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Efficiency Aspects of Government Secondary School Finances in New South Wales: Results from a Two-Stage Double-Bootstrap DEA at the School Level

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Efficiency Aspects of Government Secondary School Finances in New South Wales: Results from a Two-Stage Double-Bootstrap DEA at the School Level

by

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Abstract

This study measures the efficiency of government secondary schools in New South Wales, Australia, using a recently developed methodology of two-stage semi-parametric modeling. In contrast to previous research comparing school performance, we control for prior academic achievement of students by looking at the changes in academic achievements over a two year period, at the school level, from 2008 to 2010, and employ detailed financial data for deriving the envelope for the production frontier of the schools. Using Simar and Wilson's (2007) double bootstrap procedure for data envelopment analysis (DEA), the study finds that schools with higher student retention rates, higher total student numbers, boys or girls only, and selective admissions do better than other schools. On the other hand, a negative influence comes from a school's location in provincial and outer metropolitan areas, a higher ratio of disadvantaged students at a school, and a school's specialization in areas such as languages, performing arts, sports, etc. A surprising result is that the socio-economic characteristics of the families of students attending the school has no significant effect on their academic performance, nor does the average of the years of service of the teachers at a specific school.

JEL Code: C44, C61, H53, I21, I22

Key Words: Two-stage data envelopment analysis; double-bootstrap; efficiency of high schools in New South Wales, Australia.

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1. Introduction

Over the last decade increasing attention has been paid to greater efficiency and public accountability of Commonwealth (federal) and State government funds devoted to school education in Australia. Since the publication of 'League Tables' for individual schools on the "My School" website of the Australian Curriculum Assessment and Reporting Authority (ACARA), starting in 2008, the major debate in public education has focused on whether such tables portray a complete picture of a school's effectiveness in supporting children's fullest development potential.[1] Critics have been arguing that the publication of 'league tables' may lead to a market-based approach to education, resulting in the diversion of more government money to non-government schools because conventionally state programs are generally associated with low levels of allocative and technical efficiencies. The main argument is that the lower levels of efficiency would lead to a lower level of resources and services offered by those schools, which will limit the scope of reducing educational inequality, under-achievement, and social de-segregation. In 2010, two-thirds of all children went to public (government) schools and the combined Commonwealth and State funding for public schools was $26.3 billion and for private schools $2.1 billion. The federal funding for public and private schools in 2010 was $2.5 billion and $5.5 billion, respectively (Hinz, 2010). Considering the amount of money spent on public education, there is only a very limited number of studies available exploring how efficiently the resources are being spent by the public schools in Australia.

The few studies that have measured cost efficiency for public schools in Australia using state or national data are Mante and O'Brien (2002), Bradley *et al*. (2004) and Perry and McConney (2010). However, as far as we are aware, no study has examined the effects of school and non-school inputs, such as financial resources, teacher characteristics, family socio-economic status and student composition, on student outcomes in the context of Australian primary and secondary schools. The need for school efficiency studies as measured by the academic performance of students in relation to the money spent on schooling, while considering socio-demographic variables outside the control of the schools, has been recognized since 2008.

[1] League tables are commonly created using student results from standardized tests. Schools are ranked according to their students' results with highest scoring schools at the top. The tables are reported on the website "My School" at www.myschool.edu.au.

With the introduction by the Commonwealth Government of the "My School" website in 2008, which reports student test scores and financial variables for each school, it has become more important to measure the overall performance of each school and report a cost efficiency index for public school funding policy. In addition, the recent Gonski Inquiry report into the funding of Australian schools has increased the demand for well-constructed school efficiency studies (Gonski, 2011). Furthermore, Bradley *et al*. (2004) found that unadjusted test scores reported in the 'league tables' as signals of school performance in a quasi-market model are misleading and will increase social segregation between schools.

This paper seeks to address some of the requirements for the future research directions into school efficiency as outlined in the Gonski report. The focus of our paper is on the analysis of New South Wales (NSW) school efficiency utilizing the two-stage double-bootstrap data envelopment analysis (DEA) procedure, which is a production-function approach with multiple inputs and multiple outputs. However, the DEA methodology is a methodology that does not require the availability of all output and input prices and quantities, as is the case in traditional production function analysis in economics. It is therefore ideally suited for the analysis of non-profit public sector organizations that do not have a full set of prices available, such as schools. Furthermore, the DEA approach allows for simultaneous multiple outputs. The two-stage double-bootstrap DEA has previously been applied to New Zealand secondary schools by one of the authors (Alexander *et al*., 2010). However, in contrast to that study, we have data that allows us to control for prior academic achievement of students. The bootstrap method is used to bias-adjust coefficient estimates and also for calculating proper confidence intervals for statistical inference. Many previous studies reported large and imprecise confidence intervals (e.g., Miller and Voon, 2011). The bootstrap method generally produces more precise confidence bands. Our Australian data set covers the period from 2008 to 2010 and approximately 380 NSW secondary schools and includes variables that have not been used in other studies on Australian secondary schools. In the next section, we provide the background for this study including a brief survey of previous studies undertaken in the Australian school finance literature.

2. The New South Wales Secondary School System

New South Wales operates a centralized system of funding for government schools. The NSW State Budget process is the mechanism used to determine, monitor and control the overall level of funding associated with the provision of school level education and training services. Approximately 82.5% of school recurrent resources are from NSW state allocations. Commonwealth government allocations make up 13%, this amount having grown since 2009 through increased federal funding under the Building the Education Revolution and National Partnership programs (Keating *et al*., 2011). School derived revenue makes up about 4.5% of school funding.

The expenditure that is incurred at the school level from these State and Commonwealth allocations is met through two basic methods: (1) Central allocations of resources (including staff) and funds that schools can utilize, and (2) direct central payments of school based costs. The funding is provided through two core mechanisms, centralized staffing allocations and grants which are either 'tied' or 'untied'. The resources applied to schools can be categorized into five categories: (1) staffing and salaries for school based staff (both teachers and school administration and support staff (SASS), (2) global funding, (3) tied and untied grants, (4) capital works and maintenance and (5) cleaning.

