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Two dimensional efficiency measurements in vocational education

Evidence from Australia

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Abstract

Purpose – In Australia, the vocational education and training (VET) sector accounts for approximately A$8 billion of public spending, of which around A$6.6 billion is spent on government providers that include Technical and Further Education (TAFE) institutes. The TAFE institutes in Australia are large, public VET providers, generally funded and managed by state government. Measuring the efficiency and effectiveness of TAFE institutes is of great interest to policy makers, regulators, consumers and to the institutions themselves. The paper aims to discuss these issues.

Design/methodology/approach – In this study the authors use data relating to student cohort demographics, institutional characteristics and educational outcome data, while employing stochastic frontier analysis, to develop two distinct efficiency measures and models. The first model examines institutional efficiency in the transformation of financial resources into teaching loads. The second model evaluates efficiency in the transformation of institutional resources into post-study employment outcomes. *K*-means cluster analysis is used to establish groupings of similar institutes and subsequent canonical discriminant analysis is employed to develop a typology of these clusters.

Findings – In both models the authors find significant inefficiencies in the Australian TAFE system. The relationship between both efficiency measures is then assessed. While there is no direct linear relationship, a distinct pattern could be detected. Finally the authors develop a typology of efficient institutions.

Originality/value – This study contributes to the existing research by defining efficiency in vocational education in two distinct ways and by the utilisation of the derived efficiencies in the development of a typology of efficient institutes. In doing so, this research makes an original contribution to the understanding of the drivers of efficiency in vocational education.

Keywords Efficiency, Productivity, Effectiveness, Input/output analysis

Paper type Research paper

1. Introduction

In Australia, the vocational education and training (VET) sector accounts for approximately A$8 billion of public spending, of which around A$6.6 billion is spent on government providers that include Technical and Further Education (TAFE) institutes (NCVER Financial Information, 2014). The TAFE institutes in Australia are large, public VET providers, generally funded and managed by state government. They are geographically dispersed, providing important access to tertiary education in regional and remote areas, as well as in urban locations.

In Australia's Federal system of government, education and training is a shared activity of the states and the central (Federal) government. The VET element of education, however, has traditionally been dominated by state-funded and managed providers although the Federal government has taken an active role in its regulation and funding over recent decades (Burke, 2015). Unfortunately, this surplus of regulatory and funding attention has led to a VET system that is arguably in crisis, exhibiting all of the characteristics of over-bureaucratisation, inefficiency, waste and ineffectiveness (Garrick, 2011). VET is thus a politically contested domain, dominated by vertical duplication between states and Federal agencies, and significant variance between states in relation to public spending rates per capita and teaching quality (Billett, 2014).

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To further complicate matters, various Australian jurisdictions (at both the national and state levels) have been promoting a variety of market-based reforms to increase competition and anticipated efficiency. Generally these deregulatory reforms have favoured private education providers to the detriment of established, government owned training providers like TAFE institutes. These changes have thus caused considerable uncertainty in the provision of VET in Australia (Toner, 2014). Even aside from these exogenous pressures, finite governmental resources, and the demand for greater accountability in vocational and higher education training spending, have led to increased scrutiny in relation to training outcomes and measuring returns on investment in public training expenditure.

Quite clearly, while the skills generated by vocational education are important for the economy and society, the overall efficacy of the vocational education system in generating those skills is regularly questioned.

In this dynamic and politicised policy context, measuring the efficiency and effectiveness of TAFE institutes is of great interest to policy makers, regulators, consumers and to the institutions themselves. It is a matter of significant conjecture whether the market-based reforms are indeed improving systemic efficiency and effectiveness (Harris, 2015). A key problem in making this determination relates to the manner in which efficiency is determined in publicly funded VET institutes like TAFEs. 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.

Compounding the problems of measurement are the longstanding problems with VET's status within the Australian educational sector. Generally considered the "poor cousin" to university education (Harris, 2015), the outcomes from VET are often difficult to determine due to its student body's lower socio-economic status and generally lower academic credentials. As such, any appropriate set of performance measures must investigate both educational processes/activities and also educational outcomes.

