Estimations of Educational Production Functions and Technical Efficiency of Public Primary Schools in Tasmania

by

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Submitted in fulfilment of the requirements for the Degree of Doctor of Philosophy in Economics

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Declaration

This thesis contains no material which has been accepted for the award of any other higher degree or graduate diploma in any university, and, to the best of my knowledge and belief, contains no material previously published or written by another person, except when due reference is made in the text of the thesis.

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Mohd Nahar Mohd Arshad
May 2012

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ABSTRACT

The study here examines the performance of Tasmanian public primary schools over the period of 2000 to 2007. The three principal objectives of the study are (i) to investigate the effects of school resources on students' academic achievement; (ii) evaluate schools' technical efficiency; and (iii) to identify the factors that affect the schools' technical efficiency. To explore the first objective, an educational production function is estimated. The second and the third objectives are examined by employing two techniques, namely, Stochastic Production Frontier (SPF) and Data Envelopment Analysis (DEA).

On the basis of the estimation of a Fixed Effects model of a Tasmanian educational production function, a one per cent increase in educational expenditure per student is associated with an increase in the reading, writing and numeracy scores of 0.38%, 0.36% and 0.43%, *ceteris paribus*. Male students' performance was on average lower than female students. Evidence of relatively lower performance by indigenous students was found. Students' performance was also negatively affected by their level of absenteeism. Positive effects of parental education on Tasmanian students' academic achievement were found but the effects of parental occupation were not statistically significant.

The SPF estimates suggest that Tasmanian public primary schools are almost technically efficient with the average technical efficiency score constant at 97% from 2003 to 2007. No technical efficiency change in the public primary educational sector in Tasmania over the period could be detected. The schools' technical inefficiency scores

were positively associated with students' suspension rates. Mothers' occupational status had a significant negative effect on technical inefficiency.

The average technical efficiency obtained under the DEA (assuming variable returns to scale) was constant at 95% over the study period (implying no technical efficiency change). On the basis of Tobit regression results, positive effects of parental occupation on technical efficiency were also found. The number of Aboriginal and Torres Strait Islander students; students who had English as a second language; the number of disability students; students' absenteeism rate and that a school was classified as rural all had a negative effect on technical efficiency.

Urban schools were found to be more scale efficient than rural schools. Lower scale efficiency for rural schools was due to non-optimal school size (due to remote location and low population density).

The efficiency rankings of schools based on the SPF and DEA methods vary due to (i) the different ways the SPF and DEA discriminate between schools in the construction of the production frontiers, and (ii) the different methodologies SPF and DEA apply to control for environmental factors.

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1 Introduction

1.0 A Brief Overview

Over the past 10 years, Tasmanian education has been marked by rising concerns over declining student performance in literacy and numeracy. The *Progress Report 2008*, by the Progress Board Committee of Tasmania Together (2008), for example, revealed that the *Tasmania Together Goals and Benchmarks* in education for literacy and numeracy of primary schools for 2005 had not been met. The Board also warned that the targets for 2010 were unlikely to be achieved (Tasmania Together Progress Board, 2008).[1] Rising community concern over the poor performance of students has put consecutive Ministers of Education[2] under scrutiny.

One suggestion to fix the problem of low students' academic achievement has been to provide more resources to schools, as voiced by various interested parties (such as parents, teachers and some politicians) in Tasmania. The State Government, however, has faced budgetary constraints in meeting the demand for more resources. In fact, there has been a declining trend in real educational operation expenditure in Tasmania from 2000 to 2007.[3] Interestingly, the decline in educational expenditure coincided with the decline in literacy and numeracy performance in Tasmania. It is well-known, however, that correlation does not imply causation. The observation raises an important question; does educational expenditure matter in affecting Tasmanian students' academic achievement.

[1] The Board is an independent statutory authority that reports directly to the State Parliament.
[2] For the study period—from 2000 to 2007, Tasmania had two Ministers of Education, namely, Paula Wriedt (September 1998-April 2006) and David Bartlett (April 2006-February 2010). In the media the position was regarded as something of a poisoned chalice.
[3] The real expenditure decreased by -9.4% between 2003/04 to 2004/05, but from 2004/05 to 2005/6 rose by 12.08%, before declining again in the following financial year by -14.65% (Tasmania Together Progress Board, 2008).

One serious issue surrounding the demand for more resources to schools is the lack of informed debate as to whether educational expenditure significantly affects Tasmanian students' academic performance and whether the investment made in Tasmanian education has been efficient. To the best of my knowledge, there is no published research and systematic study of the issue within the Government itself. To help policymakers intervene effectively, there is an urgent need to address the whole issue.

In order to explore the issue, three empirical methods are employed. The first method examines the relationship between educational inputs and educational outputs based on the framework of educational production function. In terms of the extant literature that deals with the estimation of an educational production function, the research here is unique in that the estimation is made using student-cohort level panel data. The second method involves an estimation of a Stochastic Production Frontier (SPF). The method is employed in order to evaluate the level of technical efficiency of Tasmanian public primary schools. The third method is based on Data Envelopment Analysis (DEA). I employ the DEA as another way to measure the level of schools' technical efficiency. Accordingly, the SPF and DEA are employed in measuring the level of technical efficiency in order to ensure the robustness of the evaluation.

1.1 Statements of Issue and Motivation

In this section, I discuss further the importance of the research, which seeks to identify the determinants of students' academic achievement and evaluates the level and the determinants of school efficiency in Tasmania. A major policy objective of the Australian Government is to ensure that all students attain sound foundations in literacy and numeracy. In 1997, all State Education Ministers agreed to a National Literacy and

Numeracy Plan that provides a coherent framework for achieving improvement in student literacy and numeracy outcomes. The 1999 *Adelaide Declaration of National Goals for Schooling in the Twenty-First Century* contains the national literacy and numeracy goals. In 2005, the Tasmania Together Progress Board identified that improvement in literacy and numeracy to be among the main concerns of people in Tasmania (Tasmania Together Goals and Benchmarks, 2006).[4]

In *The 2006 Progress Report*, the Progress Board Committee of Tasmania Together (2006) revealed that the goals and benchmarks for literacy and numeracy of primary schools for 2005 had not been met. The target for Tasmanian students for Year 3 was 98% of the national benchmark in reading and numeracy. The 2005 actual achievement, however, fell short by 3.1 percentage points for reading and 6.8 percentage points for numeracy. Similarly, the results for Year 5 in numeracy fell short by 8.9 percentage points of the 98% target set for 2005 (Tasmania Together Progress Board, 2006, p. 11). In *The 2008 Progress Report*, due to a significant variation in the literacy and numeracy performance of each Year[5] 3, 5 and 7 over the past 2004 to 2007, the Progress Board Committee of Tasmania Together (2008) described the performance of students in Years 3, 5 and 7 as inconsistent. The Progress Board Committee (2008) also warned that the set targets for 2010 were unlikely to be achieved (Tasmania Together

[4] Tasmania Together is a project that allows the people of Tasmania to say what they want, and work together to achieve their long-term social, economic and environmental future of Tasmania by 2020. The project sets goals for the future, and monitors the progress towards 12 goals and 143 benchmarks that reflect the concerns people expressed during two of the biggest community consultation processes ever undertaken in Tasmania (in 2000 and 2005). The Progress Board Committee monitors progress towards the achievement of the goals and benchmarks. The Board is an independent statutory authority that reports directly to the State Parliament.

[5] In this thesis, for the word ‘Year’ (with a capital Y) refers to the grade of schooling. The word ‘year’ (with a small y), on the other hand, refers to calendar year.

Progress Board, 2008). The findings point to a need for more attention to improve Tasmanian students' academic achievement.

Driven by the rising political and community concern about the level of students' academic achievement, there is a pressing need to investigate the determinants of literacy and numeracy of Tasmanian students. The identification of the variables that significantly affect students' literacy and numeracy performance is a crucial ingredient to a more informed debate about education policy in Tasmania. If the State Government wants to improve student performance, there is a need to understand where the dollars should be spent. Perhaps, some factors may simply out of reach of government policy. In the analysis, I will discriminate between the effects of the discretionary and non-discretionary determinants of students' academic achievement. The discrimination of the effects provides crucial information for policymakers to prioritise any intervention policy and to understand what is part of the feasible set. Since budgetary resources are scarce, I also investigate the level of school technical efficiency and the determinants of technical efficiency of schools in Tasmania. Whether the investment in education has been efficient, is another crucial issue to be addressed because of the State Government's budgetary constraints. The answers to these questions are vital in helping policymakers to plan for schools to become more efficient given the available resources.

