differs from institution to institution and reliable data about this proportion is difficult to obtain. Furthermore, TAFEs do not consistently award grades in the same way for some or all of their courses through 'competency based' assessments.

It is therefore clear that there are some circumstances that encumber the specification of frontier efficiency models for TAFE providers. The majority of those circumstances can be categorized into three groups: a) the absence of functional data for the entire sector (e.g. staff qualification data was not reported in a standardised way by institutions), b) partial data only available for a subset of TAFEs (e.g. certain financial data), and c) data that is too dissimilar in nature due to the lack of a comprehensive national reporting standard (e.g. assessment beyond competency based assessment).

Despite the aforementioned difficulties we have been able to assemble and derive a dataset containing adequate information to undertake the course of research set out in earlier paragraphs. The data used in this study came from several sources. These sources included institutional annual reports, information on institutional websites, personal requests to institutional administrators and state regulators, the Australian TAFE Student Outcome Survey (SOS), and the Australian TAFE Students and Courses database at NCVER. Of significance was the choice of year(s) for which data should be obtained. It was intended to assemble a panel of data comprising a number of years in an effort to a) maximize the number of data points and b) enable analysis of changes in efficiency over a given period. However, data collection was more difficult than anticipated as institutes do not publish financial data in a uniform pattern. Specifically the collecting of several consecutive years of financial data appeared to be difficult. It was thus decided to focus on one particular year with the following stipulation: a) the year had to be as recent as possible, b) it had to be an augmented SOS year[2] to enable the use of the most robust institutional data, and c) the chosen year had to have the maximum of available data points. Taking these considerations into account 2011 was chosen as the year of analysis.

The initial plan was to include all 69 Australian TAFE and TAFE like institutions[3] in this analysis. However, this intention was impeded by a number of factors. In addition to those institutes that did not provide data, some institutions proved to be too specialised to be compared on an equal footing with the majority of TAFE institutes. Some of the TAFE units of universities did not have delineated financial data for their TAFE division available. After considering availability of data for the remaining institutes it was decided to include those units in the final data set that had data for the total expenditure variable in 2011 available. This yielded 56 TAFEs for inclusion in the analysis.

[2] Odd years feature an augmented sample of the SOS, containing about 300,000 questionnaires, of which about one third receives a response. In these years the SOS is designed to enable estimates at an institutional level. In even years the SOS sample contains about 100,000 questionnaires, and the focus of estimates is the state level.

[3] In the context of this study, the term 'TAFE and TAFE like institute' refers to TAFE institutes, TAFE divisions of a university, Skills Institutes and Polytechnics. From here on only referred to as 'TAFE'.

In addition to financial expenditure data the ‘teaching hours’ variable used in the efficiency analysis was sourced from the Students and Courses database. This variable indicates the number of student contact hours by institution. A number of further items were sourced predominantly from the 2011 SOS. These included institutional proportions in terms of sex, student type (module completers/graduates), indigenous students, students who used a language other than English at home, and disabled students. Other variables included were the average age of the student body at individual institutions, and an average institutional remoteness score derived from the Australian Bureau of Statistics’s ARIA variable. We also used the SOS to determine the number of different courses offered by each institution which had at least one student enrolled. A categorical variable indicating size was derived from the total expenditure variable. The categories created were ‘very large’, signifying total expenditure in excess of \$120,000,000, large (\$70,000,000 to \$120,000,000), medium (\$45,000,000 to \$ 69,999,999), small (\$25,000,000 to \$44,999,999), and very small with total expenditure of less than \$25,000,000.

V. Results of empirical model 1: Teaching load efficiency

The first model in this study aimed to evaluate the teaching load efficiency of a number of TAFE institutes. Our interest was in determining institutional efficiency based on basic financial expenditure and administrative input and the produced output as measured by teaching contact hours. The starting point to operationalise our efficiency model was in the form of a production function as expressed by a Cobb-Douglas equation:

$$T = e^{\beta_0} E^{\beta_1} C^{\beta_2} e^{\varepsilon} \qquad (3)$$

where T denotes the output in teaching hours, E the total expenditure, and C the number of courses offered by a given TAFE. C was included as it is an indicator of the complexity of college administration. Taking the natural logarithm of (11) and accounting for the SFA specific error component as shown by Battese and Coelli (1995) resolves to:

$$\ln(T_i) = \beta_0 + \beta_1 \ln(E_i) + \beta_2 \ln(C_i) + v_i - u_i \qquad (4)$$

Descriptive statistics for variables used in estimating this model can be found in table 1.

Table 1 Descriptive statistics teaching load efficiency SFA model

Variable	N	Mean	StdDev	Minimum	Maximum
Teaching Hours	56	5,521,177.5	4,174,682.5	473,279	22,346,943
Total Expenditure	56	79,966,968.0	53,563,163.2	12,324,312	288,974,000
Number of courses offered	56	172.6	83.3	32	439

In addition to the frontier production function (12) we intended to investigate which exogenous variables may be influencing technical efficiency. We therefore specified a second component in which we included some variables which were hypothesised to influence efficiency:

$$\mu = \delta_0 + \sum_{k=1}^{K} \delta_k z_k \qquad (5)$$

Here, z represents the hypothesised K predictors of efficiency and δ the parameters that needed to be estimated. In our model we hypothesized that predominantly demographic factors influence efficiency, as these factors may require administrative adjustments to TAFE operations. We therefore entered the variables with institutional indicators for English as a second language, disability, remoteness, age and sex, into our efficiency model (for descriptive statistics see Table 2).

