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16/03: THE EFFICIENCY OF AUSTRALIAN SCHOOLS: A NATIONWIDE ANALYSIS USING GAINS IN TEST SCORES OF STUDENTS AS OUTPUTS

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The efficiency of Australian schools: A nationwide analysis using gains in test scores of students as outputs*

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Abstract

This study examines the efficiency of schools in Australia and its determinants using the gain in NAPLAN test scores of students in 6,774 schools in 2009-2011. The results show that, based on input-output combination, the growth of NAPLAN test scores in Australian schools could be improved by 64 per cent by learning from best practice, on average. The average target for schools in the sample is to improve the gain in NAPLAN test score by 90 points. At the primary level, Catholic and independent schools are less efficient than public schools. At the secondary school level, though, public schools are found to be less efficient than other (non-public) schools.

Key words: DEA, Australia, double bootstrap, gain of test scores

JEL classifications: I21, D24

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1 Introduction

The efficiency (i.e., the degree to which inputs can be converted to outputs as compared to best practice) of education has long been of interest to policy-makers, educators and parents worldwide. In Australia, the debate about school efficiency has intensified in recent years. In 2008, all Australian Education Ministers released the Melbourne Declaration on Educational Goals for Young Australians, setting out the future directions for Australian schooling in the next 10 years (MCEERYA, 2008). To support the Melbourne Declaration, a series of action plans including curriculum designs, school assessments and financing have been proposed and implemented. One of the major reforms that was instituted was the introduction of a National Assessment Program—Literacy and Numeracy (NAPLAN) in 2008. The NAPLAN was initiated to provide a "rigorous and comprehensive" assessment of student progress across Australia. To strengthen accountability and transparency of schooling, test results are then made available to the public via a website called "My School" (www.myschool.edu.au).

In this paper, we take advantage of the availability of the test results to produce econometrically-robust estimates of school performance. We do so by examining the efficiency of almost all Australian schools and by investigating the variations in input combinations and environmental factors that affect the level of efficiency achieved by schools. As far as we are aware, Haug and Blackburn (2013) is the sole existing study that uses test scores to examine the efficiency of public secondary schools, and it does so only for the State of New South Wales (NSW).

Our study extends previous work along several dimensions. First, we apply the value-added approach to measure the school output as the gain in test scores of the same students, and hence are able to address the selection bias issue at the student level. Second, we examine the efficiency of virtually all mainstream schools in Australia.[1] Third, unlike previous work that has focused on public schools, this study examines both on public and non-public schools and distinguishes between Catholic and independent schools. Fourth, while this previous study examined the efficiency of secondary schools we also investigate the efficiency of primary schools.

2 Literature review

The literature on school performance is vast, so our review focuses strictly on studies that are relevant to efficiency measurement of schools. The review includes two parts: namely, international literature and Australian literature. Our discussion of the international literature focuses on the variety of methodologies that have been used, while our discussion of the Australian literature is more detailed due to the relative smaller number of studies on school efficiency.

[1] We exclude special schools that educate children with disabilities and distance education schools from the study for reasons that are provided below.

2.1 International studies

There is a large international literature on school efficiency, including a wide range of approaches. For instance, a number of efficiency studies assume that schools are output maximizers and adopt an output-based approach (Bradley, Johnes, and Millington, 2001; Grosskopf and Moutray, 2001; Grosskopf, Hayes, and Taylor, 2009) whereas other studies start from the (dual) assumption that the school's objective is to minimize the costs of the inputs (Gronberg, Jansen, and Taylor, 2012). We argue that schools are probably concerned more with improving their results and reputational capital rather than minimizing costs, and hence, the output-based approach is likely to be more appropriate. The output-based studies also use a variety of output measures, including the number of students (Ouellette and Vierstraete, 2005; Burney et al., 2011), academic performance (Bradley, Johnes, and Millington, 2001; Alexander, Haug, and Jaforullah, 2010; Agasisti, 2011; Kirjavainen, 2011; Mancebón et al., 2012), non-academic performance (Bradley, Johnes, and Millington, 2001), changes in students' academic performance (Grosskopf, Hayes, and Taylor, 2009; Gronberg, Jansen, and Taylor, 2012), or combinations of those outcome measures (Bradley, Johnes, and Millington, 2001; Gronberg, Jansen, and Taylor, 2012).

Studies that follow an input-based approach typically measure inputs by adopting a monetized value, namely the cost per student (Chakraborty and Poggio, 2008; Gronberg, Jansen, and Taylor, 2012; Haelermans, De Witte, and Blank, 2012). We argue that by choosing the number of students as the output of interest one ignores the quality of schooling, and hence this may lead to a biased ranking of schools. The use of both academic and non-academic performance in the output set would be ideal but data on standardized measures of non-academic performance are hard to find. Also, choices of non-academic performance such as the attendance rate, as used in Bradley, Johnes, and Millington (2001) is questionable; we conceive of the attendance rate as, at best, an intermediate output of schools or, at worst, a throughput measure that concerns (student time) input as much as it does conceptions of output.[2]

Another source of variation in the approach in the international literature is the choice of methods. Some of the existing studies (Chakraborty and Poggio, 2008; Conroy and Arguea, 2008; Kirjavainen, 2011; Gronberg, Jansen, and Taylor, 2012) apply parametric methods, such as stochastic frontier analysis (SFA), while others use non-parametric methods such as Data Envelopment Analysis (DEA)[3]: Grosskopf and Moutray (2001); Grosskopf, Hayes, and Taylor (2009); Alexander, Haug, and Jaforullah (2010); Agasisti (2011); Essid, Ouellette, and Vigeant (2011); Haelermans and Ruggiero (2013). The SFA approach requires behavioural assumptions such as cost minimization and profit maximization, which are not necessarily as relevant to the objectives and operational environments of schools (Worthington, 2001) as they are in other economic spheres.

Finally, the international literature on school performance also differs ac-

[2]Indeed, conceptually, one could question whether the rate of attendance is better considered as an environmental factor that is largely, if not wholly, outside the control of schools.

[3]More detailed discussions of DEA and SFA are presented in Section 3.

cording to the educational levels of the schools that are examined: some studies focus on primary schooling (Conroy and Arguea, 2008), while others focus on secondary schooling (Alexander, Haug, and Jaforullah, 2010; Mancebón et al., 2012; Grosskopf and Moutray, 2001; Kirjavainen, 2011; Haug and Blackburn, 2013), mixed level education (Burney et al., 2011; Blackburn, Brennan, and Ruggiero, 2014), or tertiary education (Zoghbi, Rocha, and Mattos, 2013). Some studies have also attempted to compare relative performance of different education sectors, comparing public and private schools (Cherchye et al., 2010; Mancebón et al., 2012), or charter schools and traditional public schools (Grosskopf, Hayes, and Taylor, 2009; Gronberg, Jansen, and Taylor, 2012).