This research is undertaken within the context of public primary schools in Tasmania. The focus is on the primary schools because that stage of schooling is critical when the objective is to develop strong literacy and numeracy skills (Masters & Margaret, 1997; Frigo & Isabelle. 2002; Rothman, 2002). In the next section, I outline the objectives of the research.

1.2 Objectives of Research

The discussion so far suggests that there are three principal objectives of the research, namely:

i) To identify the determinants of students' academic achievement, in particular, the effects of education expenditure on students' academic achievement.

ii) To evaluate the level of technical efficiency of public primary schools in Tasmania.

iii) To identify factors that affect schools' technical efficiency in Tasmania.

With the objectives in mind, the potential outcomes and contributions of the research are offered in Section 1.3.

1.3 Potential Outcomes and Contributions of the Research

The findings of the research are important as a source of reference for policymaking. On completion of the research, the Tasmanian educational production function will have been estimated. The purpose of the estimation is to identify the determinants of Tasmanian students' academic achievement. The effects of educational expenditure on students' academic achievement are of particular interest to the study. With such knowledge, the Department of Education is in a better position to make an informed intervention policy to improve students' academic achievement. An evaluation of the effects of other variables on students' academic achievement is also of equal importance to the study. With more understanding of the factors that affect students' academic achievement, more effective and specific intervention policies could be better designed by the Department of Education.

Another potentially important contribution of the research is to assess the level of technical efficiency of public primary schools in Tasmania. The aim of the exercise is to address questions such as: (i) Are schools in Tasmania efficient in utilising the allocated educational resources in terms of improving schools' performance? (ii) Which schools are efficient/inefficient? (iii) By how much do the inefficient schools need to improve their performance in order to catch up with the efficient schools? (iv) Does the socio-economic background of the school affect school efficiency? To answer such questions, I will apply Stochastic Production Frontier (SPF) and Data Envelopment Analysis (DEA).

In addition, a comparison of the application of SPF and DEA approaches to the questions at hand will be offered. While both approaches provide measures of efficiency, strengths and weaknesses of each approach in providing robust efficiency evaluation will be analysed. In the next section, the broad structure of the research is outlined.

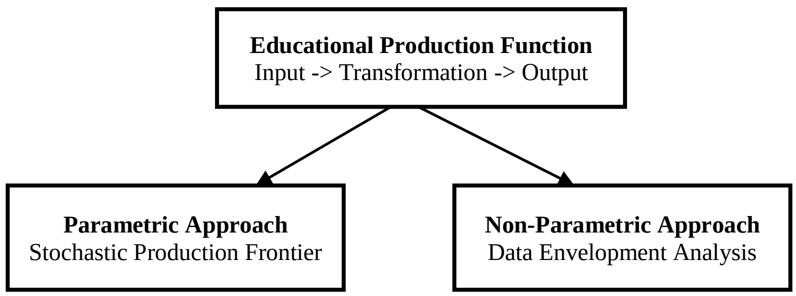
1.4 Structure of the Research

The research consists of seven chapters. This introductory chapter sets out the debates on Tasmanian education, provides statements of the issues, objectives of the research and potential contributions of the research. This chapter is important because it establishes the lines of inquiry and direction of the research.

In Chapter 2, I survey the performance of Tasmanian students' in literacy and numeracy from 2000 to 2007, examine the level of public investment in education for the period and review the studies that have investigated the performance of Tasmanian students' literacy and numeracy. The chapter is important in providing background details of the educational system in Tasmania, emphasising the urgent need for better understanding of the relationship between public discretionary measures and students' academic achievement.

In Chapters 3 and 4, literature reviews of educational production functions and frontier efficiency techniques are offered. Both chapters are important in probing the major limitations of, and gaps in, the approaches, so that a proper selection of technique and a choice of method can be made. The mathematical specifications of educational production function are specifically reviewed in Chapter 3. The concept, models and empirical evidence of educational production functions are also discussed. A review of techniques used to evaluate school efficiency, namely, Stochastic Production Frontier (SPF) and Data Envelopment Analysis (DEA) follows in Chapter 4.

Figure 1.1: Development of Techniques to Measuring School Technical Efficiency



To measure technical efficiency of schools, two popular approaches have emerged: (i) the econometric (parametric) approach, based on Stochastic Production Frontier (SPF), and (ii) the linear programming (non-parametric) approach, based on Data Envelopment Analysis (DEA). Measurement of technical efficiency[6] of schools is only possible when the production technology underlying an education system is identified. In Figure 1.1, the development of the techniques used to measure technical efficiency is

[6] The terms technical efficiency and technical inefficiency are two sides of one coin. Both terms can be used interchangeably. Under the application of the SPF, the term technical inefficiency is normally used because the error term is divided into noise and inefficiency effects. Under the application of DEA, on the other hand, the term technical efficiency is more common since the linear programming of DEA is set to calculate technical efficiency.

illustrated. The research on educational production functions (the upper box in Figure 1.1) sets out the production technology that underlies educational input-output relationships. From there, the two techniques used to measure technical efficiency of schools have emerged. The underlying theory for both the parametric and non-parametric techniques is based on the economic production model as established under the educational production function. The difference between the reviews in Chapter 3 as compared to Chapter 4 (and between the estimations undertaken in Chapters 5 and 6) rests on the level of aggregation. The review in Chapter 3 and the estimation of educational production function in Chapter 5 are based on student-cohort level data while the review in Chapter 4 and the estimation of efficiency in Chapter 6 are based on school-level data. The two approaches used across Chapters 5 and 6 allow an assessment of student-cohort level effects and school effects on academic performance.

In Chapter 5, the techniques found appropriate in Chapter 3 are applied to the estimation of Tasmanian educational production function. The evaluation of technical efficiency of public primary schools in Tasmania follows in Chapter 6. In the chapter, there is also an investigation of the determinants of schools' technical efficiency. The theoretical foundation and strategies discussed in Chapter 4 are applied to the estimation of technical efficiency of Tasmanian schools based on the SPF and DEA. In the last chapter, Chapter 7, I venture some tentative policy recommendations, emphasise the limitations of the research and suggest possible directions for future research.

2 A Survey of Tasmanian Students' Academic Achievement

2.0 Introduction

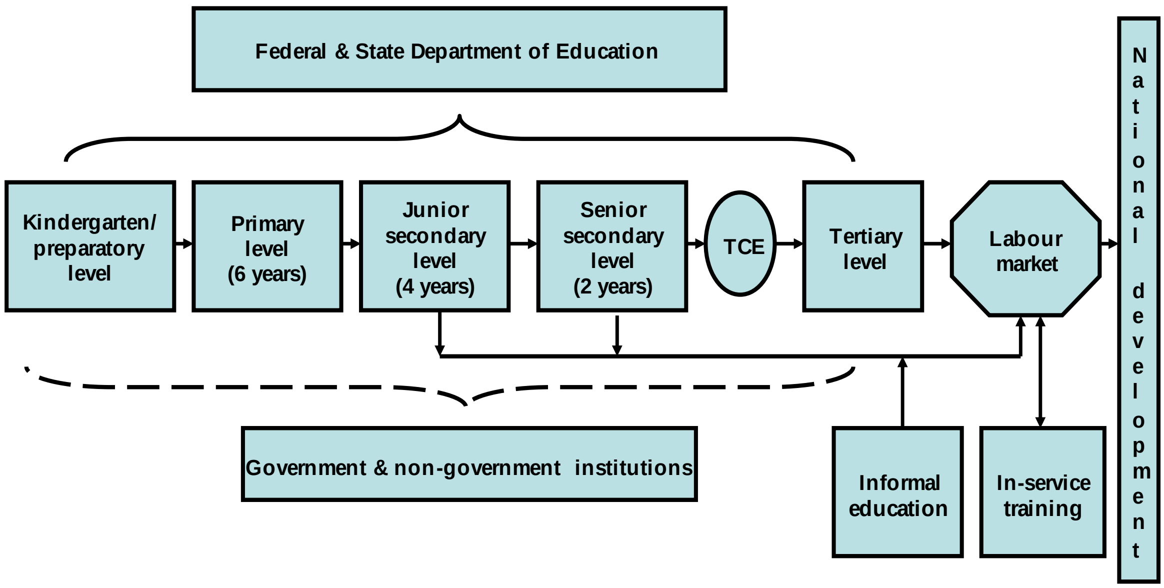
An analysis of Tasmanian students' achievement and the State Government's commitment towards education is presented in this chapter. The aim is twofold. First, the chapter provides insight into issues that have sparked the motivation to undertake this research. Second, the chapter emphasises the direction of the research, highlighting the need for an economic analysis to better understand Tasmanian students' literacy and numeracy performance.