This paper seeks to provide such an analysis through the application of an integrative approach to efficiency measurement to explore both activity and delivery efficiency (teaching load) and outcome efficiency (employment outcomes).

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.

In the next section a review of the literature in relation to the analysis of productivity in public institutions is provided, with a special focus on SFA. This is followed by a narrower review of the extant empirical literature exploring efficiency in the Australian vocational education sector. The paper then proceeds in Section 3 to present an overview of the method employed in the analysis and an outline of the data utilised to explore institute-level efficiency. Section 4 presents the results of the analysis, drawing on a variety of visualisations to illustrate the various drivers of efficiency, with Section 5 discussing the practical implications of or findings for the Australian VET sector.

2. Review of Literature

The contemporary approach to analyse the productivity of public institutions is based on the 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 to determine production frontier have emerged since the 1970s. The first followed from Aigner *et al.* (1977). They 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 *et al.* (1978) published their work on a non-parametric linear programming method entitled data envelopment analysis (DEA). This method focusses 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. In such contexts, the appropriate measures of inputs and outputs can often difficult to capture. Furthermore, traditional accounting methods for the measurement of inputs and outputs are often inadequate to measure the complex nature of varying inputs and outcomes. In the educational context, for example, simple measures of graduations that do not take into account quality and occupational outcomes are not appropriate measures of performance. 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.

2.1 Efficiency in the vocational education sector

Efficiency analysis utilising SFA or DEA has been applied frequently in educational contexts (Bayraktar *et al.*, 2013; Grosskopf *et al.*, 2014). Such analyses have proven particularly important in decomposing institutional effects from those effects driven by student cohort capabilities. The derived information has proven useful in determining the most important inputs and processes of providing efficacious educational arrangements.

There is, however, a paucity of econometric frontier analysis, utilising SFA or DEA, in the Australian educational context. That which does exist tends to focus on Australia's universities, leaving the very large vocational education sector relatively under-researched. Among the former work in 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 *et al.* (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.

The vocational education sector in Australia generally services a student cohort with lower levels of academic preparation and capacity and generally lower educational and career aspirations (Chesters and Smith, 2015). This tends to complexify notions of efficiency and performance measurement in the VET context, especially as compared to the university context.

Lower academic preparation can predispose students to poorer academic achievement and often lower career aspirations and outcomes. Generally, specific communities (in Australia, e.g. the indigenous community) are over-represented in VET but are also over-represented among the unemployed. Measuring the success and efficiency of VET is thus challenging, as even a low level of educational and occupational outcome may indeed be far superior to the outcome that may have been achieved in the absence of VET.

Only a small number of studies involving Australian TAFEs and other VET providers could be identified. These were notably the research by Abbott and Doucouliagos (2002) that performed DEA applications utilising data from Victorian institutes only and one nationwide DEA study by Fieger (2010). Significant research that could be considered case-based has been undertaken (Toner, 2014; Pillay *et al.*, 2013). Much of this research, which is informed to a greater or lesser degree by institution-level data, tends to explore the often complex arrangements by which public funding supports vocational education arrangements. Characteristically, this research does not provide robust empirical evidence relating to the drivers and outcomes of institute-level (in) efficiencies. Specifically in relation to this research, there has been no previous published efficiency analysis of the Australian TAFE sector which utilised the stochastic frontier approach.

3. Method of analysis

We will be estimating "teaching hours" efficiency and "employment outcome" efficiency based on the stochastic frontier methodology developed by Aigner *et al.* (1977). The main contribution of these authors 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:

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

This model can then be transformed by taking the log of both sides and the error term 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:

$$\mathrm{TE}_i = e^{-u_i} \tag{2}$$

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.