One noteworthy observation from international studies is that non-Catholic independent schools have often been excluded due to their diverse objectives and quality. But these schools are regarded as mainstream in Australia, accounting for 11 per cent (1,017 out of 9,425 schools in our 2012 data) of all schools (ABS, 2012). Therefore, we chose to include non-Catholic independent schools in our study. Also, we found that the selection bias issue[4] was addressed mainly at the school level using fixed effects (Grosskopf, Hayes, and Taylor, 2009; Gronberg, Jansen, and Taylor, 2012) and the inclusion of lagged outputs in the input sets (Bradley, Draca, and Green, 2004). We argue, though, that individual-level unobserved characteristics may still lead to selection bias when school-level fixed effects are controlled.

2.2 Australian studies

A number of studies have attempted to assess the performance of Australian schools using either state or national data. As far as we can ascertain, Mante and O'Brien (2002) was the first Australian study on school efficiency. The authors examined the efficiency of 27 public secondary schools in Victoria in 1996 using two outputs (the proportion of students with tertiary entrance scores of 50 and above, and the Year 12 apparent retention rates) and two inputs (the number of staff per student and expenditure per student). The authors found that most Victorian schools were in a position to improve their outputs using the same level of inputs. The authors noted the importance of controlling for the socio-economic status of students in their study: omitting this variable would have resulted in some schools being identified as inefficient when, in fact, lower performance was due to intakes of students from lower socio-economic backgrounds.

Lamb et al. (2004) also examined patterns of schools performance in Victoria in the early 2000s. The study by Lamb et al. (2004) differs from that of Mante and O'Brien (2002) in several ways. First, Lamb et al. (2004) studied both primary and secondary schools. Second, they measured school efficiency by calculating the standardized residuals from regressions of school academic outcomes on a set of variables that describe school characteristics such as prior academic

[4]This issue refers to situations where performance of schools differ due to unobserved characteristics of schools (e.g., cultural attitudes towards education) or students (e.g., persistence, diligence, discipline) that may result from differences in socio-economic background.

achievement but excluded measures of resources such as labor and expenditure. Lamb et al. (2004) found that the socio-economic backgrounds of students exerted a major influence over educational outcomes, and that students were highly segregated along social and academic lines, noting that this segregation and sorting intensifies the differences in outcomes between students. Notwithstanding these observations, the authors found examples of efficient schools in each sector, and considerable variation in school efficiency for both primary and secondary schools. Their results also indicated that, at the secondary school level, independent schools were the most efficient at improving students' academic outcomes, followed by Catholic schools, with public schools being the least efficient.[5]

Bradley, Draca, and Green (2004) focused on the performance of public primary schools in Queensland in 2001. They took into account the effects of students' ability, which can lead to selection bias, by taking the average of numeracy and literacy scores for each school at Year 7 as outputs and the respective scores in Year 5 as inputs. However, their specification could only address the selection bias at the school level. Also, their choice of household income and proportion of students from indigenous background as inputs may be questioned, as these factors arguably are largely beyond the control of schools, especially public schools. Their results highlight the importance of controlling for the socio-economic backgrounds of children and for the quality of student intake when assessing school efficiency. Based on variations in efficiency scores of schools in local government areas, they suggest that increasing competition between government schools may hold promise as a way to increase school efficiency.

Arshad (2012) examined the efficiency of primary schools in Tasmania over the 2000-2007 period using both DEA and SFA. The author found that public schools are the most technically efficient, with an average technical efficiency score, estimated using SFA, of 97 per cent. As a result, no technical efficiency changes were identified in the study period. Also, they found that a one per cent increase in the expenditure per student was associated with increases in reading, writing and numeracy scores of 0.38, 0.36 and 0.43 per cent, respectively. The DEA results also produced a very high technical efficiency score of 95 per cent. The socio-economic background of students was considered as an environmental factor in this study. In second stage Tobit regressions, the author found that the proportion of students from non-English speaking background, absenteeism rates and schools in rural locations negatively affected their technical efficiency.

Two studies (Chakraborty and Blackburn, 2013; Haug and Blackburn, 2013) used data from Australia's most populous state, New South Wales (NSW), to examine the performance of public schools. Blackburn, Brennan, and Ruggiero (2014) examined the efficiency of NSW public primary and secondary schools in 2010 using an output-oriented DEA. The authors measure output as test scores at the third and fifth grades for primary schools and the seventh and ninth

[5] Unfortunately, it was not possible to make such a comparison between public and non-public schools at the primary level because there are no data available for non-public primary schools.

grades for secondary schools. They separated the input set into a discretionary input (as proxied by expenditure per student) and a non-discretionary input (as proxied by the family occupation employment and income index). By comparing the target inputs of DEA results using the discretionary input only and those using both types of inputs, the authors calculated the environmental costs (i.e., extra costs incurred by schools that face harsher environmental factors). Blackburn, Brennan, and Ruggiero (2014) found that schools in NSW are moderately inefficient and that schools with more favorable environments–as measured by the socio-economic background of students and school location–tended to be more efficient. The authors also found that the inclusion of number of students enrolled had little effect on their efficiency, thus suggesting that scale effects–in the range covered by the data–were unimportant.

Similarly, Chakraborty and Blackburn (2013) measured the efficiency of public primary and secondary schools for the period 2008-2010. The authors used the same outputs as were used by Blackburn, Brennan, and Ruggiero (2014) but applied a more complex model that contained a richer set of controls for school resources. They also implemented a two-stage DEA approach in which the first stage estimated school efficiency, and the second stage examined determinants of school efficiency using regression analysis. Chakraborty and Blackburn (2013) found that by learning from best practice, schools could, on average, reduce costs by 12 per cent at the primary level and by 11 per cent at the secondary level. Social disadvantage was found to be negatively associated with the efficiency of primary schools. The authors also found that, over the study period, the efficiency of primary schools decreased, while the efficiency of secondary schools increased slightly.

Haug and Blackburn (2013) also studied the efficiency of public secondary schools in NSW during 2008-2010. The authors used three value-added measures of academic results as outcomes: (i) the difference between schools' median Year 12 Higher School Certificate university entrance "Australian Tertiary Admission Rank" (ATAR) results in 2010 and 2008, (ii) the difference between schools' 2008 and 2010 median Year 10 School Certificate Exam results, and (iii) the difference between the average test scores for Year 9 in 2010 and the average test score for Year 7 in 2008. The authors also exploited the double bootstrap procedure for DEA by Simar and Wilson (2007) to examine the determinants of school efficiency. They found that schools with higher student retention rates, larger enrollments were more efficient, as were single-sex schools and selective-admissions schools. By contrast, schools from more remote areas, with a higher ratio of students from English as secondary language and Aboriginal backgrounds, or with a higher rate of students required special education, were less efficient. They also found that the socio-economic background of students (proxied by the Index of Community Socio-Educational Advantage –ICSEA) and experiences of the teachers had no statistically significant impact on the efficiency of schools. We note that the ICSEA already includes, by construction, indicators of geographical location (i.e., remoteness) and socio-economic advantage, and hence collinearity may have been a driver of statistically insignificant coefficients when Haug and Blackburn (2013) included all three such measures (ICSEA, locations, and socio-economic index) in their regressions. Parenthetically, we also note that the conceptual issue of whether such environmental factors are properly conceived as affecting efficiency *per se*, as opposed to the constraints faced by schools, is worth further consideration.