Here I provide an outline of the chapter. In Section 2.1, an overview of Tasmanian education system is provided in order to familiarise readers with the institutional setting upon which the research is undertaken. The evaluation of literacy and numeracy performance is given in Section 2.2. The central focus of the section is to assess the trend in literacy and numeracy performance of Tasmanian students. An evaluation of the level of public investment in education is offered in Section 2.3. The degree of government commitment to improve student academic achievement via discretionary measures is evaluated in the section. In Section 2.3, a review of the extant literature on literacy and numeracy performance in regard to the Tasmanian case is explored. In Section 2.5, the conclusion of the chapter is offered.

2.1 Tasmanian Education System

In this section, I provide a brief overview of the Tasmanian education system. As explained in Chapter 1, the focus of this research is to evaluate the performance of primary school students in Tasmania. In order to understand the context within which the research is undertaken, the institutional setting of Tasmanian education system is described below.

Figure 2.1: Tasmanian Education System



Note:
TCE = Tasmanian Certificate of Education.

An overview of the Tasmanian education system is illustrated in Figure 2.1. Education in Australia is a shared responsibility between the Federal and State governments.[1] Under the Tasmanian education system, pre-school or kindergarten

[1] Constitutionally, in Australia, education is a responsibility of the States. Over the years, since education has become a major national issue in economic and social development, there has been a significant involvement of the Federal government. Payments by the Federal government to the States, for example, come with conditions on the purposes to which those funds may be utilised. As a result, education funding and policy has become a shared responsibility between the Federal and State governments. Refer to Department of the Premier and Cabinet, Victoria (2004, pp. 12-15) for more details of the roles between the Federal and State governments.

commences from the age of four.[2] Compulsory schooling starts at age six (Year 1) until age 16 (Year 10). Primary schooling is from Year 1 until Year 6, and junior secondary schooling is from Year 7 until Year 10. After completing Year 10, students may join the job market but most[3] students continue their education to the senior secondary level.

Students enrolling into senior secondary education (Years 11 and 12) need to choose between the academic or polytechnic pathway. The two pathways provide students with an early exposure to the subjects related to their future educational and career options (such as engineering, economics or arts under the academic pathway, and music, nursing, and hairdressing under the polytechnic pathway). Institutions that provide senior secondary education are the Tasmanian Academy, senior secondary colleges and the Tasmanian Polytechnic. Upon completing of the senior secondary level, successful students receive the Tasmanian Certificate of Education (Department of Education, Tasmania, 2008). Students then may choose either to join the job market or continue onto the tertiary education. Enrolment into tertiary education depends on tertiary entrance (TE) score or equivalent.

In 2008, the Department of Education, Tasmania, had 206 public schools under its authority. Of that total, there were 139 primary schools, 31 secondary schools, and 27 combined schools that provide education to 75 per cent of the students. The remaining students attend non-government (Catholic and independent) primary and secondary schools (Department of Education, Tasmania, 2009, p. 13). With the overview of the

[2] In Tasmania, early childhood education starts with kindergarten or pre-school (non-compulsory). It is offered to children aged four to five. Following the kindergarten year is a preparatory year (prep) before Year 1. Children who are five (minimum age of five years as at Jan 1st) to six years old attend the preparatory session. The preparatory year is also not compulsory but enrolment is almost universal. The curriculum is linked to the primary curriculum, with a focus on literacy, numeracy, physical skills, and personal and social skills (Department of Education, Tasmania, 2008).

[3] The retention rate of full-time Tasmanian students from Year 7 to Year 12 was 65.4% in 2007, compared to 58.6% in 1997 (ABS, 2009).

Tasmanian education system in mind, the performance of Tasmanian students in literacy and numeracy from 2000 until 2007 is analysed in the next section.

2.2 Literacy and Numeracy Performance of Tasmanian Primary Schools

The aim of this section is to evaluate the performance of Tasmanian primary students in literacy and numeracy from 2000 until 2007. Focus is given to the achievement of students in Years 3, 5 and 7 because an annual national assessment is given to all students in those years of schooling[4]—there is no such assessment at Years 1, 2, 4 and 6.

One goal of the Tasmania Together 2020 Project is to ensure that students are given a high quality education and training with the aims to promote lifelong learning and to provide a skilled workforce (Tasmania Together Progress Board, 2006).[5] High literacy and numeracy targets[6] have been set to realise the goal.[7] From 2000 until 2007, an evaluation of literacy and numeracy performance was based on the proportion of Tasmanian students who achieved national benchmarks in reading, writing and numeracy tests.[8] The measure of the performance took a student's test result and compared it

[4] Although Year 7 falls under the lower secondary school level, I include that level in the analysis in order to provide a better perspective of primary students' achievement. Note the inconsistency—see Section 5.2.3.c for further discussion.

[5] To realise the goals, targets and benchmarks have been established. In order to establish the targets, the Benchmarking Committee of Tasmania Together works with Australian Bureau of Statistics, relevant State Government agencies and other relevant key stakeholders. The Board then circulates the draft proposal of targets and benchmarks to key stakeholders for consultation and place the draft for public comment on the Tasmania Together website. After taking into account the relevant comments from the consultation, the Board makes recommendations to the Tasmanian Parliament on the benchmarks for the Parliament to accept or reject them (Tasmania Together Progress Board, 2007).

[6] Refer to Sections 2.2.1 and 2.2.2 for details about the targets.

[7] Literacy and numeracy scores are a common measure of school or student academic achievement. In Section 2.3, a few examples of how educationists have used the measure in their research are discussed. The measure also has been used by economists in their research (see Chapters 3 and 4).

[8] Other educational performance indicators used were: (i) proportion of children meeting the Kindergarten Development Check, (ii) proportion of persons (15-74) who were considered to be functionally literate, (iii) retention from Year 10 to 12, (iv) proportion of Tasmanians with high level skills/qualifications (Certificate III +), (v) participation in post-secondary education and training, and (vi) number of Tasmanians commencing apprenticeships and traineeships (Tasmania Together Progress Board, 2006).

against nationally sampled student control groups (Tasmania Together Progress Board, 2006). A national benchmark was established. Performance below the benchmark means a student would have great difficulty proceeding to the next level of schooling (Ministerial Council on Education, Employment, Training and Youth Affairs [MCEETYA], 2000).

A new assessment program, however, commenced in 2008, known as the National Assessment Program–Literacy and Numeracy (NAPLAN). All students in Years 3, 5, 7 and 9 were assessed using national tests in reading, writing, language conventions (spelling, grammar and punctuation) and numeracy.[9] Accordingly, there are two different sets of results of performance evaluation. The performance measure used from 2000 to 2007 was not comparable with the performance measure under NAPLAN (MCEETYA, 2008).

In order to utilise a longer time span, I employ the assessment from 2000 until 2007 and put aside the data from NAPLAN.[10] Two advantages of having a longer time span for the dataset are: (i) the possibility to construct a panel dataset (if observations are collected on the same sample of respondents over a period of time), and (ii) a larger dataset can also be constructed (for example by pooling data).[11]

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[9] From 2000 to 2007, no standardised examination papers were given to students in Australia. In other words, every State had its own set of examination papers. Under NAPLAN, however, examinations were standardised across all States.

[10] The assessment based on NAPLAN only provided me with a one year of observations when I started this research in 2008.

[11] In Chapter 5, I utilise both the advantages of having longer time span of data when I employ a panel data and a pooled data for my econometric estimations.