Table 2 Descriptive statistics teaching load inefficiency model

Variable	N	Mean	StdDev	Minimum	Maximum
English second language	56	16.3	9.8	4.6	40.2
Students with disability	56	9.4	2.9	4.4	18.5
Remoteness (ARIA)	56	2.1	1.0	1.1	4.7
Student age	56	33.0	2.2	27.6	37.1
Proportion of males	56	57.2	10.7	32.8	96.6

This two component scenario would have originally been estimated in a two step approach, where the first step specifies the stochastic production frontier and leads to the estimation of efficiency scores and the second step is to estimate the relationship between efficiency scores and efficiency predictors. Wang and Schmidt (2002) have demonstrated that this two step procedure is biased and that instead stochastic frontier models and the way in which efficiency u_1 depends on predictors can and should be estimated in one single step using maximum likelihood estimation.

Analysis by Waldman (1982) has shown that for the specification of a stochastic frontier model it is beneficial to examine the third moments of the least squares residual. If this quantity is positive, then the least squares slope estimates and λ=0 represent a local maximum of the likelihood. Conversely, if the third moment is negative, the likelihood has a greater value at some other point where λ=0. This means that negative skewness of the residuals of the OLS regression indicates that maximum likelihood estimation is indeed the appropriate procedure to estimate the production frontier. We thus began our analysis with the formulation of a linear regression model identical to our proposed SFA model. The results can be seen in table 3 (Model 1). The third moment based of the OLS residuals was estimated to be -0.63, thus indicating to be a satisfactory prerequisite for the maximum likelihood estimation of the stochastic frontier. While the estimates of the OLS model only have limited usefulness, they provide a meaningful starting point for the maximum likelihood estimation (Cullinane & Song 2006). The R-squared estimate of the OLS was with 0.91 fairly substantial and indicated that most of the variation in teaching hours can be explained by total expenditure and number of courses offered by institute. The two independent variables themselves are highly significant and both exhibit the sign that would be expected, e.g. higher expenditure and increasing number of courses tend to be associated with a rise in teaching hours.

We could then estimate our basic stochastic frontier model, using the same variables (Table 3, Model 2). While coefficients and intercept have the same sign as in OLS regression, along with similar magnitude and strong significance, the real interest here were the estimated variance parameters. The strong significance of the Wald test indicates that the coefficient(s) were significantly different from zero and thus confirmed the model's explanatory power. σ_u and σ_v were both significant. This suggests the statistical significance of the random error and inefficiency component of the model. The significance of λ confirmed the presence of inherent statistical inefficiency in the data. The estimate for γ at 0.9 was quite high and denoted that 90% of the variability in delivered teaching hours could be attributed to technical inefficiencies. The closeness of $\gamma$to 1 pointed towards the existence of a deterministic production frontier (Parsons, 2004). The significance of $\gamma$and λ affirmed the preponderance of inefficiency in the composite error term and also validated SFA as the appropriate tool for this specific analysis (Chen, 2007). Additionally a test was performed to determine wether the units investigated by our Cobb Douglas model use constant returns to scale technology.

Table 3 Estimates for OLS and SFA models – teaching load efficiency

Variables	OLS		MLE			
	Model1		Model2		Model 3	
	Est	P>|t|	Est	P>|z|	Est	P>|z|
Stochastic Frontier Model						
Constant	-4.221	<.001	-4.022	<.001	-2.730	<.001
Total Expenditure	0.926	<.001	0.989	<.001	0.968	<.001
Number of courses offered	0.553	<.001	0.345	<.001	0.134	0.025
Inefficiency Model						
Constant					-17.631	0.001
English second language					0.129	0.027
Students with disability					0.053	0.726
Remoteness (ARIA)					2.708	<.001
Student age					-0.074	0.768
Proportion of males					0.112	0.048
R-squared	0.913					
Wald Chi-squared			385.4	<.001	983.5	<.001
Sigma v			0.126	<.001	0.127	<.001
Sigma u			0.387	<.001		
Lambda			3.073	<.001		
Gamma			0.904			

The test of this hypothesis determined whether the sum of the coefficients in the model were statistically different from 1. The sum of the coefficients for ‘total expenditure’ and ‘number of courses’ was calculated as 1.33 and the test for equality to 1 yielded a chi squared value of 6.54 (p=0.0106), so that we could reject the hypothesis of constant returns to scale technology and assume an increasing returns to scale setting. In the scenario considered, this meant that outputs would increase disproportionally when inputs are increased.