Two recent papers have also used national data to study the performance of schools across Australia. Miller and Voon (2012) documented that the average test scores for independent schools were consistently the highest across the three sectors, while the scores for the government schools were the lowest. This study offered an interesting "decomposition" approach but it was based on a simple test for mean differences between groups. By contrast, Ryan (2013) used the Programme for International Student Assessment (PISA) data to examine academic achievements of 15 year-old secondary school students from 2003 to 2009. The author conducted two SFA specifications using the PISA test scores in math and reading as separate outcomes. He found that private schools were the most efficient, followed by Catholic schools and public schools. He also found that school level variables such as student–teacher ratios, information on admission practices and levels of school resources added little to the explanation of school performance. We note that, by using SFA, Ryan (2013) could have incorporated the effects of environmental variables in a single step using models such as that of Battese and Coelli (1995), rather than using the chosen two-step estimation process.

In summary, there is quite a rich extant literature on school performance but the room to contribute to this literature remains ample. International (Elder and Jepsen, 2014; Hanushek and Taylor, 1990; Jepsen, 2003) and the Australian (Bradley, Draca, and Green, 2004; Lamb et al., 2004; Marks, 2009; Nghiem et al., 2015) literature on this topic has shown that, due to problems associated with school selection, care is required in the econometric specification if misleading conclusions about the relative performance of schools are to be avoided. To the best of our knowledge, only a handful of studies (Bradley, Draca, and Green, 2004; Grosskopf, Hayes, and Taylor, 2009; Gronberg, Jansen, and Taylor, 2012; Haug and Blackburn, 2013) have controlled for selection bias but they only addressed the issue at the school level. This study contributes to the literature by addressing the selection bias issue at the student level. Also, we consider the socio-economic background as an environmental factor because schools, especially public schools which usually enroll students on a residential catchment basis, do not actually have much choice about which students to enroll. This approach has also been applied in a number of international studies (Alexander, Haug, and Jaforullah, 2010; Haelermans and Ruggiero, 2013) and Australian studies (Mante and O'Brien, 2002; Chakraborty and Blackburn, 2013; Haug and Blackburn, 2013).

3 Methodology

In this study, we apply a non-parametric approach and use DEA with bootstrapping to study school efficiency in Australia. An output-oriented technical efficiency in DEA is measured by solving a linear programming problem below:

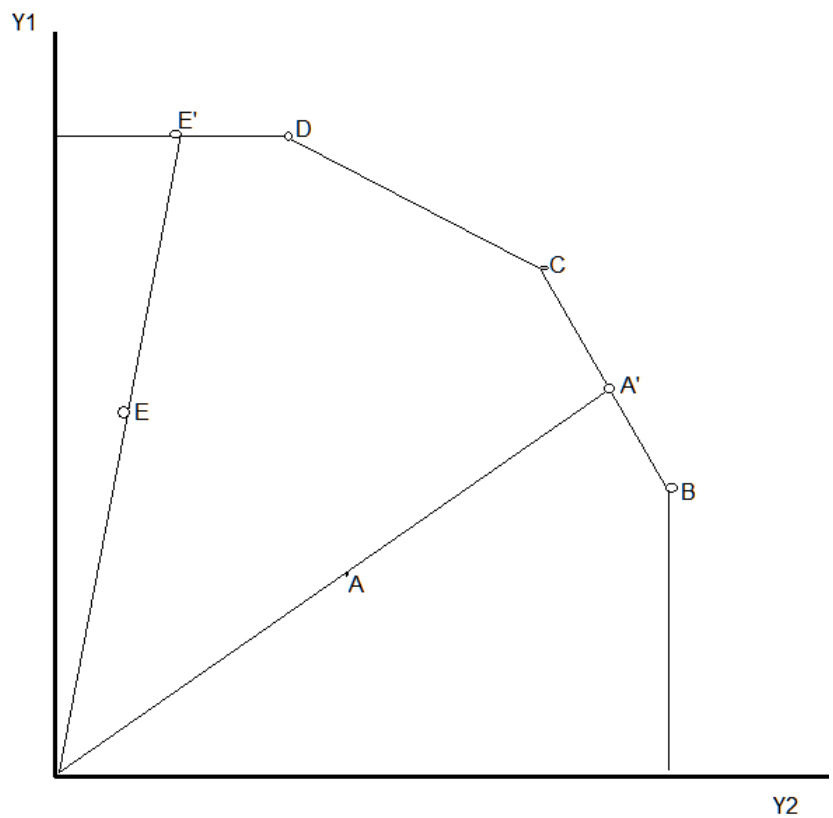
$$D_o\{x_i, y_i\} = max\{\theta_i | \lambda_i Y \geq \theta_i y_i;\ x_i \geq \lambda_i X;\ \theta_i \geq 1; \lambda_i \geq 0; \sum \lambda_i = 1\} \qquad (1)$$

where D_o refers to an output distance function, which represents the relationship between inputs x and outputs y of school i; θ is a scalar representing technical efficiency ($\theta - 1$ represents the proportional increase in outputs that can be obtained while using the same level of inputs); λ is a vector of weights (also referred to as "peer weights") that represent the distance between an efficient school and its peers (i.e., inefficient schools with similar characteristics in the input-output structure); and Y and X represent the matrices of outputs and inputs, respectively, of all schools in the data set. Empirically, the reciprocal of θ, which ranges from 0 to 1, is in fact used to measure the technical efficiency of the ith school. The last constraint $\sum \lambda_i = 1$ measures the scale efficiency of a school, which represents the degree to which schools can further improve efficiency by operating at the optimal scale.

One advantage of DEA is that inefficient schools will be compared to efficient schools with a similar input-output structure, which may be due to having similar unobserved characteristics such as the schools' socio-economic backgrounds. The output-oriented frontier (Figure 1) shows that inefficient school A will be more efficient if it moves to A', which is estimated based on the input-output structure of two similar schools, B and C. These schools share similar characteristics of having an advantage in the production of producing $Y2$ over $Y1$. Figure 1 also admits of slacks.[6] For example, school E could be technically efficient if it achieved the input/output combination at E', but it could improve further by producing more $Y2$ at D (i.e., the movement from E' to D is possible due to the presence of input or output slacks).

[6]The term "slacks" is used in the production literature to refer to congestion in inputs such that firms would be able to produce more output with less input. In the context of schools, factors like workplace regulations or the unionization of labor may prevent schools from using more efficient combinations of inputs than could otherwise be chosen. For a more detailed discussion about the concept of slacks, see, for example, Coelli et al. (2005).