3.1 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 such that 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 categorised into three groups: the absence of functional data for the entire sector (e.g. staff qualification data were not reported in a standardised way by institutions); partial data only available for a subset of TAFEs (e.g. certain financial data); and 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 data set 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 maintained by the National Centre for Vocational Education Research.

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: maximise the number of data points and 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: the year had to be as recent as possible, it had to be an augmented SOS year[1] to enable the use of the most robust institutional data, and 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[2] 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.

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 the proportion of students by institute 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' ARIA variable. We also used the SOS to determine the number of different courses offered by each institution which had at least one student enroled. A categorical variable indicating size was derived from the total expenditure variable. The categories created were based on the intention to achieve a reasonably uniform distribution of institutions across categories and comprised "very large", signifying total expenditure in excess of $120,000,000, large ($70,000,000-$120,000,000), medium ($45,000,000-$69,999,999), small ($25,000,000-$44,999,999), and very small with total expenditure of less than $25,000,000.

4. Results

4.1 Teaching load model

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:

$$T = e^{\beta_0} E^{\beta_1} C^{\beta_2} e^{\varepsilon} \tag{3}$$

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 (3) and accounting for the SFA specific error component consistent with Kumbhakar and Lovell (2000) resolves to:

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

Descriptive statistics for variables used in estimating this model can be found in Table I.

In addition to the frontier production function (4) we intended to investigate which exogenous variables may be influencing technical efficiency. To address this question, we estimate the relationship between the inefficiency measure and various exogenous variables. There are several authors that have adopted these approach, including Kumbhakar *et al.* (1991), Reifschneider and Stevenson (1991), Huang and Liu (1994) and Battese and Coelli (1993, 1995). We therefore specified a second component in which we included some variables which were hypothesised to influence efficiency.

In general, the inefficiency effects model in cross-sectional form is given as:

$$u_i = \delta_0 + \sum_{i=1}^{K} \delta_i z_i \tag{5}$$

where, z represents the hypothesised K predictors of efficiency and δ the parameters that needed to be estimated. In our model we hypothesised 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 II). Equations (4) and (5) enable us to estimate the

Variable	n	Mean	SD	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

Table I. Descriptive statistics teaching load efficiency SFA model

Variable	n	Mean	SD	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

Table II. Descriptive statistics teaching load inefficiency model marginal effects of the total expenditure and the number of courses offered by TAFE on the teaching hours by taking into account the institute-specific variables. A negative coefficient of the exogenous variable in Equation (2) indicates that the institutes with larger values of the variables tend to have lower level of inefficiency, thus they are more efficient.

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_i 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 $\lambda = 0$ 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 $\lambda = 0$. 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 III (Model 1). The third moment based on the OLS residuals was estimated to be −0.63, thus indicating it 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 and Song, 2006). The R^2 estimate of the OLS was, at 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 III, Model 2). While coefficients and intercepts have the same sign as in OLS regression,

	OLS		MLE			
	Model1		Model2		Model 3	
Variables	Est	$P > \|t\|$	Est	$P > \|z\|$	Est	$P > \|z\|$
Stochastic frontier model						
Constant	−4.221	< 0.001	−4.022	< 0.001	−2.730	< 0.001
Total expenditure	0.926	< 0.001	0.989	< 0.001	0.968	< 0.001
Number of courses offered	0.553	< 0.001	0.345	< 0.001	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	< 0.001
Student age					−0.074	0.768
Proportion of males					0.112	0.048
R^2	0.913					
Wald χ^2			385.4	< 0.001	983.5	< 0.001
σv			0.126	< 0.001	0.127	< 0.001
σu			0.387	< 0.001	0.201	< 0.001
λ			3.073	< 0.001	2.048	< 0.050
γ			0.904		0.715	

Table III.
Estimates for OLS and SFA models – teaching load model

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 0 and thus confirmed the model's explanatory power. The estimate of the variance of the standard deviations of the inefficiency component σ_u and idiosyncratic component σ_v were both significant. This suggests the statistical significance of the inefficiency and random error components of the model.