Having gained insights into the characteristics of our basic frontier model we could proceed to specify the SFA model that included explanatory variables for the technical inefficiency variance function (Table 3, Model 3). First we noted that parameters and significance of the frontier function were comparable to the model without the inefficiency terms. The Wald chi-squared value and the variance component of the random error term of the whole model were also significant and of similar magnitude. The main items of interest in model three were thus the inefficiency effects. We note that the proportion of students with a disability and the institutional mean age of the student body were not related to institutional inefficiency. The strong significance of remoteness pointed to inefficiency being a function of remoteness. This result confirmed the findings of Fieger (2010), who found remoteness to be the key variable associated with inefficiency. This finding may be partially attributed to Australia’s unique geography and related issues of infrastructure and demographics, however, it must also be noted that ‘remoteness’ acts also as a proxy for institution size as many urban institutes tend to be significantly larger than rural institutes. Internationally, remoteness is rarely identified as driver of inefficiency, although Izadi, Johnes, Oskrochi, & Crouchley

(2002) found some incidental relationship between remoteness and inefficiency. In Model 3 we found further, albeit weaker, positive associations between the proportion of males and inefficiency, and the proportion of students with English as a second language and inefficiency. Possible explanations here may be that males tend to be engaged at higher rates in apprenticeships, which require larger administrative and financial efforts on the part of the institution. An assessment of the correlation between the proportion of males and the proportion of apprentices and trainees in 2011 revealed an overall correlation of 0.44 ($p<0.001$), thus supporting this explanation. Greater financial, educational and administrative efforts may also be at play when considering the relationship between increasing inefficiency and higher rates of non-native English speakers. Larger proportions of students with English as a second language may necessitate more intensive teaching modes, such as lower teacher/student ratios, which may in turn explain some variation in institutional inefficiency in respect to the percentage of non-native English speakers. After verifying the suitability of our model and discussing the interpretation of model statistics and coefficients we were interested in the actual estimated efficiencies of individual institutions. The efficiencies follow from (2) and specifically for the half-normal production model are derived by

$$TE = \{\frac{1-\Phi(\sigma_* - \mu_{*i})}{1-\Phi\left(-\frac{\mu_{*i}}{\sigma_*}\right)}\}\exp(-\mu_{*i} + \frac{1}{2}\sigma_*^2) \qquad (6)$$

where Φ signifies the cumulative distribution of the normal distribution and μ_{*i} and $\sigma_*$are defined as

$$\mu_{*i} = -\epsilon_i \sigma_u^2 / \sigma_s^2 \qquad (15) \qquad \text{and} \qquad \sigma_* = \sigma_u \sigma_v / \sigma_s \qquad (7)$$

The calculated efficiencies for Model 3 can be found in appendix A.

VI. Results of empirical model 2: Employment outcome efficiency

Our second frontier model was designed to assess the efficiency of institutions in the transformation of resources into positive labour market outcomes for their graduates. The dependent variable in the model was the ‘employment outcome’. This variable was created via a hierarchical regression model which produced an employment score for each institute (Fieger, forthcoming). The purpose of this method was to produce an employment outcome measure which enabled the comparability between institutes after covariates such as demographic composition of the student body and local labour market conditions were taken into account. The mean of this employment outcome variable was zero, with increasing values indicating better employment outcomes. Predictor variables for the employment were funding per teaching hour (in A$), institutional completion rate for qualifications (in %), proportion of students enrolled in Certificate III or higher qualifications, proportion of graduates (in %) and the size of the respective institute. Our hypothesis was that increased per hour funding for teaching would be related to improved employment outcomes. All other predictors were also thought to impact on the outcome and added to the model to adjust for those variables. Descriptive statistics of all dependent and independent variables in the employment outcome efficiency model can be found in Table 4.

Table 4 Descriptive statistics employment outcome efficiency SFA model

Variable		N	Mean/%	StdDev	Min	Max
Employment outcome		56	0.0	0.1	-0.3	0.3
Funding per hour		56	17.9	11.8	8.9	87.3
Completion rate		56	27.3	11.8	4.6	72.2
Certificate 3 or higher		56	82.1	8.7	52.3	96.7
Group		56	38.9	14.3	15.7	76.2
Institute Size %	**Very large**		23%			
	Large		23%			
	Medium		21%			
	Small		25%			
	Very small		7%			

As in the teaching load efficiency model, we were interested in how a number of extraneous variables related to the inefficiencies that may become apparent in the model. Here we added the variables age, sex (proportion of males), degree of remoteness of the individual institute (1 indicated 'urban' to 5 indicated 'very remote'), proportion of students with a disability (in %), proportion of students with English as a second language (in %), and the average pass rate for individual modules by institute (in %) into the inefficiency component of the model. Descriptive variable statistics can be found in Table 5.

Table 5 Descriptive statistics employment outcome inefficiency model

Variable	N	Mean	StdDev	Min	Max
Age	56	33.0	2.2	27.6	37.1
Sex	56	57.2	10.7	32.8	96.6
Remoteness (ARIA)	56	2.1	1.0	1.1	4.7
Disability	56	9.4	2.9	4.4	18.5
English 2nd language	56	16.3	9.8	4.6	40.2
Load pass rate	56	81.6	6.6	57.0	94.3

The starting point for the employment outcome model was again an OLS regression model (Table 6, Model 1 (full model in Appendix B)). The R-squared value for the OLS employment model was 0.30, a value considerably smaller than in the 'teaching load efficiency' model. Coefficients of the predictor variables displayed some unexpected properties. Only the proportion of graduates was significant at the 95% level. A higher proportion of graduates was associated with a lower employment score. Another interesting result was that funding per teaching hour was not related to employment outcomes. With respect to institutional size, compared to very large institutions, medium and smaller institutions had strong to marginally significant superior employment outcomes. We calculated the third moment of the residuals of the OLS model as -0.54. This negative skewness validated the intended SFA approach.