Staff positions in schools are allocated centrally on the basis of formulae, with some capacity for variation based on negotiations between the school and Department of Education and Communities. Schools may seek additional staff if they have a budget surplus. Staffing constitutes about 81% of the operational costs of a school. The effective budget allocations, using the same formula across schools, will vary due to the different salary steps of teachers. The staffing formulae and the appointment and transfer systems are influenced by Enterprise Bargaining Agreement outcomes. The classification of a secondary school and its principal is based on total school enrolments, including regular class enrolments and student support enrolments. The general teacher category is allocated separately upon the basis of Year 7-10 and 11-12 enrolments. Low socio-economic status (SES) schools also receive allocations under the Priority School Funding Scheme. School Administrative Support Staff and Specialist Staff are also allocated on the basis of student enrolments as are nonteaching staff, including a school manager, administrative officers and general assistance staff. Global funding allocations are calculated annually for each school at the beginning of each school year and at the commencement of Semester 2 and are intended to help schools meet operational costs.

Special factor loadings are additional entitlements to compensate schools affected by specific circumstances such as urgent minor maintenance and isolated location. A Global Funding enhancement element also operates to take account of rural location and socio-economic considerations. Beyond the above allocations a range of services and grants are delivered by central and regional staff including school cleaning and maintenance and professional development programs. Additional equity and needs allocations are also delivered to schools mainly through the staffing formulae. Student population factors utilized include SES, English as a second language (ESL) and New Arrivals, Indigenous, Isolated and Disability characteristics. School circumstances recognized include location, enrolment size (diseconomies of scale) and complexity. Factors that contribute the most are disabilities and SES dimensions. Allocations to schools for capital works and maintenance are based on regular condition assessments and facilities planning related to population growth conducted by NSW Department of Education and Communities central staff.

The government in NSW recently announced a change of direction through devolving decision making to school principals and school councils called the “Local Schools, Local Decisions” initiative. To accomplish this transition a new Resource Allocation Model was designed in mid-2012 for staged implementation from 2013 for 229 schools, with the balance of the other 2,000 schools being incorporated by the end of 2015. By that time schools will manage more than 70% of the total NSW school education budget. The efficiency modeling contained in this paper using school input and output data for 2008-2010 should be a very useful prior tool to evaluate the impact of the subsequent devolution of school budgetary and staffing on variations in school efficiency levels. It is hoped that this study will lead to a series of “before” and “after” assessments of the intended improvement in school performance and to greater “value for money” in schooling arising from such reforms.

3. Background and Literature Review

In the Australian context of schooling most studies exploring school effectiveness focus on the bivariate relationship between the socio-economic status of students or schools and academic achievements. For example, Perry and McConney (2010), using data from the 2003 Program for International Student Assessment (PISA) for Australian students, compared quintiles of the mean performance scores in each of reading, mathematics and science for individual student SES to those for school group average SES. They found: (1) increases in the mean SES of a school are associated with consistent increases in student academic achievement, (2) the relationship between school SES and academic achievement is similar for all students regardless of their individual social background, and (3) the strength of the relationship between school SES and achievement increases as the SES of the school goes up. Furthermore, they analyzed the relationship of each performance score to gender, individual SES and school-level SES with three hierarchical regression analyses and argued that each contributed "…for independent and unique portions of variance, over and above that accounted for by gender, in reading, math, and science achievement..." (p. 1150). However, other potential predictors (explanatory variables) are not considered and it is not obvious what hierarchical order should be used for the inclusion of predictors. Indeed, Marks (2010) also used 2003 PISA data in order to examine school-level effects on student performance for tertiary entrance in Australia and found opposite results with respect to the role of SES. He controlled for schools' academic context and found (p. 267) that "The socio-economic context of schools has no effect on student performance when taking into account schools' academic context."

An earlier study by Mok and Flynn (1996) analyzed a sample comprising 4,949 Year-12 students from randomly selected NSW Catholic high schools suggested that students from larger Catholic high schools, on average tended to achieve more highly than their peers from smaller schools, even after controlling for students' background, motivation and school-culture variables. The estimation method used accounts for intra-class correlations due to clusters of students coming from the same school. Mok and Flynn (pp. 77-74) pointed out in their conclusion that two "powerful predictors" were unavailable for their study: students' ability and previous academic achievements. They acknowledged that the inclusion of these two variables in their analysis might lead to the variable measuring school size becoming statistically insignificant and that "a carefully mapped list of control variables" is needed for further research on Australian high schools.

The first study on school efficiency in Australia by Mante and O'Brien (2002) assessed the technical efficiency of 27 Victorian secondary schools in 1996 using the Charnes *et.al.*

(1986) DEA model. Mante and O'Brien used a one-stage regression DEA model with only one or two inputs. In contrast, we use a two-stage regression DEA model with multiple inputs in stage one and multiple environmental controls in stage two and we also apply double bootstrapping in order to get unbiased results. Nevertheless, their paper provided a good discussion of the advantages of applying DEA to public-sector non-profit organizations (schools) for performance evaluation when input and/or output prices are unavailable so that a standard empirical production function cannot be specified. Mante and O'Brien found that most of the 27 schools were in a position to increase their outputs through a more efficient use of their available resources.

Bradley *et al*. (2004) discussed the role of league tables in providing signals and incentives in a school education quasi-market framework. They compared a range of unadjusted and model-based league tables for primary school performance in Queensland government schools. Their results indicated that model-based tables which account for SES and student intake quality vary significantly from the unadjusted tables. On the other hand, a report for the Victorian Department of Premier and Cabinet (Lamb *et.al*. 2004) examined the effects of core funding, locally raised funds and a number of special sources of funding (English as a Second Language or ESL funding) together with variables measuring teachers' background using multi-level models. They concluded that the resource variables had positive effects on student outcomes, though these effects were small, generally statistically insignificant and varied between outcome measures examined.