The estimate for the ratio of the variance of the inefficiency component to the variance of the idiosyncratic component γ at 0.9 was quite high and denoted that 90 per cent of the variability in delivered teaching hours could be attributed to technical inefficiencies. The closeness of γ to 1 pointed towards the existence of a deterministic production frontier (Parsons, 2004). The significance of γ 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 whether the units investigated by our Cobb-Douglas model exhibit constant returns to scale.

The test of this hypothesis determined whether the sum of the coefficients in the model was 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 χ^2 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 III, Model 3). First we noted that parameters and significance of the frontier function were comparable to the model without the inefficiency terms. The Wald χ^2 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 *et al.* (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, or other remedial programmes, 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 inefficiency term of a stochastic frontier model can be assumed to follow several distributions, such as half-normal, exponential, truncated normal or γ forms. It has been suggested that it is reasonable to assume that in empirical work efficiency terms follow a half-normal distribution (Kumbhakar and Lovell, 2000). The efficiencies follow from (5) and specifically for the half-normal production model are derived by:

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

where Φ signifies the cumulative distribution of the normal distribution and μ_{*i} and σ_* are defined as:

$$\mu_{*i} = -\epsilon_i \sigma_u^2 / \sigma_s^2 \tag{7}$$

and:

$$\sigma_{*} = \sigma_u \sigma_v / \sigma_s \tag{8}$$

The calculated efficiencies for Model 3 can be found in Table AI.

4.2 Employment outcome model

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, 2016). 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 0, with increasing values indicating better employment outcomes. Predictor variables for employment were funding per teaching hour (in A$), institutional completion rate for qualifications (in per cent), proportion of students enroled in Certificate III or higher qualifications (in per cent), proportion of graduates (in per cent) 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 IV.

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.

Variable	n	Mean/(%)	SD	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 III 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			

Table IV.
Descriptive statistics employment outcome 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 per cent), proportion of students with English as a second language (in per cent), and the average pass rate for individual modules by institute (in per cent) into the inefficiency component of the model. Descriptive variable statistics can be found in Table V.

The starting point for the employment outcome model was again an OLS regression model (Table VI, Model 1). The R^2 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 per cent 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.

Model 2 (Table VI) 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 (χ^2 for difference from one was 16.43 ($p < 0.001$)) 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 VI. 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[3]. 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.

4.3 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).

Variable	n	Mean	SD	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

Table V. Descriptive statistics employment outcome model

Variables	OLS Model1 Est	OLS Model1 $P>\lvert t \rvert$	MLE Model2 Est	MLE Model2 $P>\lvert z \rvert$	MLE Model 3 Est	MLE Model 3 $P>\lvert z \rvert$
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^2	0.302					
Wald χ^2			28.08	<0.001	22.87	<0.001
σv			0.037	0.001	0.043	<0.001
σu			0.131	<0.001	0.122	<0.001
$\sigma 2$			0.018	<0.001	0.165	<0.010
λ			3.51	<0.001	2.838	<0.010
γ			0.925		0.739	

Table VI.
Estimates for OLS and SFA models – employment outcome model

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 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 observable characteristics, including 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 VII.

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

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 (per cent), remoteness, graduates (per cent), age, male gender (per cent), satisfaction, salary, indigeneity (per cent), SES, Certificate III or higher (per cent), English as a second language (per cent), Australian born (per cent), 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 VIII.