Table 6 Estimates for OLS and SFA models – employment outcome efficiency

Variables	OLS		MLE			
	Model1		Model2		Model 3	
	Est	P>|t|	Est	P>|z|	Est	P>|z|
Stochastic frontier						
Constant	-0.167	0.8	0.285	0.651	0.228	0.836
Funding per hour	0.01	0.828	0.001	0.976	0.018	0.711
Completion rate	-0.025	0.477	-0.03	0.309	-0.008	0.923
Cert III or higher	0.19	0.154	0.107	0.384	0.03	0.872
Graduates	-0.092	0.024	-0.077	0.014	-0.008	0.794
Very large	-	-	-	-	-	-
Large	0.046	0.227	0.051	0.1	0.052	0.172
Medium	0.078	0.053	0.089	0.005	0.152	0.003
Small	0.073	0.084	0.077	0.014	0.052	0.103
Very small	0.05	0.401	0.023	0.638	0.007	0.917

Model 2 (Table 6, full model in Appendix B) represented the basic SFA model without inefficiency effects. Variances of the idiosyncratic (σ_v) and inefficiency (σ_u) components were significantly different from 0. The γ value of 0.92 pointed to the existence of a deterministic frontier and the significance of λ denoted the presence of inefficiency. The test for the hypothesis of constant returns to scale technology was performed by determining the sum of the coefficients. This summation yielded 0.24 (chi-squared for difference from one was 16.43 ($p<.001$)) which suggested that TAFEs under this model operated under a decreasing returns to scale environment. This can be interpreted as if inputs were increased under this scenario, outputs would increase at a lower rate than inputs.

The full SFA model including inefficiency effects can be found as model 3 in Table 6 (full model statistics in Appendix B). Parameter estimates and slope signs of this model were comparable to the basic SFA model, although the proportion of graduates was not negatively associated with employment outcomes anymore. The inefficiency component of the model indicated that remoteness was strongly associated with inefficiency. This replicated the main result of the 'teaching load efficiency' model, which also ascertained remoteness as a key predictor of inefficiency. Two additional inefficiency predictors exhibited marginal significance[4]. These included the proportion of students with a disability, and average age of the student body. Students with disabilities may have greater difficulty in obtaining post study employment which could contribute to lower employment outcomes and thus explain why higher proportions of them appear to be associated with lower employment efficiency. The average age of the student body was negatively related to inefficiency. We speculate that this result may be due to the generally poorer employment outcomes for younger age groups.

VII. Relationship between 'teaching load' and 'employment outcome' efficiency

To investigate a possible relationship between teaching hours efficiency and employment outcome efficiency we graphed the two measures in a scatterplot (Figure 1).