Miller & Voon (2011) examined Australia's National Assessment Program – Literacy and Numeracy (NAPLAN) results for 2008 and 2009 using the education production function methodology of the type popularized by Hanushek (1986). Test score data for 3rd, 5th, 7th, and 9th graders were regressed against SES characteristics, type of school, percent of female students, student attendance, school size, and state and region. They applied mostly least squares regressions with a heteroscedasticity adjustment for the standard errors of the regression estimates. In order to explore differences across school types (government, independent and Catholic schools), they used an Oaxaca (1973) decomposition. They found large differences in educational outcomes by state and school type. Their findings indicated that some schools had academic achievements both better and worse than their other characteristics would suggest. Their study did not include variables measuring school resources and they suggested that future studies should include such variables. However, Miller and Voon (forthcoming) examined the issue of different outcomes across states further, using regression discontinuity analysis in order to account for school distance from the state boundary for NSW and Queensland. They used a similar specification with NAPLAN data for Year 3 in 2009 and found that institutional and not state effects account for the different performance outcomes in these two states.

The major objectives of our study are: (1) to identify those New South Wales schools that are inefficiently managing their resources while delivering the state mandated educational outcome; and (2) to identify the factors which account for efficiency differential*s* among school*s*. To achieve these objectives, we define and estimate a two-stage double-bootstrap DEA. To the best of our knowledge, this model has not yet been applied for measuring cost efficiency for Australian public schools. Also, in contrast to a related study for New Zealand (Alexander *et al*., 2010), we control for prior academic achievement of students. We consider our two-stage DEA approach as novel for Australian data.

4. Econometric Methodology

We apply two-stage data-envelopment analysis (DEA) with the double bootstrap. DEA is a linear programming technique to construct a model that measures the efficiency differences between schools.[2] Each school is treated as a decision-making unit in this setup. Schools are compared to each other in terms of their efficiency in transforming a given set of inputs into outputs. One advantage of DEA is that it allows for multiple outputs, without having to make assumptions about "firm" (school) behaviour such as profit maximization or cost minimization. It means that there is no need to construct a composite single output, which would be difficult in our case because the outputs do not have clearly defined market values and the choice of weights for combining outputs would be difficult. Another advantage of DEA is that it is not necessary to specify the mathematical form of a production function because DEA is a non-parametric method (in its first stage, the DEA stage). In particular, we do not need input and output prices

[2] Worthington (2001) provided an explanation of DEA and a review of empirical studies applying it to schools. Cook and Seiford (2009) surveyed DEA advancements over a thirty year period. Recent applications of DEA analysis include, among many others, Alexander *et al*. (2010) to study New Zealand secondary school efficiency, Barkhi and Kao (2010) to appraise the performance of decision making tools in information science, Erhemjamts and Leverty (2010) and Cummins *et al*. (2010) to analyze the efficiency in the insurance industry, and Chang *et al*. (2004) to assess the operating efficiency of hospitals.

as is the case for standard parametric production functions. DEA allows us to identify the group of the most efficient schools that inefficient schools should ideally follow in order to become efficient by adopting their best practices for managing a school. In contrast to estimations of production functions with methods related to least squares or maximum likelihood, DEA produces an envelope around the production points on the production frontier instead of focusing on an average of production points.

The DEA involves a second stage parametric regression in our application, i.e., it is a two-stage semi-parametric DEA. The second stage regression assesses the factors that determine the differences in the efficiency scores of each school as calculated from the first stage DEA. The second stage involves truncated regression analysis, due to the limited range of the efficiency scores (between 0 and 1) and some lumpiness in the estimated values (due to several values of 1 for the most efficient schools). The second stages explains the efficiency score differences as a function of environmental factors, such as school location, type of school (boys only, girls only, or mixed gender) and other variables that are not inputs in the production process per se.

Simar and Wilson (2007) gave a long list of two-stage DEA studies applied to efficiency analysis in different setting. However, they criticised almost all of those studies, including those on school efficiency, because they ignored serial correlation in the DEA efficiency estimates leading to biased inference. They also pointed out that a naive bootstrap for correcting for serial correlation is inconsistent due to the non-parametric nature of the efficiency estimates. We therefore follow the double bootstrap methodology as outlined by Simar and Wilson (2007). This method bias-adjusts the efficiency scores with the bootstrap method and allows for conducting consistent inference for the effects of environmental variables on school efficiency, using again the bootstrap method in connection with truncated regression analysis.

The importance of the second bootstrap that is applied by Simar and Wilson (2007) in order to calculate accurate confidence intervals is illustrated by several previous studies on school performance, though they generally used different estimation methods. Miller and Voon (2011) explained that their relatively large confidence intervals (or bands) are in line with other research assessing the effects of school factors on student performance. Such large and imprecise confidence intervals may lead a researcher to incorrectly conclude that a factor has no statistically significant influence on student performance because the, say 95%, confidence band includes zero. Such a result could then, for example, be used to argue that a policy that focuses on the schools that disadvantaged students attend, instead of focusing on the individual disadvantaged students directly, is misguided as it will not improve the performance of the schools attended by the disadvantaged students so that there is no benefit to them. Therefore, bootstrap-based confidence bands in the second-stage regression of our DEA model, where we determine the significance of the influence of environmental variables, are necessary in order to avoid biased statistical inference.

Farrell (1957) defines efficiency with an input orientation so that input efficiency is measured for a given level of outputs. Efficiency is measured as the radial distance while keeping fixed the direction of the input vector to the production frontier. We allow for variable returns to scale. For DEA, the unobservable production frontier is estimated by linear programming, with the observed data on schools. For each school an efficiency score is estimated that ranks the school relative to the estimated frontier, i.e., relative to the most efficient schools in the sample.

Simar and Wilson (2007) described the statistical assumptions needed in order to derive the properties of the DEA estimator that leads to logical consistency for the second-stage regression involving the environmental variables. They also specified the separability conditions for the two-stage procedure. The second stage regression involves a censored variable, the efficiency score. Furthermore, the second stage truncated regression involves a generated regressor and the efficiency scores are also correlated in an unknown fashion. Simar and Wilson's (2007) methodology overcomes these problems by applying a double bootstrap to a well specified statistical DEA model.

A major drawback of the standard DEA method had been that it is deterministic and does not allow for random influences so that any deviations from the production frontier are assumed to be due to inefficiency. Standard DEA analysis could therefore not accommodate measurement error or other random fluctuations. The recent methodological advance by Simar and Wilson (2007) with bootstrap sampling solved this problem. The construction of proper confidence bands for estimated efficiency scores and a statistically correct second-stage DEA analysis became possible.