Figure 1: Example of an output-oriented frontier



In the extant literature many of the previous studies applied bootstraps to obtain the statistical properties of the resulting efficiency scores from DEA. Simar and Wilson (1998), though, have drawn attention to the fact that that most of the naive bootstraps that have historically been applied do not take into account the property that technical efficiency scores range from 0 to 1. Simar and Wilson (1998) overcome this problem by using a truncated distribution to redraw the sample.[7]

In this study, in order to take into account the effects of environmental factors (e.g., the socio-economic backgrounds of students, types of school) we, like e.g. Chakraborty and Blackburn (2013)Arshad (2012), regress the technical efficiency scores estimated against environmental variables using the following equation:

[7]Note that the bootstrap procedure by Simar and Wilson (1998) does not actually take into account random noise or measurement error but it checks the sensitivity of results due to sample variability; hence, it is not necessary or appropriate to apply the bootstrap in DEA studies that use complete population enumerations, such as census data (Coelli et al., 2005, pp.202-203).

$$y_i^* = z_i\beta + \varepsilon_i \quad (2)$$

where z_i is a vector of factors affecting technical efficiency of schools (e.g., socio-economic background of students, school location), β is a vector of unknown parameters to be estimated, ε_i is a random error, and y_i^* is the latent variable that has the relationship with the observed technical efficiency as:

$$y_i = \begin{cases} y_i^* & if\, 1 > y_i^* > 0 \\ 1 & if\, y_i^* \geq 1 \\ 0 & if\, y_i^* \leq 0 \end{cases} \quad (3)$$

As already noted above, since efficiency scores are bounded between zeros and ones, we apply a truncated regression to estimate parameters of Equation (3).[8] A problem with this regression is that it violates an assumption in regression analysis that the error term is uncorrelated with covariates, and hence estimated parameters will be biased (Simar and Wilson, 2007, pp. 39–40). Simar and Wilson (2007, pp.42–43) introduced a double bootstrap procedure to produce bias-corrected estimates. To summarize, their double bootstrap procedure involves the following two main steps:

Construct the bias-corrected technical efficiency scores using original DEA estimates and re-sample the data using the original truncated regressions; and

Construct the bootstrapped confidence interval for the second stage truncated regression using the bias-corrected efficiency scores obtained from the first step.

This estimation procedure is implemented in this paper using the FEAR package for the R statistical computing language (R Core Team, 2013) by Wilson (2008). The sampling procedure uses 1,000 repeats in both steps.

4 Data

4.1 Data source and variable selection

This study uses the National Assessment Program–Literacy and Numeracy (NAPLAN) data provided by the Australian Curriculum, Assessment and Reporting Authority (ACARA). The NAPLAN, which was initiated in 2008, is a common national assessment program for all students at grade 3, 5, 7 and 9 in all Australian government and non-government schools.[9] Students are tested across five domains: Grammar and Punctuation, Numeracy, Reading, Spelling and Writing. In May of each year, all students in the same grade across Australia

[8] Tobit regression is used widely in the literature but a Monte-Carlo experiment by Simar and Wilson (2007, p.48) shows that parameters produced by a truncated regression are much closer to the true values. In addition, the parameter estimates from the second stage of a double bootstrap procedure introduced by Simar and Wilson (2007) are interpreted as marginal effects.

[9] Some students are, however, exempt from the tests. These include students from a non-English speaking background who have been in Australia for less than one year before the tests and students with substantial intellectual disabilities.

are assessed using the same tests. The tests are designed in such a way that test results are measured on common scales, ranging from 0 to 1,000, rendering them comparable across grades. Specifically, the results of the tests are not only comparable across schools for the same classes in the same year, but also across school years (ACARA, 2013b). Our data contains school-level aggregate results of these tests in two main forms: levels and gain of scores between the two test periods.

We select the gain of test score as the main output measure (more detailed below). For that reason, we restrict our empirical sample to schools with a sufficient number of students who took NAPLAN tests in both 2009 and 2011.[10] We also exclude special schools that serve students with a disability from the analysis because students with a substantial intellectual disability are not required to take NAPLAN exams.[11] Finally, we exclude 23 schools with missing information on expenditure, one school with zero capital expenditure as well as 18 schools that are distance education providers.[12] We also exclude three secondary schools in Queensland, South Australia and Western Australia because secondary schools in these states usually serve students from Grade 8 and test score gains are calculated using test scores of a sample of students who did not change schools between two consecutive test years (ACARA, 2013b), hence we do not have data on test score gains for them. Our final sample consists of precisely 6,774 schools.

While the levels of school test scores are available in all five test domains, we focus on the levels and gains in test scores from the Numeracy and Reading domains as indicators of school outputs because ACARA does not report student gains in other test domains (ACARA, 2013a). School-average test score levels (gains) in Numeracy and Reading domains are then further averaged by schools to get a combined test score levels (gains) to be used as our main measures of school outputs. For the purpose of comparing our results with those of other studies (Miller and Voon, 2012) that use the same data set but different measures of output, we use the level of scores in Numeracy and Reading domains as the first school output. Two additional measures of school outcomes are calculated using gains in student test scores at the school level. The first is school-level "unadjusted score gain" which is calculated as the school average of the difference in test scores of the same students who took the tests at the same school in two different grades in 2009 and 2011.[13] The use of score gain as a measure of school

[10] At the time we obtained the dataset used in this study, this was the most recent period that test score gains were available from ACARA. According to ACARA, score gains are available only for schools with five or more matched students.

[11] In addition, ACARA excludes these schools when calculating average for schools with similar backgrounds or starting scores.

[12] Our rationale for excluding providers of distance education is that these schools are liable to have a fundamentally different production processes than the majority of schools in our sample.

[13] Unfortunately, our data does not have scores in two years that ACARA uses to calculate the gain of scores for us to include the initial scores (i.e. in 2009) as an input. Note that the study by Haug and Blackburn (2013) which also uses NAPLAN data, defines the score gain differently. Specifically, the authors calculate the score gain as the difference between the average scores in two years for the same cohort (not the same students). As they note,

output is a significant improvement in the literature, which had been unable to address selection bias at the student level. In particular, the gain of test scores of each student eliminates time-invariant unobserved characteristics of students (e.g., innate academic ability as explained by Todd and Wolpin, 2003), which is responsible for selection bias. Note that while the unadjusted score gain measure provides an attractive way to examine school efficiency, it does not capture the characteristics of the learning process as well as the structure of the full test results would. Furthermore, test results are to be regarded as indicators of the latent variable of interest. It is possible, too, that the rate at which current learning builds on past performance varies along the test score distribution (Hanushek et al., 2007; Grosskopf, Hayes, and Taylor, 2009). For instance, it may perhaps be easier to improve the test scores of students who start from a lower score base than to improve from a high base. We address this concern by comparing the gain in test results of students with the same starting level. In particular, we follow some of the US literature (Reback, 2008; Gronberg, Jansen, and Taylor, 2012; Grosskopf, Hayes, and Taylor, 2009) to measure a school's output as its deviations from the expected score of the schools with the same previous test scores. We name this output the "adjusted gain" to distinguish it from the "unadjusted gain" concept that was introduced previously.