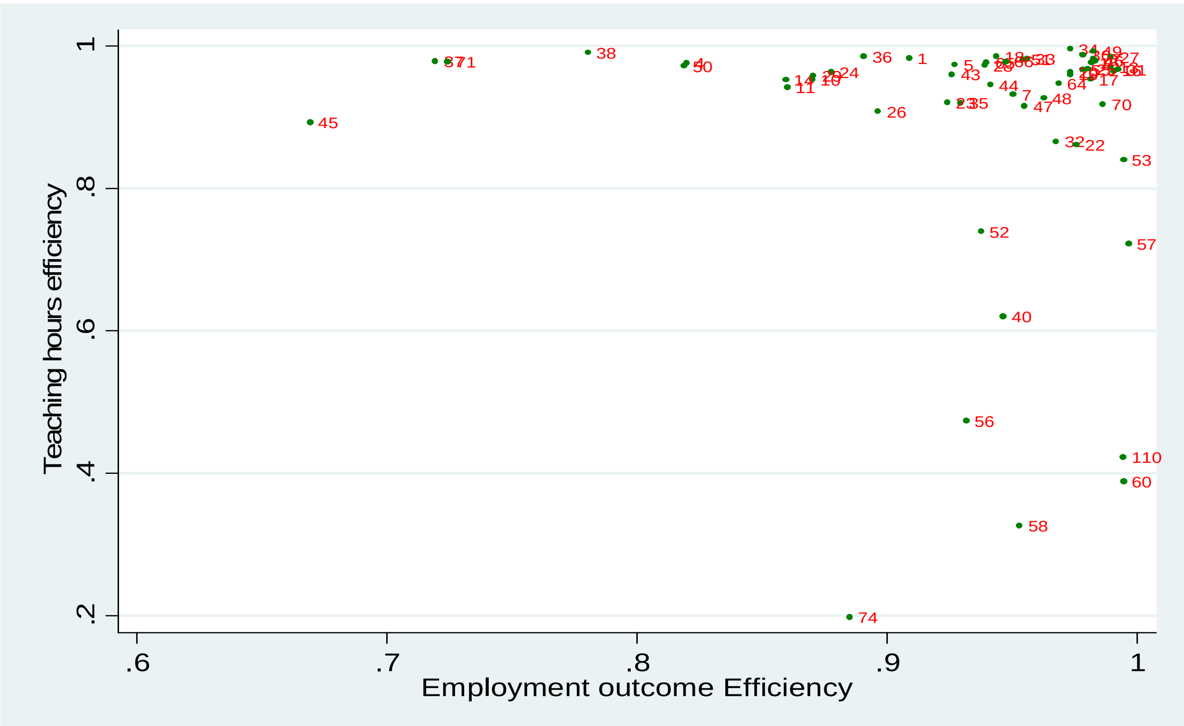

Figure 1 Location of institutes in teaching hours and employment outcome efficiency graph

An interesting pattern became evident from this graph. There appeared to be three major constellations: Some institutes scored relatively low on 'teaching hours' efficiency and high

[4] In this paper, we consider a p-value of $0.05 < p < 0.10$ 'marginal'

on employment outcome efficiency, whereas others attained a high teaching hours efficiency and low employment outcome efficiency, and the remainder rated relatively high on both efficiencies. Interestingly, there were no institutions that displayed low scores on both types of efficiencies examined in this study. It was of interest to statistically separate these three possible combinations of teaching hours and employment outcome efficiency (e.g high/high, high low, and low high) and to evaluate the institutions that constituted the pattern in Figure 1 with respect to possible demographic, educational and environmental variables as determinants of group membership thereof. We performed a partition cluster analysis, using the k-means method with three target clusters. This technique involved an iteration process in which each institute was initially randomly assigned to a cluster, and then subsequently was allocated to the cluster with the closest mean, as calculated using the Euclidean distance method. After this, new cluster means were determined and the process iteratively continued until no institute changed groups. The resulting clusters can be seen in Table 7.

Table 7 Institutions by cluster location

Location	Institutes
Location 1	40, 56, 58,60, 74, 110
Location 2	4, 10, 11, 14, 24, 29, 37, 38, 45, 50, 71
Location 3	1, 5, 7, 13, 15, 16, 17, 18, 19, 20, 22, 23, 25, 26, 27, 28, 30, 31, 32, 33, 34, 35, 36, 43, 44, 46, 48, 49, 51, 52, 53, 55, 57, 64, 65, 66, 70, 77

The location allocation following from the clusters in Table 7 can be seen in Figure 2.

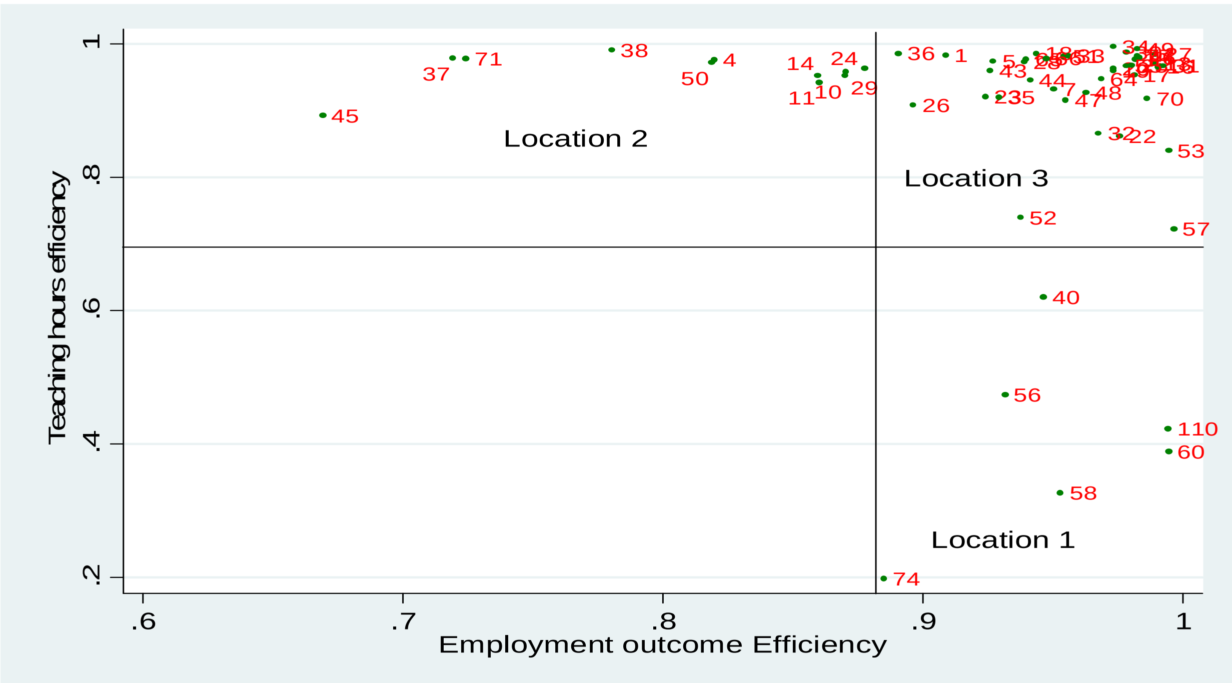

Figure 2 Institutes by cluster location

We then employed canonical discriminant analysis to examine the extent to which several covariates could be utilised to statistically differentiate between locations 1, 2, and 3. The covariates entered into the discriminant function were age, completion rate, load pass rate, disability (%), remoteness, graduates (%), age, male gender (%), satisfaction, salary, indigeneity (%), SES, Certificate III or higher (%), English as a second language (%), Australian born (%), the percentage of apprentices and trainees, and the size of the institution as measured by the number of student delivery hours. The essential statistics for the two resulting discriminant functions can be found in Table 8.