We use the statistical software package FEAR 1.15 of Wilson (2008) in connection with programming language R, version 2.12.0. Efficiency can be measured in terms of Shephard's

(1970) input distance function that is the reciprocal of Farrell's measure. Shephard's measure is therefore one or larger, and Farrell's measure is one or less. The results of Kneip, Park and Simar (1998) can be translated into Shephard's distance measure in a straightforward manner. The simplex method of Hadley (1962) is used in order to calculate the distance function estimates for the DEA efficiency estimates.

We program in R the double bootstrap following Algorithm No. 2 in Simar and Wilson (2007). First, we use the DEA procedure in FEAR to estimate Shephard's efficiency scores for each school in a given year. Second, we carry out the truncated normal regression by maximum likelihood estimation, regressing estimated efficiency scores that are larger than one on the environmental variables. We use the "treg" command in FEAR. Third, we program a bootstrap, drawing 100 samples each of size 345, from the truncated empirical normal distribution of the estimated efficiency scores.[3] We use the pseudo-random-deviates generated with "rnorm.trunc" in FEAR. Fourth, we calculate the bias-corrected efficiency scores with the bootstrap method. Fifth, we use the bias-corrected efficiency scores to re-estimate the marginal effects of the environmental variables in the second stage regression. Sixth, we apply a second, the so-called double, bootstrap using the empirical distribution of the bias-corrected second-stage regression. We obtain 5,000 replications for each parameter estimate of the marginal effect of environmental variables. We also experimented with 10,000 replications but there were no improvements compared to 5,000 replications. Last, we calculate bootstrap-based 95% confidence intervals for each parameter estimate.

4. The Data

In NSW there are, depending on the year one looks at, approximately 380 government (public) secondary schools in the data set, of which about 45 are selective (or partially selective). Parents can enter their children to a "selective school" entrance examination at the end of primary school, thus allowing selective schools to get the highest achieving primary students into these government secondary schools (the selective schools contain the three agricultural high schools in NSW). Another approximately additional 50 secondary schools are "specialist" high

[3] Using instead 200 observations did not affect the results in any meaningful way. This is consistent with Simar and Wilson (2007, page 14), who found that 100 replications are "typically sufficient."

schools (languages, performing arts, sports, technology, etc.). The remainder of the secondary schools are non-selective and non-specialist "comprehensive" high schools (about 285 schools).

The data for this study come from the Departmental Annual Financial Statements in the state of NSW. The original dataset contains detailed information on several inputs, outputs and other socio-economic variables for all primary and secondary schools in NSW. For school outputs, we relied on two measures. The first measure takes the test performance of students who are in Year 12 in 2010 and compares it to their test performance two years earlier, in 2008 when the same cohort was in Year 10. The second measure takes the test performance of students who are in Year 9 in 2010 and compares it to their performance two years earlier when they were in Year 7. In other words, we want to measure how much a school contributed to learning of its students over a two year period. Students enter high school with different academic achievements. A school's performance should be measured in terms of what it adds to student achievement, controlling for the differences in numbers of teachers, support staff, and students, spending on teacher and other staff salaries, as well as differences for other expenditures such as maintenance and cleaning, all on a per-student basis.

Previous research (e.g., Marks *et al.* 2001) found that prior academic achievement is one of the main, if not the main, determinant of academic achievement. It is therefore most important to control for prior academic achievement of high school students, in particular when comparing the efficiency of high schools in transmitting new academic knowledge to students. We follow the approach of Lamb *et al.* (2004), among others, and look at the test scores of a cohort of students in 2010 and the same cohort's prior academic achievement two years earlier in 2008. Students in Year 12 in 2010 were in Year 10 in 2008, and students in Year 9 in 2010 were in Year 7 in 2008. Lamb *et al.* (2004, p.29) pointed out, in the context of schools in Victoria, that the cohort two years earlier contains many of the same students. Miller and Voon (2011) also discussed the importance of this issue but could not follow this approach due to data unavailability. They included instead in their study Year 3 achievements in 2009 as a proxy for 2009 Year 5 students' prior academic achievement and stated (p. 377) that "… our measure should be viewed as only a crude proxy for prior academic achievement."

We use a school's median Year 12 Higher School Certificate university entrance "Australian Tertiary Admission Rank" (ATAR) results in 2010.[4] We compare this result to that of the same cohort in 2008 when the cohort was in Year 10.[5] A school's 2008 median Year 10 School Certificate exam result is used.[6] For these two tests, the median is reported for every high school but the averages are not reported.[7] Next, we standardize for each school every test score by subtracting the mean across all schools in the sample and dividing the result by the associated standard deviation. Then, we take the standardized ATAR score (dated 2010) minus the standardized Year 10 score (dated 2008) and use the result as one of the two output measures. The standardization makes the two tests comparable. Also, this way we focus on the "average student" at a school.

The second output measure uses the average NAPLAN test scores for Year 9 in 2010 and the average NAPLAN test score for Year 7 in 2008. We apply the same standardization and subtract the Year 7 score from the Year 9 score to get our second measure of school output. Median school scores are not reported in the official statistics for the Year 9 and 7 tests at the school level so that we have to rely here on the averages instead.

The unit of measurement that we use for outputs as well as inputs is the individual school. The inputs used for the first-stage DEA are for the year 2010 the full-time-equivalent number of teachers, of student-support staff, the average contract salary for teachers and for support staff, the school's "own" expenditures plus all other school operating expenditures such as insurance, maintenance and cleaning. A school's own expenditure refers to school expenditures derived from the school's own income sources that include, for example, the school's interest income from bank balances. All these input variables are defined on a per-student-basis: we divided each variable by the total number of all full-time equivalent students enrolled at Years 7 to 12. Table 1 lists the variables and abbreviations used in the first stage, along with basic statistics.

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[4] NAPLAN is the "National Assessment Program – Literacy and Numeracy" initiative of the federal government that started in 2008 for every school in Australia. In Year 12 the Higher School Certificate overall median exam results are summarized in the ATAR scores, which are used to measure university entrance into undergraduate courses.