All three alternative choices of output (level test score, unadjusted gain, and adjusted gain) represent the average achievement of students in a school. For example, a school with a test score of 550 indicates that an average student in that school achieved a test score of 550 for each test subject. To keep the measurements of input consistent with that of output, some of inputs such as labour, materials, and capital are measured "per student". This choice of input-output was popular in previous studies of school efficiency (Conroy and Arguea, 2008; Agasisti, 2011; Blackburn, Brennan, and Ruggiero, 2014; Chakraborty and Blackburn, 2013). Effects of school size on efficiency are investigated in the second stage using the number of students to represent the school size.

The input measures that are used in this study include labour, measured by full-time equivalent (FTE) teacher/student ratio and non-teaching staff/student ratio; materials represented by recurrent income per student; and capital measured by capital expenditure per student.[14] To measure the impact of environmental variables on school efficiency we include the Index of Community Socio-Educational Advantage (ICSEA) which represents levels of educational advantage in the second stage regression. This index, which takes values from approximately 500 to approximately 1300, is constructed by the ACARA taking information relating to education and occupation of parent/guardian, geographical remoteness and the proportion of Aboriginal and Torres Strait Islander (ATSI) enrollments of the school into account (ACARA, 2013c).[15]

their score gain measure does not take into account the possibility that students might change schools over time.

[14]Note that the use of the recurrent income measure involves, in the production context, the inherent assumption that recurrent expenditure equals recurrent income.

[15]We do not include the school geographical remoteness and ATSI variables in the second stage because these variables are used directly in the computation of the ICSEA itself.

By construction, schools with higher ICSEA scores enroll more students from educationally advantaged backgrounds. We also include in the regression dummy variables for girls-only schools and boys-only schools to represent the characteristics of single sex schools and enable their comparison with co-educational schools. We also include the ratio of non-English speaking background students as an indicator of linguistic and cultural background that is not captured by the ICSEA. Other environmental variables selected for the second stage regressions include: school type (i.e., public, Catholic and other independent schools, taking public schools as the base), school year level (primary, secondary, or mixed level (i.e. both primary and secondary) schools, with primary schools are selected as the base), and state (dummies for states and territories with NSW/ACT is selected as the base), the natural logarithm of number of students (and its square).[16] In cases where school outputs are measured by the level of test scores, test scores in 2011 were used. Similarly, inputs and environmental variables were measured in 2011 in all cases.

4.2 Descriptive statistics

The descriptive statistics of the inputs, outputs and environmental variables (Table **??**) show that the average NAPLAN score of students in Australia in 2011 was 440, and the average unadjusted (adjusted) growth of test scores between 2009 and 2011 was 0.36 (0.34) points. One notable characteristic from the descriptive statistics is that the minimal for NAPLAN test growth, both adjusted and unadjusted, are negative. Negative values for output growth violates the basic assumption in DEA that the output measure cannot be negative. To deal with this, we thus convert the growth of outputs to be positive integers by subtracting the minimal value and adding an arbitrarily positive value of 10 (i.e., the minimum value of the transformed output is now 10). The data also show that, on average, schools in Australia have 68 teachers and 25 non-teaching staff per 1,000 students. The average capital expenditure and income of schools is A$3,100 and A$11,700 per student per year, respectively. Note that the data on capital expenditure fluctuates considerably over time: this is explained by the lumpy nature of capital investments by schools, which cause spikes and troughs in spending across the observed years (i.e., the purchase of new equipment or the construction of new buildings). Thus, we take the average of capital spending over the 2008-2011 period to smooth out the temporal variation that arises due to the temporal lumpiness of investments in school capital. The descriptive statistics show that about 69 per cent of schools in Australia are public, with Catholic schools making up 20 per cent and the remaining 11 per cent being made up of other independent schools. As expected, the mean of key charac-

[16]Unfortunately, information about teachers' characteristics is not available in our data. Missing information on teachers' characteristics may not have a large effect on our findings because previous studies such as Leigh (2010), Buddin and Zamarro (2009), Loman et al. (2012), and Haug and Blackburn (2013) have found that teacher characteristics as measured by educational background and salary explain only a small fraction of the variations in the effects of teachers on improving students' test scores.

teristics are significantly different between schools types (e.g., Public, Catholic and Independent) with the NESB rate is a rare exception (see Appendix Table 1 for more details).

Primary schools account for 73 per cent of the sample, while secondary schools account for 15 per cent of schools and the remaining schools are mixed-level schools that combine primary and secondary-level school years. Among the eight states and territories of Australia, NSW and the ACT (combined) account for the largest proportion of Australian schools, accounting for 36 per cent of schools in our sample, followed by Victoria (25 per cent) and Queensland (16 per cent). Due to the small number of schools in the Australian Capital Territory (ACT) that had NAPLAN test data in both 2009 and 2011, we combined the ACT with New South Wales (NSW), one of its geographical neighbors. The Northern Territory has the lowest share of Australian schools (1.56 per cent) and single-sex schools represent a similar proportion of all Australian schools. On average, 19 per cent of students in Australian schools come from a Non-English Speaking Background (NESB). In the regressions analyzes we divided the NESB rates by 100 and the ICSEA index by 1,000 to make their scale in the range with other covariates. This has no effect on the relationship as regressions are independent of measurement unit but it renders the parameter estimates visible at three decimal points.

5 Results and Discussion

5.1 Empirical results from main models

Table 1 presents a summary of Australian school technical efficiency disaggregated by choices of outputs, school types and level of study. The results show that the average technical efficiency scores is highest when level scores were selected as an output, followed by unadjusted and adjusted score gains. For example, when the level test score is selected as an output, Australian schools can increase the test scores by 49 per cent (i.e., $\frac{1}{0.67} - 1$) by learning from the best practices. But when adjusted gain of test score is selected as an output (our preferred choice) the potential improvement of output for an average school is 64 per cent (i.e., $\frac{1}{0.61} - 1$). The average technical efficiency scores of primary schools are slightly higher, at 0.77, 0.66 and 0.63, when output is defined as level score, unadjusted score gains and adjusted score gains, respectively. Secondary schools are the most technically efficient with the average efficiency scores of 0.76, 0.82 and 0.86 when output is defined as level scores, adjusted score gains and unadjusted score gains, respectively. The respective average technical efficiency scores for mixed schools are 0.81, 0.73 and 0.82. Among school types, independent schools appear to be the most efficient type with the exception at the mixed schools where Catholic schools are slightly more efficient.[17] By

[17]Note that the average technical efficiency scores by school type (i.e., Public, Catholic and Independent) are higher than that estimated by the pooled frontier mainly due to the lower

contrast, public schools are the least efficient in all level of study. The use of adjusted score gains are output generally produce lower technical efficiency scores.