2.2.1 Literacy (Reading and Writing) – Tasmanian Students' Performance against National Benchmark

An evaluation of literacy performance for Years 3, 5, and 7 of Tasmanian students is discussed here. An important aspect of literacy is emphasised in a policy paper entitled *Literacy for All: the Challenge for Australian Schools* (Department of Employment, Education Training and Youth Affairs [DEETYA], 1998). It outlines policies for Australian schools, where acquiring foundational skills in reading and writing is the key principle for a successful literacy program.

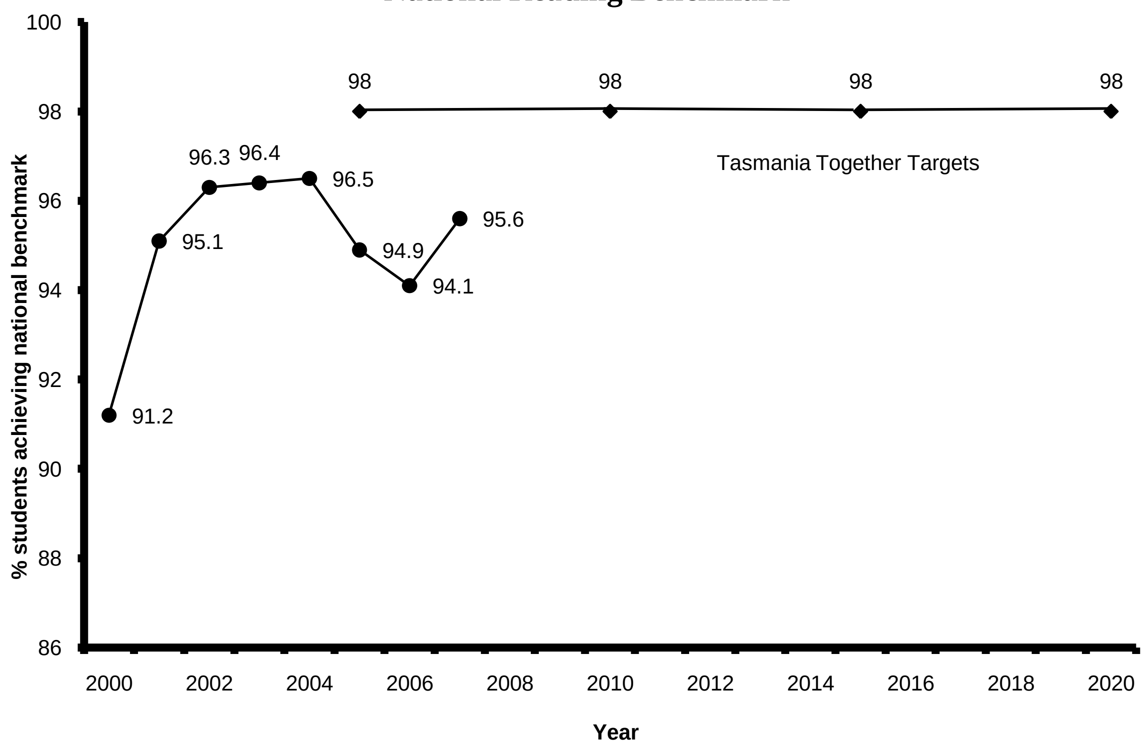
To offer an evaluation of the literacy performance of Tasmanian students, their reading performance is illustrated in Figures 2.2, 2.3 and 2.4 and their writing performance is shown in Figures 2.5, 2.6 and 2.7. I construct each figure by plotting two separate sets of information (the percentage of Tasmanian students who had achieved the national literacy benchmark, and the 5-year achievement target[12] of the Tasmania Together 2020 Project) in a line chart for a convenient comparison. From the figures, some worrisome trends can be observed. In the case of reading, of the three grades where benchmarks were set, only students in Year 5 had surpassed the Tasmania Together target for 2005, and were on course to meet the 2010 target (see Figure 2.3). Year 3 students had failed to meet the reading target for 2005. As shown in Figure 2.2, the reading target for Year 3 in 2005 was 98% but the actual achievement in reading was only 94.9%. The Progress Board Committee of Tasmania Together (2009, p. 5) also warned that the reading target for 2010 for Year 3 was unlikely to be achieved. No reading target for 2005 was set for students in Year 7, but from 2004 until 2007, a declining trend in their

[12] To ensure the long-term targets in Tasmania Together 2020 are achieved, the 5-year achievement target provides a medium-term goal. In every five years, the Progress Board Committee of Tasmania Together evaluates the current education performance (and other areas in Tasmania Together goals) against the five-year achievement target. **T**he first five year review of Tasmania Together was undertaken in 2005-06.

reading performance could be observed from Figure 2.4. Further, according to the Progress Board Committee (2009, p. 5), the target for 2010 for Year 7 in reading was unlikely to be achieved.

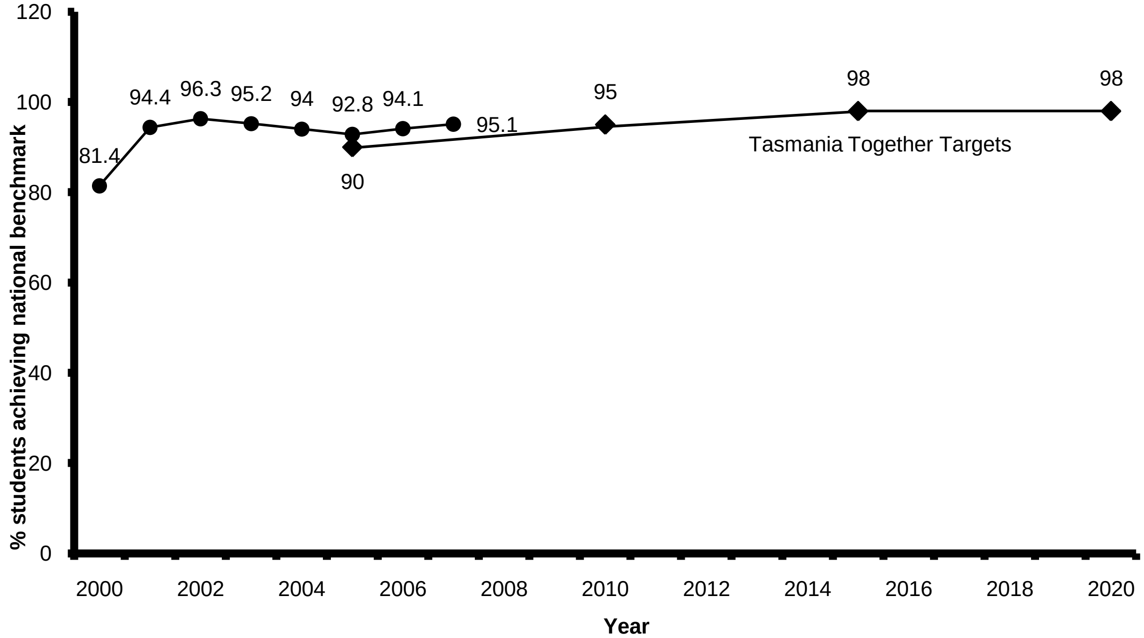
As shown in Figures 2.5, 2.6 and 2.7, declining trends in writing performance against the national benchmark were also observed from 2004 until 2007 for students in Years 3 and 7. Students in Year 5, however, had met the 2005 writing target but did not appear to be on course to meet the 2010 target. The Progress Board Committee of Tasmania Together described the performance of all Year 3, 5 and 7 in reading and writing as inconsistent, and warned that the targets for 2010 (except for Year 5 in reading,) were unlikely to be achieved (Tasmania Together Progress Board, 2009, p. 5).