Table 8 Canonical discriminant functions

Discriminant Function	Canonical Correlation	Eigenvalue	Cumulative Variance	Likelihood ratio	F	Pr>|F|
1	0.864	2.937	0.787	0.141	3.937	<0.001
2	0.665	0.794	1.000	0.558	2.064	0.035

It could be seen that both discriminant functions were significant, but that the first discriminant function captured 79 percent of the variance. The discriminating ability of the covariates was then be assessed by the evaluation of the standardised canonical discriminant function coefficients (Table 9).

Table 9 Standardised canonical discriminant function coefficients

	Function1	Function2
Load pass rate	0.222	0.021
Completion rate	-0.297	-0.601
Disability%	0.477	-0.163
Remoteness	-0.927	-0.037
Graduates%	0.136	-0.070
Age	0.300	1.100
Male%	-0.350	-0.110
Satisfaction	0.113	-0.151
Salary	-0.268	0.001
Indigenous%	-1.117	-0.632
SES	0.007	0.629
Cert III or higher%	0.141	-0.004
English 2nd language%	0.591	0.313
Australian born%	1.043	0.470
Apprentices & Trainees%	0.436	0.794
Institute size (in mill delivery hours)	-0.177	-0.422

Generally, values close to zero indicated diminishing discriminating ability to separate the three locations. The percentage of disabled students, for instance, had thus a negligible contribution to the separability of the three efficiency locations. The discriminant function coefficients were graphed for easier interpretation (Figure 3). Variables near the origin of this graph, such as load pass rate, Certificate 3 or higher, student satisfaction, and percentage of graduates provided little discriminating ability. The location of the remaining variables signified their contribution to the discriminant function, with age, remoteness, and percentage indigenous and Australian born students and apprentices and trainees were having the strongest impact.

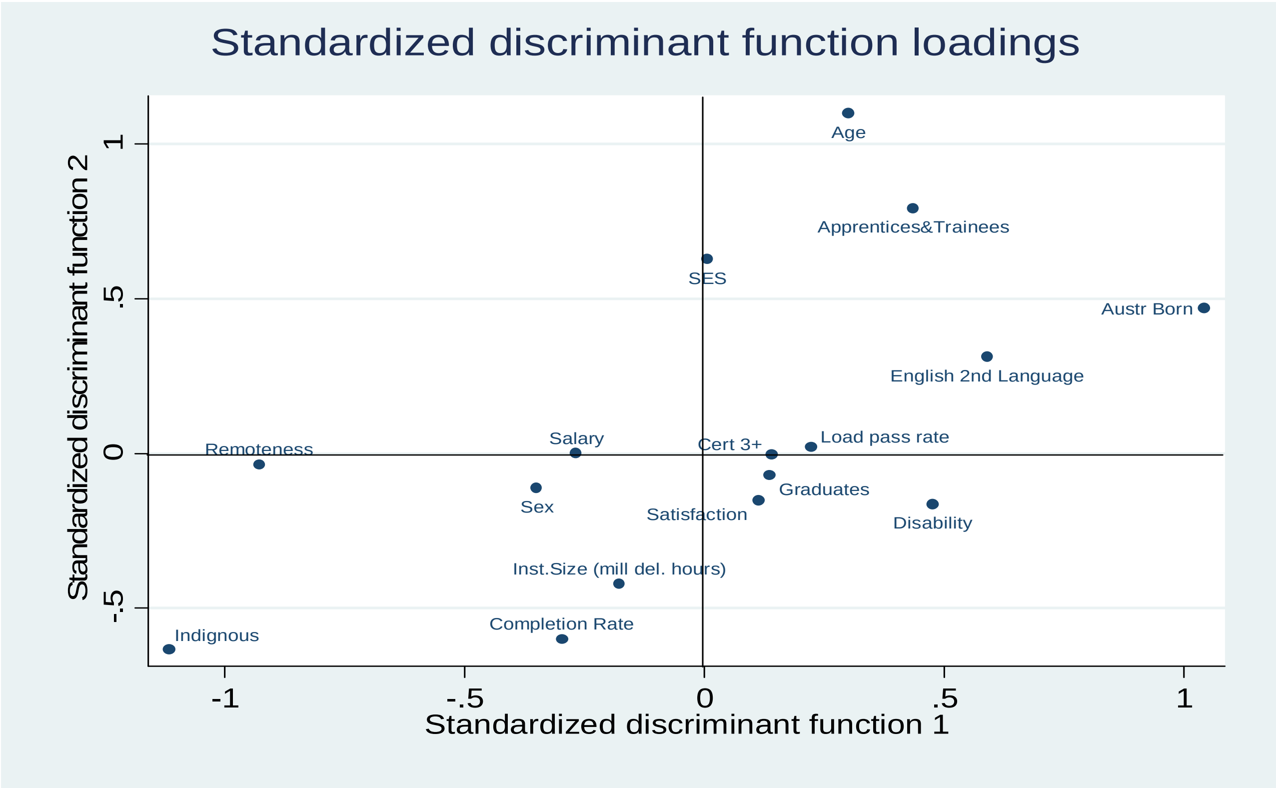

Figure 3 Standardised discriminant function loadings

Finally, we examined the confusion matrix (Table 10) and the discriminant function plot (Figure 4) to assess how well the covariates are able to separate the three efficiency locations.