Table 1: Technical efficiency of schools by output measures and school types

School types		Level scores		Unadjusted gains		Adjusted gains	
	N	Mean	SD	Mean	SD	Mean	SD
All schools	**6774**	**0.67**	**0.10**	**0.64**	**0.11**	**0.61**	**0.11**
Public	4641	0.69	0.12	0.67	0.12	0.65	0.12
Catholic	1393	0.83	0.10	0.71	0.12	0.71	0.13
Independent	740	0.84	0.07	0.75	0.08	0.72	0.08
Primary schools	**4917**	**0.77**	**0.08**	**0.66**	**0.12**	**0.63**	**0.12**
Public	3677	0.77	0.09	0.68	0.12	0.66	0.12
Catholic	1112	0.83	0.08	0.72	0.12	0.72	0.13
Independent	128	0.89	0.09	0.83	0.14	0.83	0.11
Secondary schools	**832**	**0.76**	**0.08**	**0.82**	**0.07**	**0.86**	**0.06**
Public	612	0.76	0.09	0.83	0.07	0.86	0.06
Catholic	182	0.95	0.04	0.90	0.05	0.91	0.05
Independent	38	0.95	0.07	0.93	0.07	0.93	0.06
Mixed schools	**1025**	**0.81**	**0.11**	**0.73**	**0.09**	**0.82**	**0.10**
Public	352	0.80	0.13	0.76	0.14	0.79	0.14
Catholic	99	0.88	0.10	0.88	0.08	0.92	0.08
Independent	574	0.85	0.06	0.77	0.07	0.87	0.06

Note: Each average technical efficiency score is estimated from its own frontier. Thus, results in this table are estimated from 48 separate DEA models.

Compared with the average technical efficiency scores of 75 per cent for primary schools and 89 per cent for secondary schools reported in the study by Chakraborty and Blackburn (2013), our estimates are considerably lower. Besides the differences between the data set used in that study and ours, and the selection of different inputs, the choice of output appears to be the main reason behind these differences in estimated efficiency scores. Specifically, we use only one test measure as an output at a time while they use several outputs (e.g., test scores for different subjects). When the dimension of output comparison increases the number of schools on the frontier will increase and the distance from the frontier to inefficient schools will be reduced, hence generating higher efficiency scores. For example, schools that perform well on one subject (e.g., Numeracy) and poorly on other subjects will still be considered as efficient if multiple subjects are selected as outputs, while this will not necessarily occur when a single output is selected for analysis. We believe that achievement across all subjects using total or average scores is likely to be a better measure of school

number of observations.

performance.

When all schools are included to construct the frontier, the results (see Table 2) show that schools with more favorable socio-educational conditions (i.e., higher ICSEA) are more efficient. The magnitude of the ICSEA index is also

Table 2: The determinants of school technical efficiency - results from regressions of all schools

	Adjusted gain	Unadjusted gain	Level scores
Constant	$-.218$ (.032)***	.068 (.034)*	.089 (.024)***
Catholic schools	$-.031$ (.002)***	$-.017$ (.002)***	$-.012$ (.001)***
Private schools	$-.078$ (.003)***	$-.054$ (.003)***	$-.016$ (.002)***
ICSEA Index	.465 (.010)***	.188 (.011)***	.475 (.007)***
NESB rate	.030 (.003)***	.020 (.003)***	$-.014$ (.002)***
Boys only	$-.054$ (.006)***	$-.049$ (.006)***	$-.014$ (.004)***
Girls only	$-.058$ (.006)***	$-.042$ (.006)***	$-.015$ (.004)***
Mixed schools	$-.054$ (.003)***	$-.052$ (.003)***	.024 (.002)***
Secondary schools	$-.049$ (.003)***	$-.057$ (.003)***	.108 (.002)***
Log of number students	.060 (.011)***	.065 (.011)***	$-.014$ (.008)*
Log of students squared	$-.002$ (.001)*	$-.003$ (.001)**	.003 (.001)***
Victoria	$-.034$ (.002)***	$-.013$ (.002)***	.004 (.001)**
Queensland	$-.051$ (.002)***	$-.033$ (.003)***	.012 (.002)***
Western Australia	$-.074$ (.003)***	$-.053$ (.003)***	.003 (.002)
South Australia	$-.073$ (.003)***	$-.052$ (.003)***	.007 (.002)**
Tasmania	$-.064$ (.004)***	$-.029$ (.005)***	.0001 (.003)
Northern Territory	$-.015$ (.006)**	.007 (.007)	$-.026$ (.005)***
Log likelihood	4587.671	4252.863	6558.807
R^2	.235	.119	.313
BIC	-9016.566	-8346.951	-12958.838
AIC	-9139.341	-8469.726	-13081.613
Number of observations	6774.000	6774.000	6774.000

*** p<0.01,** p<0.05, * p< 0.1. Standard errors are in parentheses. NSW/ACT are the base.

the largest, suggesting that it is the dominant determinant of school efficiency. We find that single-sex schools (i.e., all-boys and all-girls schools) are less efficient than unisex schools; but the magnitudes of these parameters are small, especially when the level of test score is selected as the output measure. Table 3 also shows that secondary and mixed schools are significantly less efficient than primary schools. When the levels of test scores are used as the output measure, though, secondary and mixed schools are more efficient than primary schools. One possible reason for this result is that the design of the test makes it relatively more difficult to achieve higher average test scores. This result is in line with findings from previous studies such as Daraganova, Edwards, and Sipthorp (2013) and Nghiem et al. (2015); while test scores generally increase with grade; the rate of gain in test scores diminished over time.

When each type of schools is examined separately in both first stage (DEA) and second stage (truncated regression), effects of education sectors on operational efficiency change considerably depending upon whether primary or secondary schools are examined (see Table **??**). In particular, at the primary level, Catholic and independent schools are less efficient than public schools but the reverse is true for mixed and secondary schools. Larger schools are significantly more efficient at the primary and mixed school levels only. Similarly, schools in all other states and territories are less efficient than those in NSW/ACT at the primary level but schools in Queensland, Western Australia, South Australia and Tasmania are more efficient than those in NSW and the ACT for mixed schools, while secondary level schools across states exhibit no appreciable differences in operational efficiency. Finally, with the noteworthy exception of boys-only schools of the secondary level, all other single-sex schools are less efficient than coeducational schools at all levels. Our finding on the effect of gender composition of schools on efficiency for secondary schools is in contrast with those found by Haug and Blackburn (2013). The latter study found that single-sex schools are more efficient than unisex schools and that the socio-economic background of parents had no significant effect on school efficiency. Our choice of different outputs to theirs – recall that they used the median tests scores of Higher School Certificate for Year 12, School Certificate exam for Year 10, and average test scores for Year 7 and Year 9 – probably explain this difference.[18] Our results for secondary schools are, however, similar with those of Lamb et al. (2004) who found that, at the secondary level, Catholic and independent schools are more efficient than their public counterparts. Similarly, the finding that primary level public schools perform better than Catholic and independent schools is also in line with the recent findings of Nghiem et al. (2015).