[5] Of course, there are students who migrate to another school and others who join as new students as we go from 2008 to 2010. This introduces some measurement error, though we believe that the effects from migration are minor and possibly random. Unfortunately, migration adjusted data are not available.

[6] At Year 10, the last year of compulsory schooling, the school's median for the NSW School Certificate is reported for the exam average over five subjects.

[7] Table 1 provides detailed statistics for all test scores that we use in our analysis.

The variables used to control for the school environment in the second stage truncated regression of the DEA analysis for the year 2010 are listed in Table 2. Our data source reports school locations for the following areas: inner metropolitan, outer metropolitan, inner provincial, provincial with 50,000 to 99,999 inhabitants, provincial with 25,000 to 49,999 inhabitants, outer provincial, remote and very remote. We consider three areas only: inner metropolitan, outer metropolitan and provincial, where the latter summarizes all others. We pick therefore two dummy variable, namely outer metropolitan and provincial.

The socio-economic status of the students is measured by an index called "Index of Community Socio-Educational Advantage" (ICSEA) computed by the Australian Curriculum Assessment and Reporting Authority (ACARA, 2010). The index is available for all schools across all six states and two territories in Australia. The mean index is 1000, implying schools above this number are declared to be more advantaged, and those below are less advantaged. Miller and Voon (forthcoming) considered in their study four alternative measures for the social and economic standing of areas as constructed by the Australian Bureau of Statistics and found that ICSEA is "by far the better predictor" (p. 6) for the variance in aggregate school outcomes that they analyzed. Nevertheless, we considered an alternative index of socio-economic status, the Family Occupation and Education Index (FOEI), developed only for NSW schools by the NSW Department of Education and Training. The correlation coefficient for the two socio-economic indices is 0.97. We applied the FOEI instead of the ICSEA as part of our robustness analysis and report results in Section 6.3 below.

We use the number of full-time equivalent students to measure school size effects and the squared number of students to capture any scale economies at the school level. Other characteristics of schooling controlled for are apparent retention rates of students[8], student attendance rates, and teachers' average years of service. The latter is a proxy for teacher experience, assuming that more teacher experience increases a teacher's effectiveness with regards to transmitting academic knowledge to students. Further, we include the decimal fraction of students enrolled in English as a second language or with a language background

[8] Retention rates are "apparent" rates that do not track individual students through to their final year of secondary schooling. They measure the ratio of the total number of full-time school students in a given year divided by the total number of full-time students in the previous year. The base year is Year 7, when secondary school starts in NSW. It is possible to have apparent retention rates above 100% because of a number of factors not considered, including migration.

other than English, the fraction of students in special education, and the fraction of students with Aboriginal status. We combine the three categories (labeled "EAS") because there are insufficient numbers in the last two categories to separate them out. We also control for the schools admitting boys or girls only, for having selective admission, and for schools specializing (Specialist High Schools). We collected information on all variables for all secondary schools in NSW. However, non-availability of exam results data and missing information on some other variables prohibit us to include them all in the sample. As a result, the current data set used contains information on 345 secondary schools.

6. Empirical Results

6.1 First Stage Bootstrap-Adjusted DEA Results

Figure 1 depicts the histogram for the calculated bias-adjusted efficiency scores in stage one of the analysis, the DEA stage that derives the production frontier envelope. Efficiency is measured with respect to how much a school adds to average student knowledge, given its available inputs per student in terms of teachers, other staff, and money. It is important to note that we do not look at the output in terms of median or average test score results achieved by a school in a given year. Instead, we assess how much a school changes test scores, on average, relative to all other schools for a cohort of students over a period of two years of schooling. In other words, we measure which schools use the best practice to deliver the most improvements in student learning as measured by test outcomes. Efficient schools that use the inputs most efficiently are on the production frontier and get assigned a score of 1. Schools that are inefficient get a score of less than one, using Farrell's measure. Of the 345 schools analyzed, 8 schools achieved a perfect score of 1.00 and altogether 24 schools have an efficiency score of 0.99 or higher. In total, 144 schools scored at or above 0.90. At the lower end, the three lowest efficiency scores are 0.38, 0.50 and 0.51. There are 12 schools with scores below 0.60.

It is interesting to note that the ranking based on the bias-adjusted efficiency scores is very different from a ranking based on the raw scores for ATAR or for Year 9 tests taken in 2010. This is also evident from the small correlation coefficient of 0.54 between the efficiency and ATAR scores and of 0.49 between the efficiency and Year 9 scores. On the other hand, the correlation coefficient between ATAR and Year 9 test scores is 0.85, which is much closer to 1.

This means that controlling for resources available to individual schools, and looking at the academic improvements of students achieved by a school, changes the position of a school in league tables compared to that solely based on raw test scores. In other words, not all schools have the same resources available (inputs used in our analysis) and schools differ in how much value they add to an average students' education. The efficiency scores account for these differences, whereas the raw scores do not. Of course, there are other factors besides the inputs that affect the differences in the efficiency scores among schools. We consider these factors next, in the second stage of the DEA.

6.2 Second Stage DEA Results for the Truncated Regression

The second stage results for the effects of the environmental variables on the bias-adjusted efficiency scores are reported in Table 3. Table 2 explains and gives detailed statistics for the variables used in this stage. There are six categorical variables relating to school location and type that are used to assist in explaining school efficiency differences. For location identifiers we include two school-type dummy variables, setting for each outer metropolitan and provincial area locations to 1 and other locations to 0. The category left out is inner metropolitan. Other dummy variables are used to examine the relative performance of boys and girls only schools. The category left out here is mixed gender (co-educational) schools. It is expected that both these variables (boys only and girls only) will exhibit positive coefficients in the regression results, thereby providing evidence of a school-level gender effect. The quality of students is an important input to a school's production process enabling assessments to be made of a school's efficiency in terms of the value it adds to its students' academic knowledge. In cases where schools are able to select students for entry at Year 7 on the basis of a competitive entrance exam at the end of Year 6, such schools should exhibit greater success in terms of subsequent examination results in Year 10 and Year 12. To capture this effect a dummy variable was used for NSW Selective High Schools. We also control for NSW Specialist High Schools, all relative to other "comprehensive" high schools.