Figure 2.2: Year 3 Tasmanian Students' Performance against National Reading Benchmark



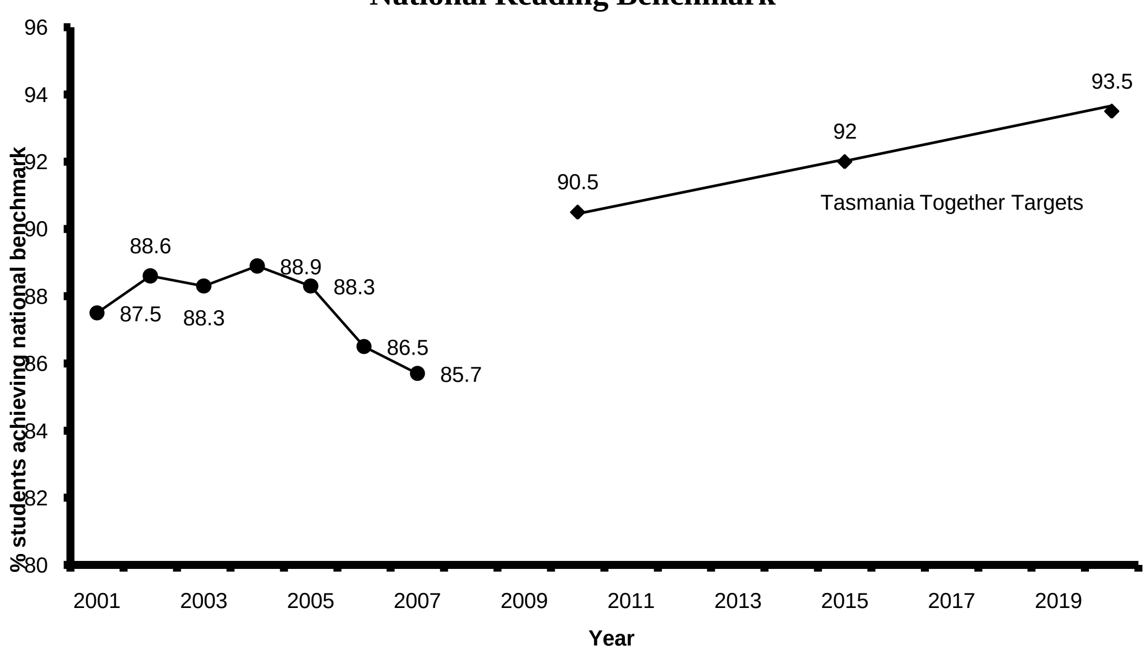
Source: Tasmania Together Progres Board,

Figure 2.3: Year 5 Tasmanian Students' Performance against National Reading Benchmark



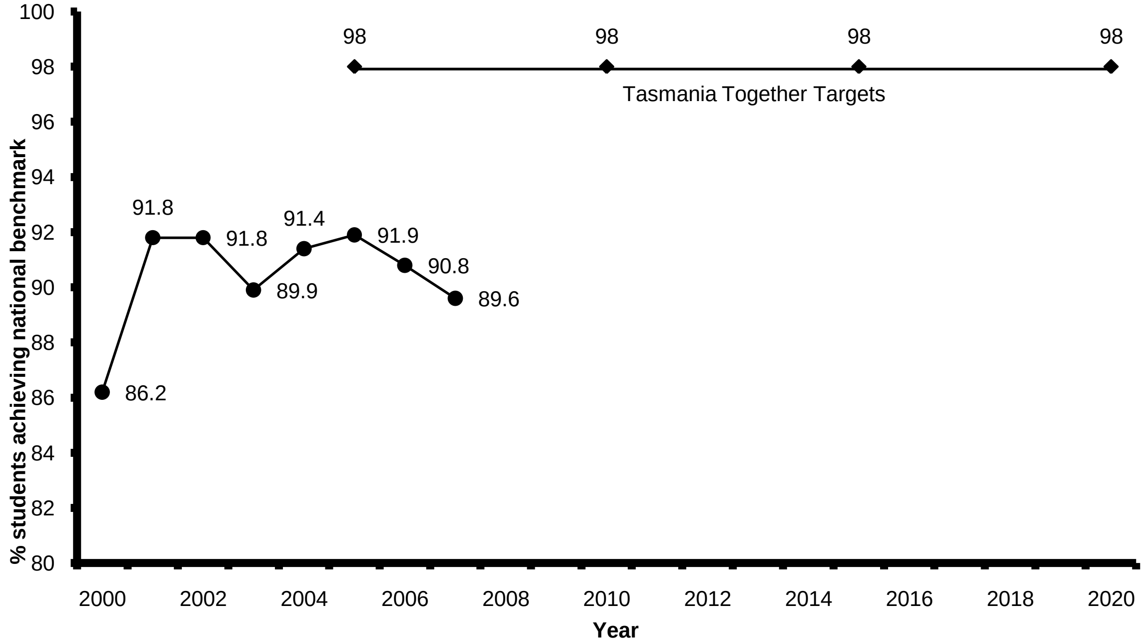
Source: Tasmania Together Progres Board, 2008

Figure 2.4: Year 7 Tasmanian Students' Performance against National Reading Benchmark



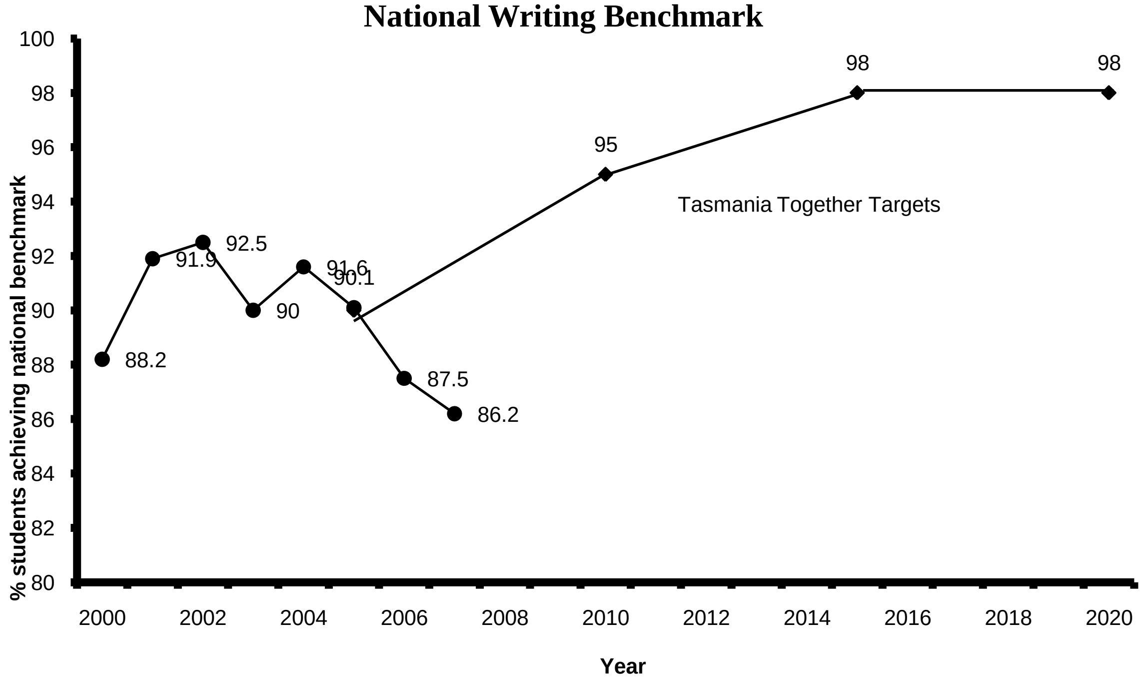
Source: Tasmania Together Progres Board, 2008

Figure 2.5: Year 3 Tasmanian Students' Performance against National Writing Benchmark