We calculate target inputs and outputs that schools can achieve, by adjusting the input-output combination, to be efficient. Table 3 shows that, on average, schools can gain an average of 227 test points between 2009 and 2011 by learning from the best practices. Note that this improvement is computed on the output that was rescaled to render it positive for the purposes of applying DEA. Due to the presence of congestion in inputs, we also calculate the target inputs that can be achieved by addressing the congestion (i.e., remove input slacks). Table 3 also shows that the teacher ratio decreases from 68 to 58 teachers per 1,000 students, the ratio of non-teaching staff decreases from 25 to 22 persons per 1,000 students, and average capital expenditure per student decreases from A$11,700 to A$10,200; the relative reduction of income per student is from A$3,100 to A$2,200. Although we choose an output-oriented approach to measure school efficiency, the reduction of inputs in targets suggests that some schools have input slacks or congestion. One possible reason for input congestion may include government regulations pertaining to maximum class sizes and structural aspects of the Australian education sector. Leigh and Ryan (2008), for instance, speculate that labor regulations, the prevalence of

[18] The authors of that paper also had a considerably smaller sample size (i.e., 380 public schools in NSW) to work with.

unionization, and the rejection of merit-based pay by the union movement as structural factors that may make it costly or difficult for Australian schools to discipline or remove teachers and non-teaching staff to achieve operational efficiency. Regarding the last input, too much spending on the "right" items or spending on "wrong" items may also cause adverse effects on the test score gain. Overall, due to input congestion, on average, schools employ 10 more

Table 3: Summary of output targets and production slacks

	Mean	Std.	Change
Test score gain (test scores)	227.80	28.223	90.55
Teachers/student (FTE)	0.058	0.006	-0.010
Non-teaching staff/student (FTE)	0.022	0.010	-0.003
Capital expenditure/student (A$1,000)	2.260	0.823	-0.824
Income/student (A$1,000)	10.233	1.247	-1.515

FTE teachers and three more FTE non-teaching staff per 1,000 students than is estimated to be optimal, resulting in A$820 more expenditure and A$1,500 more income per student above the optimum. These estimates represent the order of magnitude of estimated inefficiencies in the Australian schooling sector and seem unlikely to be realized without regulatory and structural reform in the sector.

5.2 Sensitivity analysis

To test the robustness of our results, we estimated two further specifications of the model (see Table 4). First, we used the test scores themselves as a second output together with the test gain measure. We expect higher efficiency scores to be estimated with this model because the frontier is constructed from combinations of schools with high test gains or high test scores. Second, we removed super-efficient schools, which are also the most influential schools in this study, from the frontier.[19] We also expect this to result in a frontier that forms a tighter envelope around the data and hence that the average efficiency scores of inefficient schools will increase in this specification.

The results of these sensitivity analyzes are as expected: the technical efficiency scores increase when both the level and gain of test scores are selected as outputs (0.76) and when super-efficient schools are excluded (0.63). The cumulative distributions of technical efficiency scores in Figure 2 show that when

[19]The super-efficiency score is calculated by removing one efficient school then projected their original output to the new frontier; the super efficiency score is the ratio of the resulting projected output to the school's original output. A school is considered super-efficient if its super-efficiency score is less than one, meaning that they remain on the frontier even when their output is reduced (Coelli et al., 2005). In the literature, sensitivity analyzes are done by removing super-efficient firm one-by-one but we found this has little impact with our data. Also, because we have only a few super-efficient schools, we decide to remove all these schools in the sensitivity analysis.

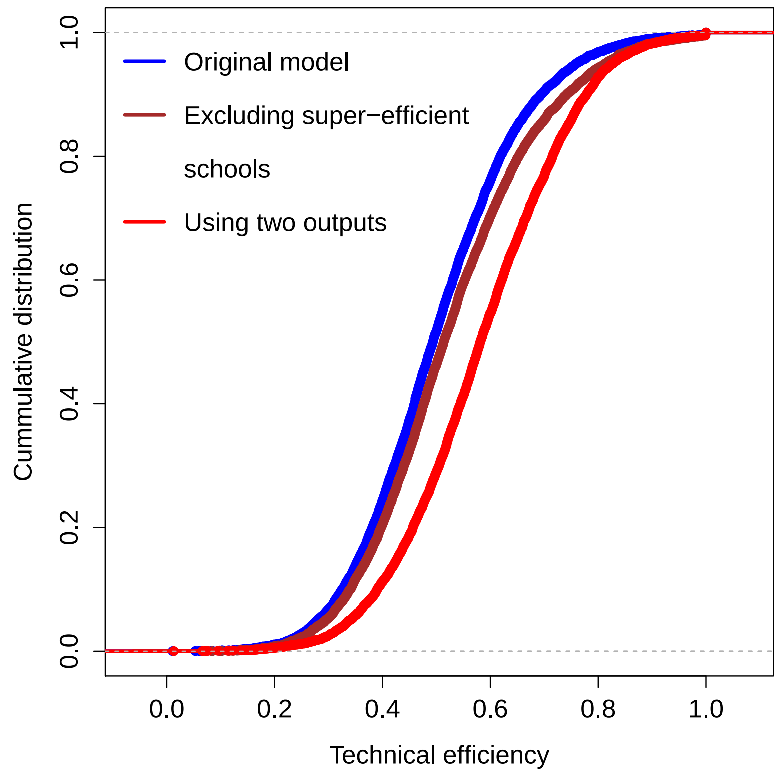
Table 4: Sensitivity analysis

	Use two outputs	Drop super-efficient schools
Constant	.094 (.023)***	−.235 (.035)***
Catholic schools	−.019 (.001)***	−.027 (.002)***
Private schools	−.027 (.002)***	−.092 (.004)***
ICSEA Index	.556 (.007)***	.520 (.012)***
NESB rate	−.003 (.002)	.025 (.004)***
Boys only	−.009 (.004)**	−.069 (.007)***
Girls only	−.015 (.004)***	−.068 (.006)***
Mixed schools	.018 (.002)***	−.073 (.003)***
Secondary schools	.075 (.002)***	−.059 (.003)***
Log of number students	−.003 (.008)	.046 (.012)***
Log of students squared	.002 (.001)**	.000 (.001)
Victoria	−.008 (.001)***	−.036 (.002)***
Queensland	−.002 (.002)	−.052 (.003)***
Western Australia	−.009 (.002)***	−.076 (.003)***
South Australia	−.014 (.002)***	−.077 (.003)***
Tasmania	−.015 (.003)***	−.074 (.005)***
Northern Territory	−.019 (.004)***	−.008 (.008)
Log likelihood	7010.345	3601.185
R^2	.336	.243
BIC	−13861.914	−7043.650
AIC	−13984.690	−7166.370
Number of observations	6774.000	6753.000

*** p<0.01,** p<0.05, * p< 0.1. Standard errors are in parentheses.

super-efficient schools were removed from the data set, the distribution of technical efficiency scores changed slightly. The distribution of technical efficiency scores when both level and gain of test scores are used as outputs, however, shows clear evidence of higher technical efficiency scores than the remaining two scenarios of single output. Nevertheless, the correlation coefficient between the choice of one and two outputs is 0.82.