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

Table VII. Institutions by cluster location

Figure 2. Institutes by cluster location

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

Generally, values close to 0 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

Table VIII.
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

Table IX.
Standardised canonical discriminant function coefficients

	Function 1	Function 2
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 and trainees (%)	0.436	0.794
Institute size (in mill delivery hours)	−0.177	−0.422

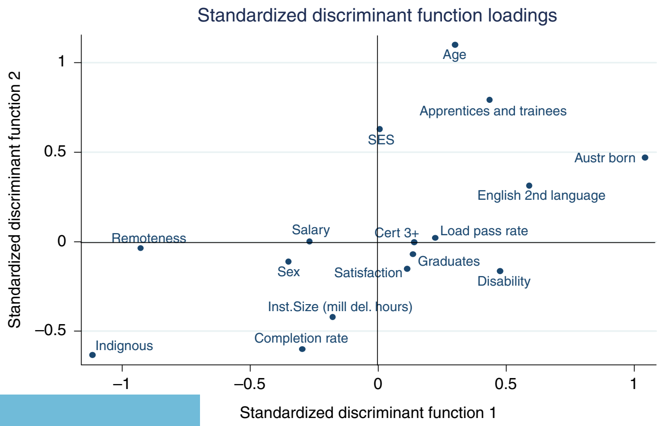

Figure 3.
Standardised discriminant function loadings

this graph, such as load pass rate, Certificate III 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.

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

Table X illustrates how many institutions were correctly classified into their location using the two significant discriminant functions. Overall 52 of the 56 institutes (92.9 per cent) 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.

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 XI

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

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 X. Confusion matrix

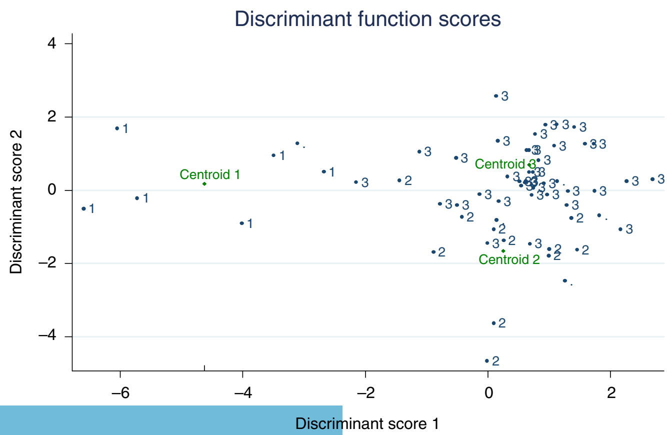

Figure 4. Discriminant function score plot

Table XI.
Location means and comparison tests

	Location means			Location differences $P > \|t\|$			
	1	2	3	1v2	1v3	2v3	$P > \|F\|$
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	< 0.001	< 0.001	1.000	< 0.001
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	68,814	53,225	55,990	< 0.001	< 0.001	0.442	< 0.001
Indigenous (%)	24.3	6.3	3.0	0.002	< 0.001	1.000	< 0.001
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 and 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

statistically different between all three locations, with location 2 exhibiting the highest completion rate. While discriminant function loadings (Table IX 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 enroled 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. 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) could be associated with other unobservable variables, that could the institutes scores 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 multi-dimensional 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.

The validity of the research results presented in this paper is somewhat limited by the small number of institutions that we were able to include in our models. While the number of possible inclusions is naturally limited to the number of TAFE institutes in Australia, some institutes did not contribute data to this analysis. To overcome this we did consider assembling a panel data set covering a number of periods. However, recent frequent changes in the Australian TAFE sector, including institutional split-ups, amalgamations, formations and mergers with universities suggested that this approach would not yield a superior data set.

5. 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.

Noting the abovementioned caveats in relation to how efficiency has been determined in this study, in both models we have observed some clear inefficiencies. These inefficiencies were mainly related to the degree of remoteness and student characteristics, both of which could be seen as exogenous to the TAFEs themselves. For example, 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.

As TAFE institutes serve a student constituency that is generally of lower socio-economic status, an acknowledgement of the higher costs and lower efficiencies inherent in providing educational activities to TAFE's traditional student body is an important finding. In the policy context where private, for-profit providers tend to "cherry pick" the most academically able and most readily geographically serviceable students, TAFEs tend to provide an "educator of last resort" service for students who would otherwise be marginalised from the tertiary education sector. This clearly drives issues associated with institutional efficiency.