A proxy for student quality commonly used is a socio-economic status indicator, whereby a higher composite index value indicates a school with higher SES student backgrounds and vice versa. We use two indexes, the Commonwealth designed ICSEA measure and the NSW designed FOEI measure. Both measure, in slightly different ways, parental income, education and employment characteristics. Their correlation coefficient of 0.97 indicates that either measure could be included in the second stage regression. School size characteristics are also examined for their effect on efficiency, reflecting underlying economies or diseconomies of scale in school operations. To capture these effects we enter the variables "Students" and "Students squared" (the square of "Students"). The school finance literature surprisingly finds little impact of teacher quality on student achievement (Hanushek 2003). Our summary measure of teacher quality (experience) is the average years of service of full time teachers, "Service". Other variables used in the second stage are indicators of student attendance ("Attendance" rate), apparent student retention ("Retention" rate), and the decimal fraction of English as a Second Language, Aboriginal and Special Education students ("EAS") in a given school.

The second stage regression equation takes the form:

$$\text{Bias-adjusted\_efficiency\_score}_i = a_0 + a_1 \text{ OutMet}_i + a_2 \text{ Provincial}_i + a_3 \text{ ICSEA}_i + a_4 \text{ Students}_i + a_5 \text{ Students\_squared}_i + a_6 \text{ Attendance}_i + a_7 \text{ Retention}_i + a_8 \text{ Service}_i + a_9 \text{ EAS}_i + a_{10} \text{ Boys\_only}_i + a_{11} \text{ Girls\_only}_i + a_{12} \text{ Selective}_i + a_{13} \text{ Specialist}_i + u_i \quad (1)$$

The subscript "i" refers to the i^{th} school, the a_j are the parameters to be estimated and u_i is the truncated regression error term. Table 3 presents the results. The second column gives the results for equation (1) that show to what extend an environmental variable explains the variation in differences of schools' efficiency scores. First, we use the bootstrap-calculated 95% confidence bands, reported in parentheses in each cell below the coefficient estimate, to find out which variables have a statistically significant influence on efficiency. The most interesting result is that the socio-economic background of students (ICSEA) has no statistically significant effects, even though the effect is positive. This result is consistent with the findings of Marks (2010), among others. In addition, we find that the variable "Students squared" has no statistically significant effects. As we allow for variable returns to scale in the DEA, this is to be expected. It confirms that the DEA model captures adequately the school size effects with respect to economies of scale. The only other variable that has no statistically significant effect is the variable "Service" that we used as a proxy for teacher quality. It may well be a poor proxy and teacher experience in terms of average years of service may not reflect teacher effectiveness in adding to student knowledge. Unfortunately, we do not have any other measure of teacher effectiveness available beyond the extent to which it is captured already by salaries in the first stage of the DEA.

We exclude the statistically insignificant variables from the model. We first delete only ICSEA and "Students squared" and leave "Service" in the regression to check the sensitivity of our results to model specification in terms of including a variable that should not matter. Indeed, the results in column 3 of Table 3 are very similar in magnitude to those in column 2 and also to those in the last column. Our model seems robust in this respect.

Table 3 lists in the last column the results for the models with only statistically significant variables included. We label this our baseline model. Compared to column 2, the results are very similar for the included factors. The location of a school has a significant influence on school performance. A school located in an outer metropolitan or in a provincial area is at a disadvantage. The coefficient estimates for these two variables show a negative impact. However, the magnitude of the negative effect is about 38 percent larger in absolute terms for provincial schools than for outer metropolitan schools, with both effects measured relative to inner metropolitan schools. The size of a school in terms of student numbers has a positive effect on school efficiency. It may be the case that larger schools can offer more specialized courses and a "richer" curriculum that improve student learning. One puzzling finding is that student attendance rates have a relatively strong negative influence on school efficiency. One would have expected a positive impact. Attendance may be a measure that is quite imprecise and inconsistent across schools in the way it is recorded. Literally interpreted it would imply schools that "enforce" attendance create a school atmosphere that hinders learning. Admittedly, we do not have a good explanation for this empirical result. On the other hand, student retention has a significant positive effect, as one would expect. The effect of EAS is negative and quite large in magnitude. EAS measures the share of ESL, Aboriginal and Special Education students in a school's total student body. Schools with higher proportions of EAS students show lower efficiency outcomes. Schools that cater to boys or girls only, or have selective admission, have better efficiency score outcomes. Girls-only schools fare much better than boys-only schools. On the other hand, Specialist Schools have worse efficiency results, though the effect is quite small in magnitude.

6.3 Robustness of the Results to Alternative Specifications

We add to the baseline model in the last column in Table 3 the alternative variable to measure the socio-economic status at the school level, labeled FOEI. Again, as in the case of

ICSEA, the FOEI variable has a positive influence on school efficiency, however its effect is also not statistically significantly different from zero. The confidence band is much wider than before, indicating that the effect is less precisely estimated when ICSEA is replaced with FOEI. In summary, this confirms our previous finding that the socio-economic background has no significant part in explaining why schools differ in term of educational value that they add, which we measured with the efficiency scores. It is not the socio-economic background of students that explains why some schools have better outcomes than others.

DEA can be sensitive to outliers in the data when the first stage production frontier analysis is carried out. We visually inspected the data for errors. In addition, we delete the three schools with the lowest efficiency scores, i.e., with scores below 0.53, and re-estimate the first and second stage DEA with 342 schools in our reduced sample. The results are listed in the third column of Table 4. The estimated coefficients have all the same sign as for the baseline model with the full sample. Furthermore, the magnitudes of the coefficients are very similar. The bootstrap-based confidence bands are also similar to those in the full sample and all coefficient estimates stay significantly different from zero at the 5% level.

As an additional check on the sensitivity of the first and second stage DEA results to changes in the sample values, we take the average of all input variables in the first stage DAE over the three years 2008, 2009 and 2010. In the second stage truncated regression, we take also the average over these three years for student numbers, student attendance and retention rates, and EAS shares. Results for the truncated regression are reported in the last column of Table 4. All signs of the coefficient estimates stay the same. While the estimated values for the coefficients of “Outer metropolitan”, “Provincial”, “Girls only” and “Selective” are all smaller in absolute terms, they stay statistically significantly different from zero. The only result that is qualitatively different is that Specialist Schools no longer show a statistically significant effect on efficiency.