Figure 2: Distributions of technical efficiency scores from different specifications



Results from the second stage regressions produce evidence of little sensitivity among the two scenarios outlined above. In particular, schools with high ICSE scores are still more technically efficient. Also, Catholic and independent schools remain less efficient than public schools in both sensitivity tests. The relative performance of schools from different states and territories relative to NSW and the ACT is also unchanged. Similarly, single-sex schools are less efficient than other schools except when two outputs are used to benchmark schools. Two noticeable changes to the results are observed when both the level and gain of tests are selected as output measures. In particular, schools with higher rate of NESB students are no longer more efficient. In addition, mixed or secondary level schools are more efficient than primary schools.

6 Conclusions

This paper has examined the efficiency of almost all Australian schools. Unlike most previous Australian studies, we used the average gain of test scores of the same students as our primary measure of school output. We applied the double bootstrap procedure of Simar and Wilson (2007) to examine the impact of environmental factors on the operational efficiency of schools.

Our results show that, based on input-output combinations and without adjustment for effects of socio-economic background, Australian schools can improve test score gain by 64 per cent; and congestion exists for all of the available inputs. If all schools are able to learn from their peers on the frontier (i.e., best practice schools) and input congestion is controlled for, the average gain of test scores can be increased by 90 NAPLAN points while capital expenditure and income can be reduced by A$820 and A$1,500 per student per year. In addition, on average, each school with 1,000 students can employ ten fewer FTE teachers and three fewer FTE non-teaching staff if input congestion can be eliminated. For structural reasons, though, such as class size limits and labor market rigidities, some of these inefficiencies may be difficult to overcome. The socio-educational factors that are positively associated with school efficiency are the ICSEA and the proportion of students from an NESB background. On average, Catholic and independent schools are less efficient than public schools at the primary level. This relative performance by sector may hold for primary schools only since at higher school levels, Catholic and independent schools are more efficient than public schools.

While this research has improved on some aspects of the previous Australian literature on this topic, future work of this kind could also improve on our work by using panel data approaches when data are available to permit this. Further studies may also be able to investigate technological gaps between school types using a meta-frontier analysis, for instance; and extend the current work study by examining the efficiency of Australian schools using a distance function SFA approach. For policy-makers, we also note that while differences in efficiency are often reported for environmental indicators (as proxied by, e.g., the ICSEA), these factors may properly be considered in production economics as forming part of the constraint faced by schools. The latter point is more important conceptually than it is technically, but it is a point that deserves serious consideration when the results produced by this literature–including ours–are considered in the formulation of public policy.

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Appendix Table 1: Test for mean differences of key characteristics

Variables/schools	Means			Test statistics (p-value)		
	Public (P)	Catholic (C)	Independent (I)	P=C	P=I	C=I
All schools						
Level test scores	430.98	443.97	494.58	0.00	0.00	0.00
Unadjusted score gains	73.56	73.00	63.08	0.40	0.00	0.00
Adjusted score gains	-1.07	1.30	7.36	0.00	0.00	0.00
Teacher/student	0.07	0.06	0.08	0.00	0.00	0.00
Non-teacher/student	0.02	0.02	0.04	0.00	0.00	0.00
Capital/student	2.85	3.47	3.80	0.00	0.00	0.00
Net income/student	11.73	10.53	14.17	0.00	0.00	0.00
ICSEA	987.45	1044.47	1083.39	0.00	0.00	0.00
NESB rate	18.92	20.29	19.74	0.06	0.39	0.61
Primary schools						
Level test scores	413.80	422.81	442.86	0.00	0.00	0.00
Unadjusted score gains	80.23	79.92	82.07	0.62	0.27	0.21
Adjusted score gains	-0.32	1.26	10.80	0.01	0.00	0.00
Teacher/student	0.06	0.06	0.07	0.00	0.00	0.00
Non-teacher/student	0.02	0.02	0.04	0.00	0.00	0.00
Capital/student	3.02	3.70	4.66	0.00	0.00	0.00
Net income/student	10.82	9.94	11.84	0.00	0.00	0.00
ICSEA	996.32	1047.33	1081.77	0.00	0.00	0.00
NESB rate	18.13	20.55	16.30	0.00	0.37	0.05
Secondary schools						
Level test scores	533.40	549.16	562.12	0.00	0.00	0.04
Unadjusted score gains	38.44	38.68	42.86	0.65	0.00	0.00
Adjusted score gains	-1.49	1.10	7.09	0.00	0.00	0.00
Teacher/student	0.08	0.08	0.09	0.00	0.00	0.00
Non-teacher/student	0.02	0.03	0.04	0.00	0.00	0.00
Capital/student	1.54	2.09	2.37	0.00	0.01	0.38
Net income/student	13.64	12.82	16.83	0.00	0.00	0.00
ICSEA	982.68	1032.16	1071.76	0.00	0.00	0.00
NESB rate	24.53	23.27	14.18	0.58	0.02	0.06
Mixed schools						
Level test scores	432.39	488.26	501.64	0.00	0.00	0.02
Unadjusted score gains	64.99	58.28	60.18	0.00	0.00	0.29
Adjusted score gains	-8.14	2.12	6.62	0.00	0.00	0.01
Teacher/student	0.10	0.07	0.08	0.00	0.00	0.00
Non-teacher/student	0.04	0.03	0.04	0.00	0.00	0.00
Capital/student	3.43	3.52	3.71	0.77	0.13	0.53
Net income/student	17.88	12.95	14.51	0.00	0.00	0.00
ICSEA	903.10	1034.94	1084.52	0.00	0.00	0.00
NESB rate	17.38	11.94	20.88	0.08	0.05	0.00

Notes: P-values are obtained from t-tests of the null hypothesis of no difference of means of variables. A statistically significant result indicates rejection of the null hypothesis.

The Bankwest Curtin Economics Centre is an independent economic and social research organisation located within the Curtin Business School at Curtin University. The Centre was established in 2012 through the generous support from Bankwest (a division of the Commonwealth Bank of Australia), with a core mission to undertake high quality, objective research on the key economic and social issues of relevance to Western Australia.

The Centre's research and engagement activities are designed to influence economic and social policy debates in state and Federal Parliament, regional and national media, and the wider Australian community. Through high quality, evidence-based research and analysis, our research outcomes inform policy makers and commentators of the economic challenges to achieving sustainable and equitable growth and prosperity both in Western Australia and nationally.

The Centre capitalises on Curtin University's reputation for excellence in economic modelling, forecasting, public policy research, trade and industrial economics and spatial sciences. Centre researchers have specific expertise in economic forecasting, quantitative modelling, microdata analysis and economic and social policy evaluation.

A suite of tailored and national economic models and methods are maintained within the Centre to facilitate advanced economic policy analysis: these include macroeconomic and time series models, micro(simulation) models, computable general equilibrium (CGE) models, spatial modelling methods, economic index analysis, and behavioural modelling methods.

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