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.

The TAFE sector in Australia has a long history of providing education to low SES students, to students in regional areas and to students with low prior academic achievement. Measures of efficiency must take into account a variety of internal and external outcome measures in determining the efficiency of the institutions.

The wider, but related, notion of institutional effectiveness would integrate questions of economic efficiency and also consider the next best alternative at the student, community and national level that would flow from the absence of the TAFE institutions. In many instances, the alternative to TAFE education and a skilled job may well be unemployment, social and economic marginalisation and welfare dependency.

This emphasises 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, and these efficiency aspects need to be considered in wide context that investigates both internal operational elements and also the social benefits that may flow from the upskilling of an archetypical TAFE student.

Notes

1. 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.
2. 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".
3. In this paper, we consider a p-value of $0.05 < p < 0.10$ "marginal".

References

Abbott, M. and Doucouliagos, C. (2002), "A data envelopment analysis of the efficiency of Victorian TAFE institutes", *Australian Economic Review*, Vol. 35 No. 1, pp. 55-69.

Abbott, M. and Doucouliagos, C. (2003), "The efficiency of Australian universities: a data envelopment analysis", *Economics of Education Review*, Vol. 22 No. 1, pp. 89-97.

Abbott, M. and Doucouliagos, C. (2009), "Competition and efficiency: overseas students and technical efficiency in Australian and New Zealand universities", *Education Economics*, Vol. 17 No. 1, pp. 31-57.

Aigner, D., Lovell, C.A. and Schmidt, P. (1977), "Formulation and estimation of stochastic frontier production function models", *Journal of Econometrics*, Vol. 6 No. 1, pp. 21-37.

Avkiran, N.K. (2001), "Investigating technical and scale efficiencies of Australian universities through data envelopment analysis", *Socio-Economic Planning Sciences*, Vol. 35 No. 1, pp. 57-80.

Battese, G.E. and Coelli, T.J. (1993), "A stochastic frontier production function incorporating a model for technical inefficiency effects", Working Papers No. 69, Econometrics and Applied Statistics, University of New England, Armidale.

Battese, G.E. and Coelli, T.J. (1995), "A model for technical inefficiency effects in a stochastic frontier production function for panel data", *Empirical Economics*, Vol. 20 No. 2, pp. 325-332.

Bayraktar, E., Tatoglu, E. and Zaim, S. (2013), "Measuring the relative efficiency of quality management practices in Turkish public and private universities", *Journal of the Operational Research Society*, Vol. 64 No. 12, pp. 1810-1830.

Billett, S. (2014), "The standing of vocational education: sources of its societal esteem and implications for its enactment", *Journal of Vocational Education & Training*, Vol. 66 No. 1, pp. 1-21.

Burke, G. (2015), "Australia's funding schemes in postsecondary education and disadvantaged students", *Journal of Educational Planning and Administration*, Vol. 29 No. 1, pp. 5-27.

Carrington, R., Coelli, T. and Rao, P. (2005), "The performance of Australian universities: conceptual issues, and preliminary results", *Economic Papers*, Vol. 24 No. 2, pp. 145-163.

Charnes, A., Cooper, W.W. and Rhodes, E. (1978), "Measuring the efficiency of decision making units", *European Journal of Operational Research*, Vol. 2 No. 6, pp. 429-444.

Chen, C.F. (2007), "Applying the stochastic frontier approach to measure hotel managerial efficiency in Taiwan", *Tourism Management*, Vol. 28 No. 3, pp. 696-702.

Chesters, J. and Smith, J. (2015), "Social capital and aspirations for educational attainment: a cross-national comparison of Australia and Germany", *Journal of Youth Studies*, Vol. 18 No. 7, pp. 932-949.

Cobb, C.W. and Douglas, P.H. (1928), "A theory of production", *The American Economic Review*, Vol. 18 No. 1, pp. 139-165.