7. Conclusion

In this paper we applied two-stage double-bootstrap data envelopment analysis (DEA) in order to compare high schools in New South Wales in regards to how much they add to the academic achievement of students. We measure school outputs by looking at two differences in test scores at the school level: Year 12 test scores in 2010 minus and the same cohort's test scores two years earlier (Year 10) in 2008; and the Year 9 test scores in 2010 minus and the same cohort's test scores two years earlier (Year 7) in 2008   In this way we control for prior academic achievement of students because we consider only changes in test scores and not their absolute levels. The first stage DEA derives bias-adjusted efficiency scores for the schools by controlling for differences in school inputs, such as financial and teacher resources available to the schools per student, when producing outputs. The most efficient schools on the production frontier get assigned a value of 1 and other less efficient schools inside the frontier a value below 1. We find that the ranking of schools based on efficiency scores differs from a ranking based on raw test scores only. Basically, the efficiency scores measure have much value a school delivers for the money it spends.

The second stage DEA analysis links the efficiency scores to variables that capture the different environments in which the schools operate. We considered the influence of school location, the socio-economic background of students, school size, student attendance and retention rates, the shares of ESL, Aboriginal and Special Education students, boys and girls only schools, and selective and specialist school types. We found no statistically significant influence on school efficiency for the socio-economic background variable, having controlled for prior student achievement in the first stage DEA. In addition, the average number of years of service of teachers at a school is not statistically significantly related to school efficiency. Variables that exert a statistically significant influence on school efficiency are as follows. School size, student retention rates, and boys-only, girls-only, and selective school dummy variables have all a positive effect. The effect is generally somewhat larger in magnitude for girls-only schools than for boys-only schools. A negative effect is attributable to a school being in the outer metropolitan or provincial area, with a sizably stronger negative effect for the latter. The larger the share of ESL, Aboriginal and Special Education students is at a school, the lower is school efficiency, keeping all else the same. This effect is relatively sizeable. Specialist school status also has a negative influence on efficiency but the magnitude is relatively small, though it is significantly different from zero, except for one specification when it is not.

Our results are relevant for government school policy. We found that schools in provincial areas and schools with higher shares of ESL, Aboriginal and Special Education students in particular have lower efficiency score. In 2013, the NSW Department of Education and Communities started developing an education reform called "Local Schools, Local Decisions" to enhance school finance and staffing autonomy, (NSW DEC, 2013). The reforms involve devolving most resource management and school staffing to local school decision making. A key feature of this reform process is the implementation of a new "Resource Allocation Model," based on individual school-based needs criteria. Furthermore, an initial tranche of 229 NSW government schools is participating in 2013 in a Commonwealth Government funded program called "Empowering Local Schools National Partnership" (NSW DEC, 2013). By 2015 this program will be rolled out State wide across the approximately 2,240 NSW Primary and Secondary Schools. By that time the NSW DEC will have devolved about 70% of total school funding decisions back to individual school-site governing bodies. It will be interesting to see what impact these reforms will have, for example, on provincial schools and schools with higher shares of ESL, Aboriginal and Special Education Students. Our results provide a benchmark for analyzing the effects of such reforms on school efficiency. There are various other directions for future research. The two-stage DEA analysis could be extended to the other five States and two Territories across Australia. It could also be extended to Catholic Schools and Independent Schools. Approximately $^1/_3$ of Australian students attend these non-governmental schools, of which about ¾ are Catholic Schools.

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Table 1. Variables used in the first stage DEA and their basic statistics for schools in the sample

Variable	Variable description	Mean	Median	Standard Deviation	Minimum	Maximum
Used for deriving two DEA output variables						
ATAR test	School's median score on Year 12 Higher School Certificate examination (ATAR score) in 2010	58.4	57.8	14.7	20.5	99.3
Year 10 test	School's median score on School Certificate examination in Year 10 in 2008	354.6	350.0	30.3	281	459
Year 9 test	Average school test score in reading, writing, language conventions and numeracy in Year 9 in 2010	567.6	560.0	41.2	485	754
Year 7 test	Average school test score in reading, writing, language conventions and numeracy in Year 7 in 2008	532.5	523	42.4	462	731
DEA input variables						
Teacher salaries	Average teacher contract salary at a school, per student	8554.51	8078.11	1573.29	6290.26	16640.27
Support staff salaries	Average support and administrative staff contract salary at school, per student	1144.33	1031.38	508.15	505.59	5736.26
Other expenditures	All other expenditures of the school per student	1436.57	1186.42	1523.89	614.27	26501.27
Number of teachers	School's teacher full-time equivalent per student	0.081	0.075	0.015	0.064	0.186
Number of support staff	School's support and administrative staff full-time equivalent per student	0.018	0.016	.006	0.011	0.055

Table 2. Environmental variables used in the second stage truncated regression

Variable	Variable description	Mean	Median	Standard Deviation	Minimum	Maximum
OuterMet	School location in outer metropolitan area	0.13	--	--	0	1
Provincial	School location in provincial area	0.34	--	--	0	1
ICSEA	ICSEA index	982.1	964.3	79.3	733	1196
FOEI	FOEI index (used in alternative specification to replace ICSEA)	996.6	980.8	79.7	845.3	1215.9
Students	Number of full time equivalent students at the school	788.6	788.4	297.8	148	2029
Attendance	Student attendance rate in decimal fractions	0.89	0.88	0.04	0.78	0.97
Retention	Student retention rate in decimal fractions	0.68	0.63	0.24	0.17	1.49
Service	Average years of service of the teachers at a school	15.69	15.9	3.43	6.4	24.8
EAS	ESL, Aboriginal and Special Education as share of all students at a school	0.39	0.26	0.29	0.03	1.09
Boys only	Boys only school	0.05	--	--	0	1
Girls only	Girls only school	0.06	--	--	0	1
Selective	Selective admissions to school	0.12	--	--	0	1
Specialist	School specializes (languages, etc.)	0.09	--	--	0	1

Note: For dummy variables, the mean value gives the proportion of schools in that category. For the location dummy variables the metropolitan area was left out and for the gender dummy variables the mixed-gender (co-educational) schools were left out. Retention rates can reach above 100% as they are “apparent” rates that do not consider a number of factors, including migration. Similarly, for EAS, some students may fall into more than one category so that the maximum can be above 1.