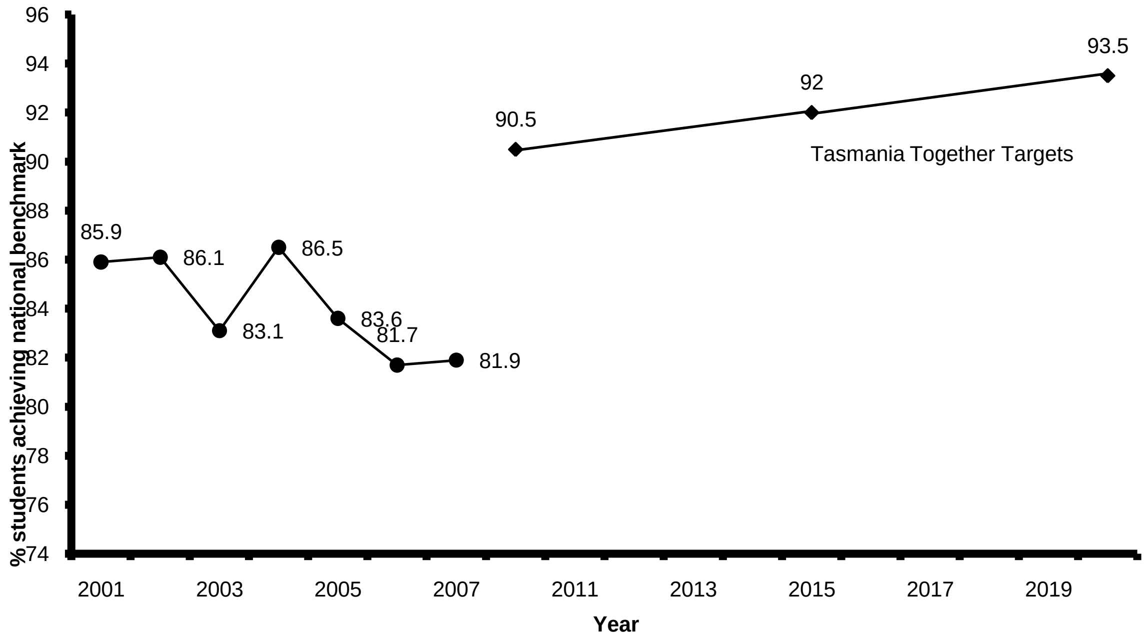
Source: Tasmania Together Progres Board, 2008

Figure 2.6: Year 5 Tasmanian Students' Performance against National Writing Benchmark



Source: Tasmania Together Progres Board, 2008

Figure 2.7: Year 7 Tasmanian Students' Performance against National Writing Benchmark



Source: Tasmania Together Progres Board, 2008

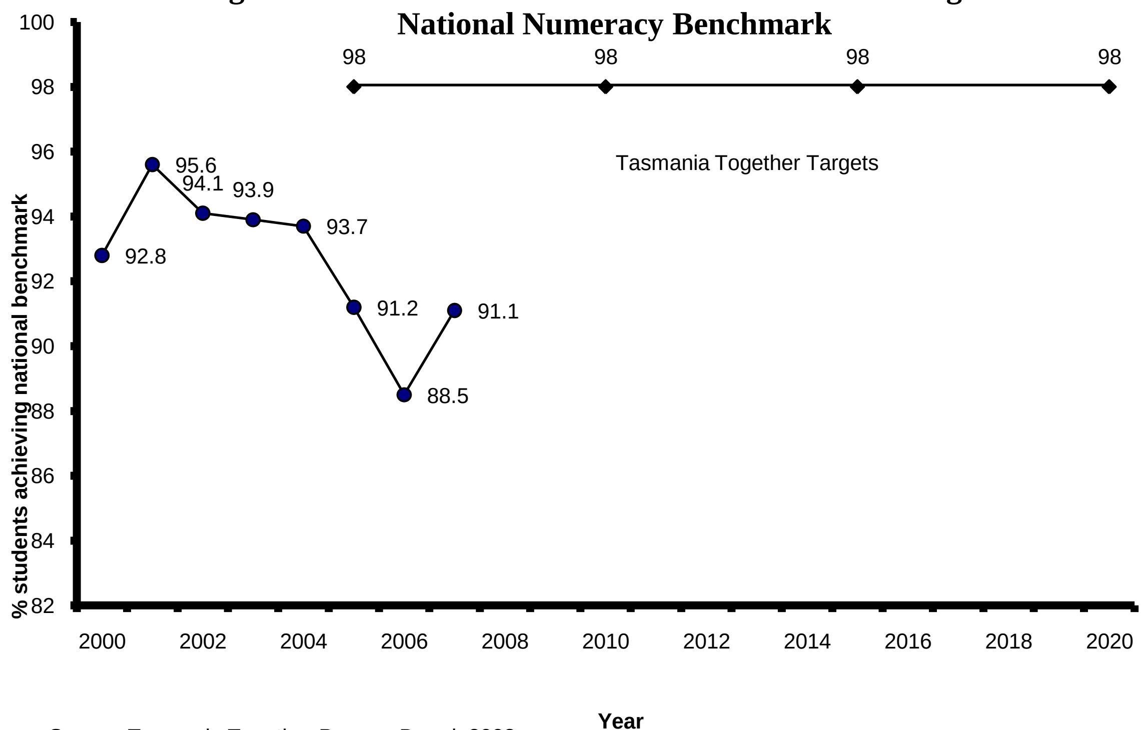
2.2.2 Numeracy – Tasmanian Students' Performance against National Benchmark

Numeracy performance of Tasmanian students for Years 3, 5, and 7 is illustrated in Figures 2.8, 2.9 and 2.10. In the figures, the proportion of students who achieved the national numeracy benchmark is graphed together with a 5-year-achievement target of the Tasmania Together 2020 Project. From the figures, simple inspection suggests that the performance of Tasmanian students in numeracy is below the Tasmania Together 2020 goals. In Figure 2.8, for example, the 2005 Tasmania Together target for Year 3 in numeracy was 98% but performance fell short by 6.8 percentage points. Although the Year 3's numeracy performance for 2007 had increased by 2.6 percentage points from 2006, the recorded decline of 7.1 percentage points from 2001 to 2006 was larger than the rise, suggesting declining performance overall. In Figure 2.9, the results for Year 5 in numeracy fell short by 8.9 percentage points of the 98% target set for 2005 (Tasmania

Together Progress Board, 2006). Moreover, according to a 2009 report, the Progress Board Committee of Tasmania Together warned that the numeracy targets for 2010 were unlikely to be achieved (Tasmania Together Progress Board, 2009).

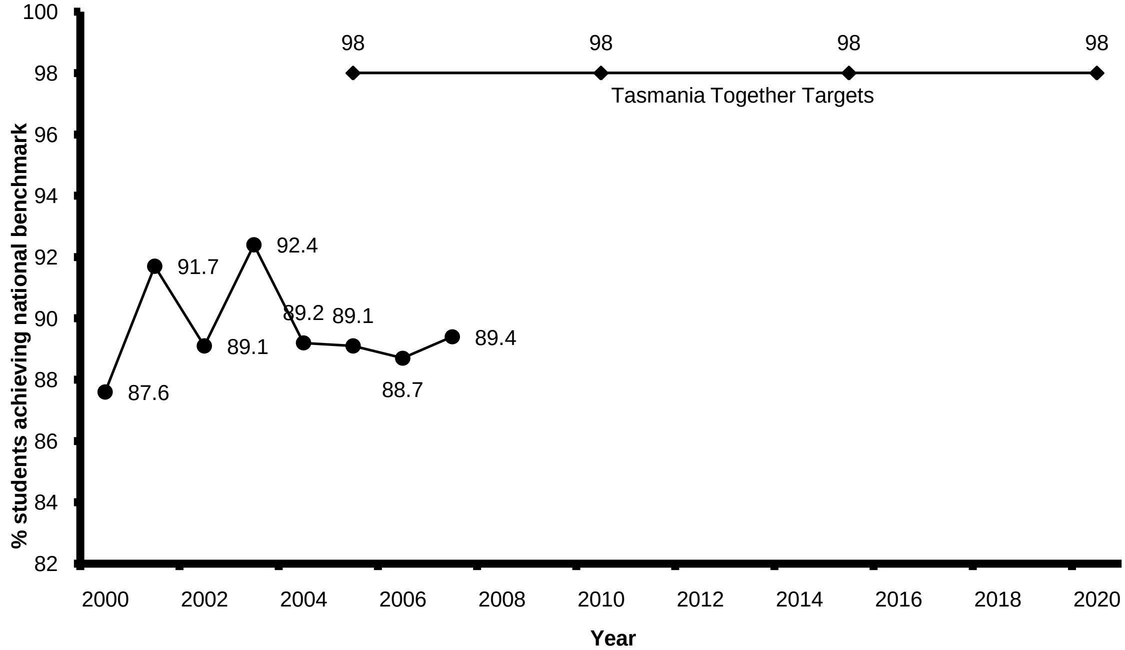
For students in Year 7, no numeracy target was set for 2005 but the target for 2010 was 90.5% (see Figure 2.10). On average, the proportion of students in Year 7 who achieved national benchmark in numeracy from 2001 to 2007 was only 80.84 %. Given the trend, the 2010 target was unlikely to be achieved (Tasmania Together Progress Board, 2009).