Cullinane, K. and Song, D.W. (2006), "Estimating the relative efficiency of European container ports: a stochastic frontier analysis", *Research in Transportation Economics*, Vol. 16 No. 1, pp. 85-115.

Farrell, M.J. (1957), "The measurement of productive efficiency", *Journal of the Royal Statistical Society. Series A (General)*, Vol. 120 No. 3, pp. 253-290.

Fieger, P. (2010), "An investigation of TAFE efficiency", *2010 AVETRA Conference*, *Surfers Paradise*, 8-9 April.

Fieger, P. (2016), "Efficiency and effectiveness in the Australian technical and further and education system", doctoral thesis, University of New England, Armidale.

Garrick, B. (2011), "The crisis discourse of a wicked policy problem: vocational skills training in Australia", *The Australian Educational Researcher*, Vol. 38 No. 4, pp. 401-416.

Grosskopf, S., Hayes, K.J. and Taylor, L.L. (2014), "Efficiency in education: research and implications", *Applied Economic Perspectives and Policy*, Vol. 36 No. 2, pp. 175-210.

Harris, R. (2015), "Quality in the Australian VET sector: what has been happening?", *International Journal of Training Research*, Vol. 13 No. 1 pp. 16-34.

Horne, J. and Hu, B. (2008), "Estimation of cost efficiency of Australian universities", *Mathematics and Computers in Simulation*, Vol. 78 No. 2, pp. 266-275.

Huang, C. and Liu, J.T. (1994), "Estimation of non-neutral stochastic frontier production function", *Journal of Productivity Analysis*, Vol. 5 No. 2, pp. 171-180.

Izadi, H., Johnes, G., Oskrochi, R. and Crouchley, R. (2002), "Stochastic frontier estimation of a CES cost function: the case of higher education in Britain", *Economics of Education Review*, Vol. 21 No. 1, pp. 63-71.

Kumbhakar, S. and Lovell, C. (2000), *Stochastic Frontier Analysis*, Cambridge University Press, Cambridge.

Kumbhakar, S., Gosh, S. and McGuckin, J.T. (1991), "A generalised production frontier approach for estimating determinants of inefficiency in US dairy farms", *Journal of Business and Economic Statistics*, Vol. 9 No. 3, pp. 279-286.

NCVER Financial Information (2014), *Australian Vocational Education and Training Series*, NCVER, Adelaide.

Parsons, L.J. (2004), *Measuring Performance Using Stochastic Frontier Analysis: An Industrial Sales force Illustration*, Institute for the Study of Business Markets, The Pennsylvania State University, PA.

Pillay, H., Watters, J.J. and Hoff, L. (2013), "Critical attributes of public-private partnerships: a case study in vocational education", *International Journal of Adult Vocational Education and Technology*, Vol. 4 No. 1, pp. 31-45.

Reifschneider, D. and Stevenson, R. (1991), "Systematic departures from the frontier: a framework for the analysis of firm inefficiency", *International Economic Review*, Vol. 32 No. 3, pp. 715-723.

Toner, P. (2014), "Contracting out publicly funded vocational education: a transaction cost critique", *The Economic and Labour Relations Review*, Vol. 25 No. 2, pp. 222-239.

Waldman, D.M. (1982), "A stationary point for the stochastic frontier likelihood", *Journal of Econometrics*, Vol. 18 No. 2, pp. 275-279.

Wang, H.J. and Schmidt, P. (2002), "One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels", *Journal of Productivity Analysis*, Vol. 18 No. 2, pp. 129-144.

Worthington, A.C. and Lee, B.L. (2008), "Efficiency, technology and productivity change in Australian universities, 1998-2003", *Economics of Education Review*, Vol. 27 No. 3, pp. 285-298.

(The Appendix follows overleaf.)

Appendix

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

Table AI.
Teaching load efficiency and employment outcome efficiency by institute

(continued)

Institute	Technical efficiency Teaching load efficiency	Employment outcome efficiency
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

Table AI.

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