Table 10 Confusion matrix

Location TRUE	1	2 Classified	3	Total
1	6	0	0	**6**
	100	0	0	**100**
2	0	8	3	**11**
	0	72.7	27.3	**100**
3	0	1	38	**39**
	0	2.56	97.4	**100**
Total	**6**	**9**	**41**	**56**
	10.7	**16.1**	**73.2**	**100**
Priors	**0.11**	**0.20**	**0.70**	**100**

Table 10 illustrates how many institutions were correctly classified into their location using the two significant discriminant functions. Overall 52 of the 56 institutes (92.9%) were accurately classified. Locations 2 and 3 appeared to have more misclassifications, implying that these two locations were harder to separate. Examination of the discriminant function score plot (Figure 4) confirmed that location 1 was fairly well separated from the others, while there was some notable overlap between locations 2 and 3.

Table 10 Confusion matrix

Location TRUE	1	2 (Classified)	3	Total
1	6	0	0	**6**
	100	0	0	**100**
2	0	8	3	**11**
	0	72.7	27.3	**100**
3	0	1	38	**39**
	0	2.56	97.4	**100**
Total	**6**	**9**	**41**	**56**
	10.7	**16.1**	**73.2**	**100**
Priors	**0.11**	**0.20**	**0.70**	**100**

Finally, we calculated the means of the covariates of the canonical discriminant analysis and performed a one way analysis of variance including a Bonferroni multiple comparison test. The results can be found in Table 11

Table 11 Location means and comparison tests

	Location means			Location differences P>|t|			P>|F|
	1	2	3	1v2	1v3	2v3	
Load pass rate	78.6	79.3	82.7	1.000	0.471	0.420	0.169
Completion rate	15.5	36.2	26.6	0.001	0.061	0.033	0.001
Disability%	7.9	10.5	9.3	0.231	0.801	0.660	0.195
Remoteness	4.0	1.8	1.9	<.001	<.001	1.000	<.001
Graduates%	27.2	49.6	37.7	0.004	0.218	0.031	0.004
Age	34.2	31.5	33.2	0.046	0.855	0.071	0.028
Male%	63.9	51.6	57.7	0.068	0.521	0.274	0.063
Satisfaction	4.3	4.2	4.2	0.036	0.188	0.481	0.041
Salary	68814	53225	55990	<.001	<.001	0.442	<.001
Indigenous%	24.3	6.3	3.0	0.002	<.001	1.000	<.001
SES	2.4	2.9	3.0	0.592	0.134	1.000	0.124
Cert III or higher%	73.3	81.7	83.5	0.154	0.020	1.000	0.024
English 2nd language%	14.2	20.0	15.6	0.732	1.000	0.567	0.359
Australian born%	84.3	77.5	79.7	0.538	0.878	1.000	0.402
Apprentices & Trainees%	18.0	15.5	17.3	1.000	1.000	1.000	0.736
Institute size (in million Teaching hours)	0.7	8.0	5.6	0.001	0.013	0.210	0.002

The table confirmed that differences were more prominent between location 1 vs 2 and 3 rather than between locations 2 and 3. Completion rates stood out as being statistically different between all three locations, with location 2 exhibiting the highest completion rate. While discriminant function loadings (Table 9 and Figure 3) indicated the strongest discriminating ability for remoteness, average age, and the percentage of indigenous and Australian born students, in terms of significant differences between their location means these categories were unremarkable. It is further worth reflecting that while institutes in location 1 displayed several traits that may be considered to have a negative connotation (such as the lowest completion rate, lowest percentage of graduates, and lowest percentage of students enrolled in certificate III or higher courses), in respect of some outcomes these institutes scored exceedingly well. For instance, graduates of location 1 institutes had higher satisfaction rates than students from other locations, and attained significantly higher post-training salaries. Generally, the lack of a coherent association between the demographic, institutional, and environmental variables on one side and combined institutional efficiency (e.g. 'teaching hours' efficiency and 'employment outcome' efficiency) indicated that there were other factors, which we did not observe, that determined if an institute scores highly on both types of efficiencies. This means that, in the practical evaluation of the productivity in the vocational education sector it should thus be kept in mind that TAFE efficiency is a multidimensional concept and its results depend on carefully defined input and output measures. Efficiencies should be defined carefully depending on the specific property that is intended to be evaluated. In our study we defined two separate types of efficiency and created rankings for the TAFE institutes under examination. We found that efficiencies calculated under one definition are not necessarily an indicator for efficiencies obtained via alternative definitions. It therefore seems prudent to conclude that any results stemming from the efficiency analysis of Australian TAFE institutes, and by extension the efficiency of any group of public institutions, should always be accompanied by a carefully phrased explanation on how efficiency was specifically defined.