Figure 2.8: Year 3 Tasmanian Students' Performance against National Numeracy Benchmark



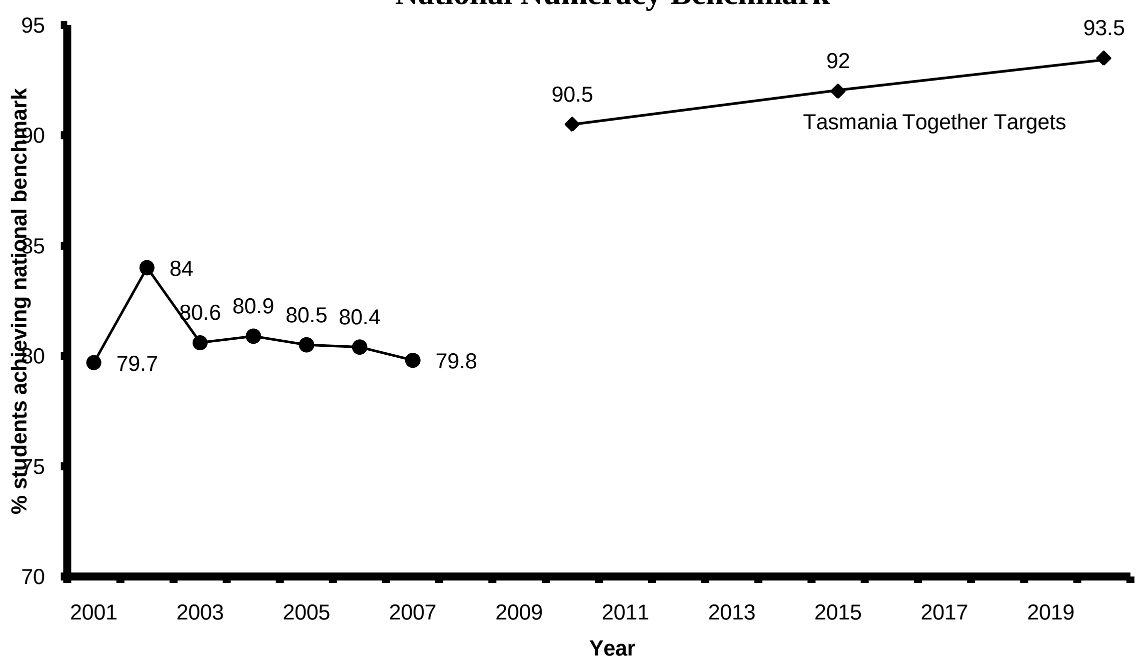
Source: Tasmania Together Progres Board, 2008

Figure 2.9: Year 5 Tasmanian Students' Performance against National Numeracy Benchmark



Source: Tasmania Together Progres Board, 2008

Figure 2.10: Year 7 Tasmanian Students' Performance against National Numeracy Benchmark



Source: Tasmania Together Progres Board, 2008

There are two points worth emphasising from the discussion in sections 2.2.1 and 2.2.2. First, only Year 5 performance in literacy (reading and writing) had met the 2005 Tasmania Together targets. Second, the results for Year 3 and 7 in literacy, and Year 3, 5 and 7 in numeracy fell short of the 2005 targets set in *Tasmania Together Goals and Benchmarks* (2006). The failure to meet the set targets raises a question regarding the effectiveness of the State Government's educational policy. In the next section, I provide an analysis of public investment in education for the period 2000 until 2007 in Tasmania.

2.3 Public Investment in Tasmanian Education

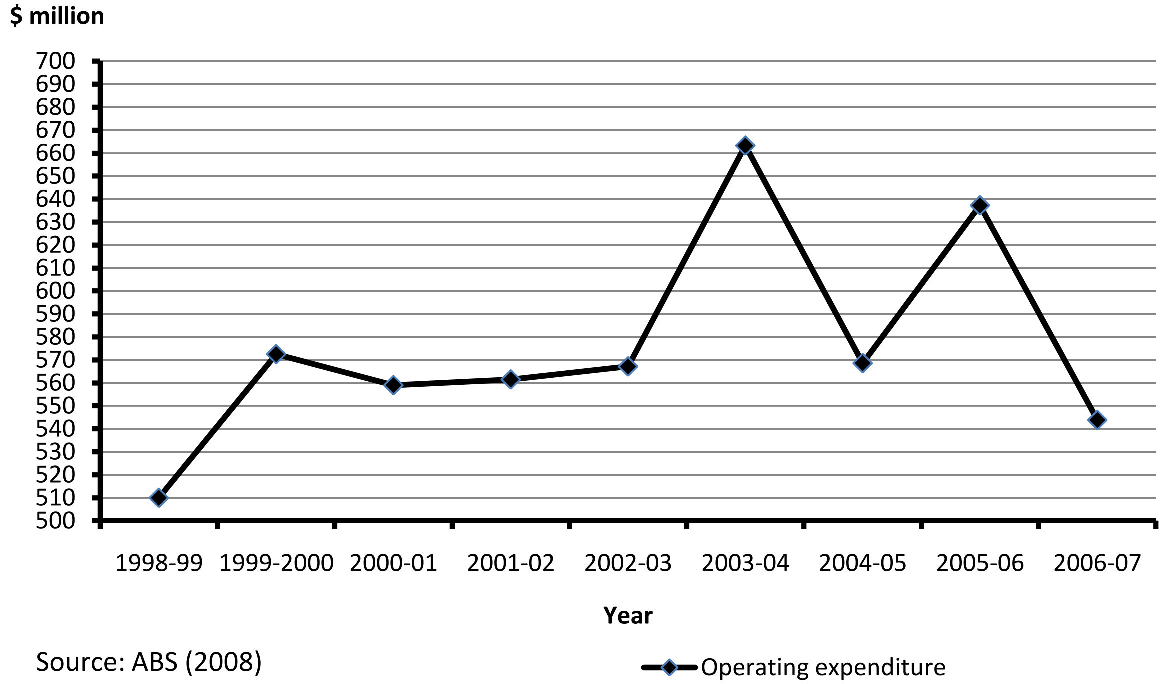
A call by the Australian Education Union (AEU) (2009) for more public funds to schools and for further reduction in class size seems to suggest that the low literacy and numeracy performance, as observed in Section 2.2, may be attributed to lack of public discretionary measures (such as public educational spending and class size) to schools. To confirm whether there has been a concerning trend in public discretionary measures to schools, I therefore investigate the level of public investment in Tasmanian education from 2000 to 2007 in this section.

Public funding to schools is one indicator of a government's commitment towards education. In Australia, investment in education is a shared responsibility between federal, state and territory governments. Funds are provided for two major categories of spending; (i) operational expenditure of schools such as employees' salaries, and (ii) gross fixed capital formation expenditure for items such as new school buildings and equipment (ABS, 2008).

The allocation of public funds under the real operating expenditure to public primary and secondary schools in Tasmania is shown in Figure 2.11. Real education operational expenditure[13] decreased by -9.4% between 2003/04 to 2004/05, but from 2004/05 to 2005/06 rose by 12.08%, before declining again in the following financial year by -14.65% (Tasmania Together Progress Board, 2008). In Figure 2.12, on the other hand, a line chart of real gross capital formation expenditure to public schools in Tasmania is shown. Between 2002/03 and 2003/04, real gross capital formation expenditure had declined by 89.14% (from $24.17 million to $10.86 million) before it rose again to $25.64 million in 2004/05. The marked instability of the two spending categories, in particular, during the period between 2003/04 to 2006/07 (as shown in Figures 2.11 and 2.12) coincided with the period during which the performance of Tasmanian students in literacy and numeracy declined—see Section 2.2. A widely held view (Jacques, 2002) is that more educational expenditure should lead to better student academic performance. Since no clear relationship between the provisions of educational expenditure and students' academic achievement is evident from the above observation, one of the primary objectives of this research is to investigate the relationship—is the widely-held view really evident in the Tasmanian case?