Figure 1. Histogram of the bias-adjusted efficiency scores (Farrell's measure)

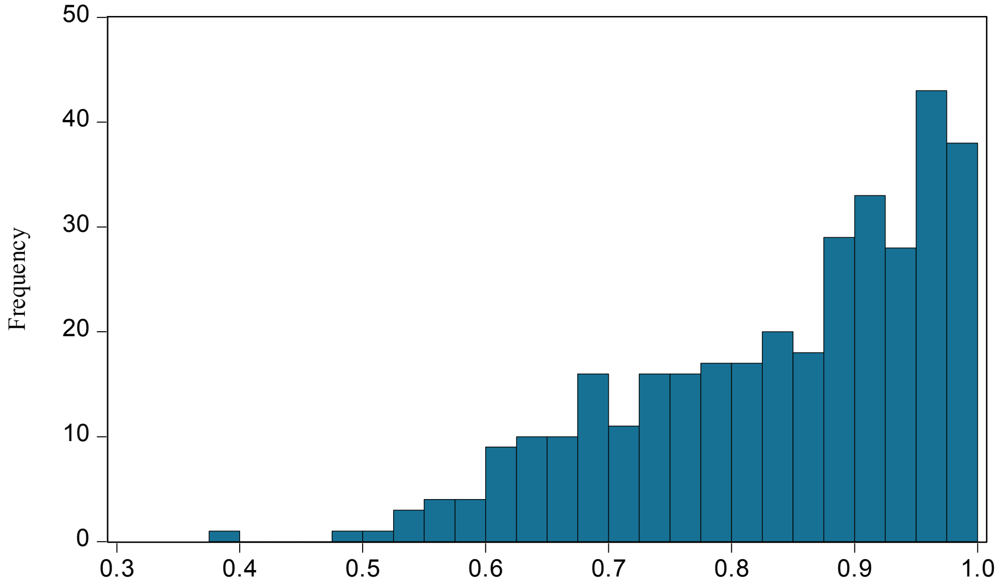

Table 3. Truncated regression results for the impact of environmental variables on bias-adjusted school efficiency scores

Variable	Model with all variables included	Model with no ICSEA and Students squared	Model with significant variables only
OuterMet	**-0.16** (-0.22, -0.13)	**-0.17** (-0.23, -0.14)	**-0.16** (-0.21, -0.12)
Provincial	**-0.21** (-0.25, -0.18)	**-0.22** (-0.26, -0.19)	**-0.22** (-0.25, 0.10)
ICSEA	0.22 (-0.09, 0.45)	--	--
Students	**0.91** (0.73, 1.0)	**0.93** (0.86, 0.98)	**0.95** (0.88, 0.99)
Students squared	0.02 (-0.11, 0.08)	--	--
Attendance	**-2.20** (-2.53, -1.96)	**-1.98** (-2.08, -1.91)	**-1.93** (-2.01, -1.87)
Retention	**0.23** (0.15, 0.28)	**0.24** (0.17, 0.29)	**0.25** (0.18, 0.31)
Service	0.30 (-0.12, 0.62)	0.40 (-0.006, 0.70)	--
EAS (ESL, Aboriginal, Special Education students)	**-0.59** (-0.66, -0.54)	**-0.61** (-0.67, -0.56)	**-0.62** (-0.69, -0.58)
Boys only	**0.17** (0.11, 0.20)	**0.17** (0.12, 0.21)	**0.17** (0.12, 0.21)
Girls only	**0.22** (0.15, 0.27)	**0.22** (0.15, 0.27)	**0.22** (0.16, 0.28)
Selective (school admission)	**0.14** (0.09, 0.17)	**0.14** (0.09, 0.17)	**0.14** (0.10, 0.18)
Specialist (school)	**-0.05** (-0.09, -0.02)	**-0.04** (-0.09, -0.01)	**-0.04** (-0.08, -0.009)

Note: The first entry in each cell is the coefficient estimate. Figures in bold indicate statistical significance at the 5% level. The second entry in each cell, in parentheses, is the 95% confidence band derived from 5,000 bootstrap replications. The sample size is 345 observations (schools).

Table 4. Sensitivity analysis for the truncated regressions

Variable	Baseline model with FOEI added	Baseline model with the schools with the three lowest efficiency scores deleted (T=342)	Baseline model with average values for variables over for the years 2008 to 2012
OuterMet	**-0.16** (-0.22, -0.12)	**-0.14** (-0.19, -0.11)	**-0.06** (-0.10, -0.03)
Provincial	**-0.22** (-0.25, -0.19)	**-0.18** (-0.21, -0.15)	**-0.09** (-0.11, -0.07)
FOEI	0.27 (-2.50, 2.35)	--	--
Students	**0.95** (0.88, 0.99)	**0.99** (0.85, 0.95)	**0.92** (0.86, 0.97)
Attendance	**-1.96** (-2.28, -1.72)	**-1.94** (-2.01, -1.89)	**-2.07** (-2.14, -2.02)
Retention	**0.25** (0.18, 0.31)	**0.22** (0.16, 0.27)	**0.27** (0.19, 0.33)
EAS (ESL, Aboriginal, Special Education students)	**-0.62** (-0.69, -0.58)	**-0.54** (-0.59, -0.49)	**-0.50** (-0.56, -0.45)
Boys only	**0.17** (0.12, 0.21)	**0.16** (0.11, 0.19)	**0.14** (0.10, 0.18)
Girls only	**0.22** (0.16, 0.28)	**0.23** (0.17, 0.27)	**0.14** (0.09, 0.18)
Selective (school admission)	**0.14** (0.10, 0.18)	**0.14** (0.10, 0.17)	**0.05** (0.02, 0.08)
Specialist (school)	**-0.04** (-0.08, -0.009)	**-0.03** (-0.07, -0.005)	-0.03 (-0.06, 0.006)

Note: See Table 3. The sample size "T" is 345 observations (schools), except for results in the third column.