VIII. Conclusion

In this study we have applied stochastic frontier models to estimate two types of efficiencies of Australian TAFE institutes, focussing on the transformation of financial and administrative inputs into teaching load outcomes on one hand and the transformation of institutional resources into employment outcomes on the other. In both models we have observed some clear inefficiencies. These inefficiencies were mainly related to the degree of remoteness and student characteristics. The least efficient TAFE institutes were more likely to be found in remote locations, had a higher percentage of males, and a larger proportion of individuals from non English speaking backgrounds. We speculate these inefficiencies were driven by a combination of interrelated factors, including geographic location, available infrastructure and the absence of occupational diversity of graduates. In the second part of this paper we analysed the association between the institutional efficiencies estimated earlier. While there was no linear relationship we could detect a distinct pattern of efficiencies. We further demonstrated that a typology could be developed that predicted the institutional membership in distinct groups of efficiency.

Our two types of efficiencies have been specifically defined for this study. Theoretically, it is possible to define an almost infinite number of other efficiencies. We showed in this paper that different types of efficiencies of the same institutes are not necessarily linearly related. For policy makers it is therefore necessary to take a multi-dimensional approach that takes into account the various aspects of different approaches to the concept of efficiency when making policy decisions. This emphasizes that in the efficiency analysis of educational institutions it is necessary that any efficiency model needs to be specified with a clear purpose in respect to which particular aspect of institutional efficiency is going to be investigated.

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Appendix A
Teaching load efficiency and employment outcome efficiency by institute

Institute	Technical efficiency	
	Teaching load efficiency	Employment outcome efficiency
1	0.984	0.909
4	0.977	0.820
5	0.973	0.927
7	0.932	0.950
10	0.953	0.870
11	0.943	0.860
13	0.971	0.989
14	0.953	0.859
15	0.978	0.982
16	0.966	0.991
17	0.953	0.981
18	0.986	0.944
19	0.960	0.973
20	0.963	0.973
22	0.862	0.976
23	0.921	0.924
24	0.964	0.878
25	0.968	0.980
26	0.908	0.896
27	0.985	0.990
28	0.973	0.939
29	0.959	0.871
30	0.987	0.978
31	0.967	0.992
32	0.866	0.968
33	0.982	0.956
34	0.996	0.973
35	0.920	0.929
36	0.986	0.891
37	0.979	0.719
38	0.991	0.780
40	0.621	0.946
43	0.960	0.926
44	0.946	0.941
45	0.893	0.669
46	0.980	0.983
47	0.916	0.955
48	0.927	0.963
49	0.992	0.983
50	0.972	0.819
51	0.981	0.954
52	0.739	0.938
53	0.840	0.995
55	0.967	0.978
56	0.474	0.932
57	0.723	0.997
58	0.327	0.953
60	0.389	0.995
64	0.948	0.969
65	0.977	0.940
66	0.979	0.947
70	0.918	0.986
71	0.978	0.724
74	0.198	0.885
77	0.983	0.983
110	0.423	0.994
Mean	0.888	0.929
SD	0.182	0.074

Appendix B Here

Estimates for OLS and SFA models – employment outcome efficiency (Full model)

Variables	OLS		MLE			
	Model1		Model2		Model 3	
	Est	P>|t|	Est	P>|z|	Est	P>|z|
Stochastic frontier						
Constant	-0.167	0.8	0.285	0.651	0.228	0.836
Funding per hour	0.01	0.828	0.001	0.976	0.018	0.711
Completion rate	-0.025	0.477	-0.03	0.309	-0.008	0.923
Cert III or higher	0.19	0.154	0.107	0.384	0.03	0.872
Graduates	-0.092	0.024	-0.077	0.014	-0.008	0.794
Very large	-	-	-	-	-	-
Large	0.046	0.227	0.051	0.1	0.052	0.172
Medium	0.078	0.053	0.089	0.005	0.152	0.003
Small	0.073	0.084	0.077	0.014	0.052	0.103
Very small	0.05	0.401	0.023	0.638	0.007	0.917
Inefficiency Model						
Constant					-1.61	0.871
English second language					0.078	0.112
Students with disability					0.416	0.061
Remoteness (ARIA)					2.233	0.004
Student age					-0.493	0.076
Proportion of males					-0.003	0.944
Funding per hour					-0.044	0.331
Completion rate					0.048	0.495
Cert III or higher					0.041	0.642
Graduates					0.017	0.684
Load pass rate					-0.025	0.735
Very large					-	-
Large					1.333	0.272
Medium					1.32	0.286
Small					-0.689	0.685
Very small					-4.861	0.275
R-squared	0.302					
Wald Chi-squared			28.08	<0.001	22.87	<.001
Sigma v			0.037	0.001	0.043	<.001
Sigma u			0.131	<0.001		
Sigma2			0.018	<0.001		
Lambda			3.51	<0.001		
Gamma			0.925	<0.001		