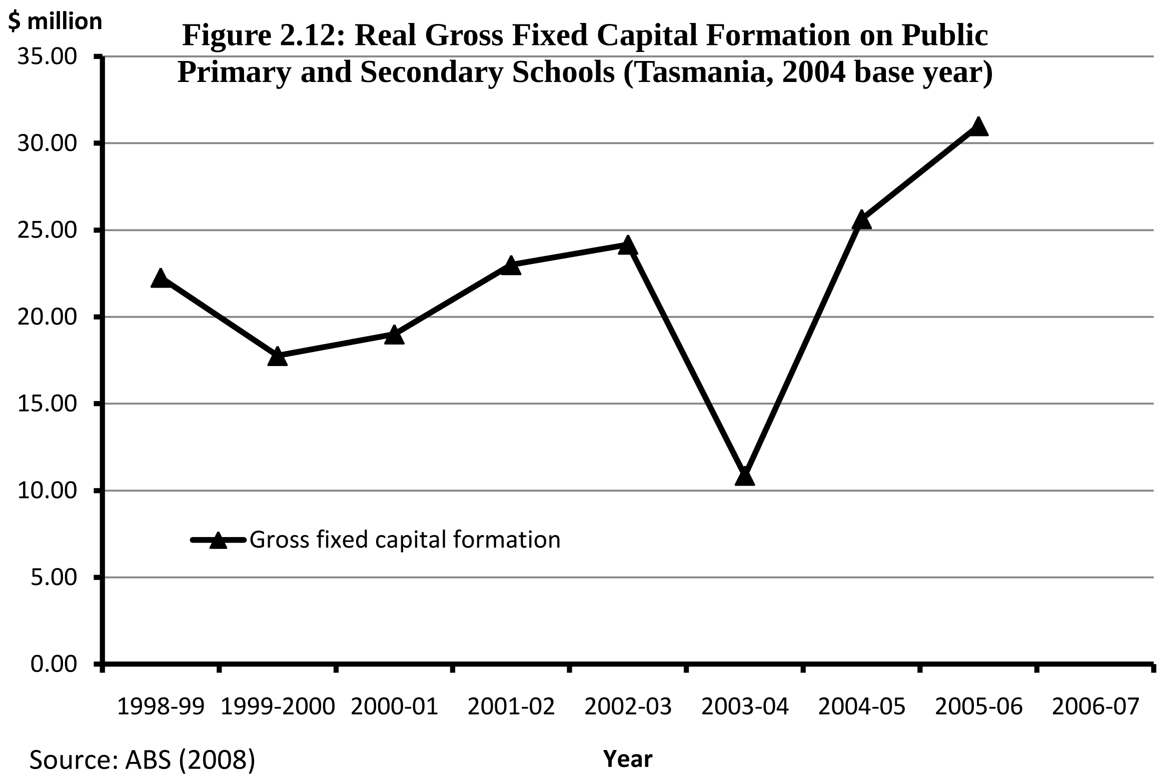
[13] Operational expenditures were categorised into employee expenses, non-employee expenses, depreciation, current transfer expenses and capital transfer expenses. About 60.9% of the total operating expenditure was for employee expenses (ABS, 2008).

Figure 2.11: Real Operating Expenditure on Public Primary and Secondary Schools (Tasmania, 2004 base year)



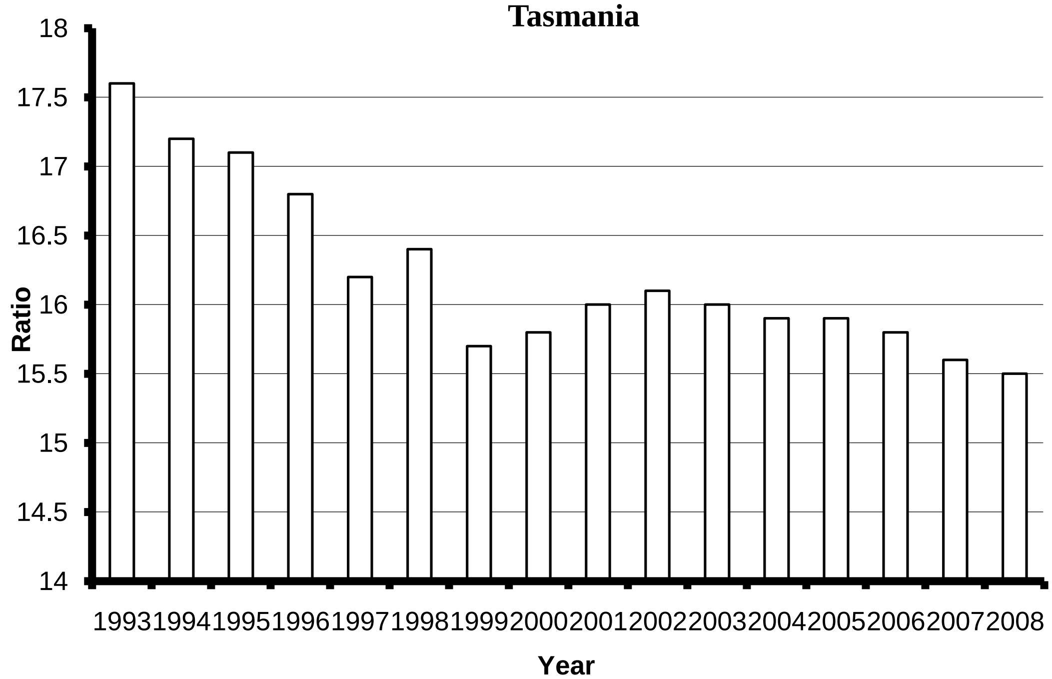
Source: ABS (2008)

Figure 2.12: Real Gross Fixed Capital Formation on Public Primary and Secondary Schools (Tasmania, 2004 base year)



Source: ABS (2008)

Figure 2.13: Student-Teacher Ratio of Public Primary Schools in Tasmania



Source: ABS (2008)

A reduction in class size is another popular educational policy pursued by policymakers (Dobbelsteen, Levin et al., 2002). The widely held hypothesis is that smaller classes result in better students' academic performance (negative relationship) because students can better engage with the learning process and teachers can give more attention to individual students. In Figure 2.13, the student-teacher ratio of Tasmanian public schools is taken as proxy[14] for class size. As shown in the figure, from 2002 until 2008, student-teacher ratio in Tasmania had in general declined. Based on the performance of Year 5 students in literacy, however, there was no clear support for the hypothesis at issue. The performance of Year 5 in writing (Figure 2.6), from 2005 to

[14] Another way to measure class size is to use the average number of students per class, calculated by dividing the number of students enrolled by the number of classes. I used student-teacher ratio as the measure of class size because the ABS used the measure in its report.

2007, for example, was declining in spite of a declining student-teacher ratio in the same period—suggesting a positive relationship. The performance of Year 5 students in reading (Figure 2.3), however, had increased for the same period (a negative relationship). With the awareness of the trend of the government discretionary measures (educational expenditure and class size) in mind, the next section explores the extant literature of Tasmanian-based studies in order to determine whether there is an explanation of the observed phenomena—relationships between the government discretionary measures and Tasmanian students' academic performance.

2.4 Tasmanian-based Studies on Literacy and Numeracy

Here I review the extant literature on the performance of Tasmanian students in literacy and numeracy. The primary aim of this section is to investigate whether the extant research has provided insight into why the literacy and numeracy performance of students in Tasmania has generally declined over the period 2000 to 2007 (see Section 2.2).

Most studies that have investigated literacy and numeracy performance of Tasmanian students examine the issue from an educationist perspective.[15] The studies relate students' academic performance to the effect of teaching techniques or methods (Watson & Kelly, 2004), teacher training (Beswick, 2008; Kertesz, 2007), information and communication technology (Webb, 2007), and school leadership (Mulford, 2005, Mulford et al., 2007).

[15] An educationist views the issue of students' academic achievement in terms of what is the most effective learning/teaching methods for knowledge transmission purposes, while an educational economist looks at the issue based on the cost-benefit analysis, taking feasibility issues seriously.

A study by Griffin and Callingham (2006), for example, found that Tasmanian students' achievement in numeracy was relatively unchanged over the period of 1978 to 1997. The focus of the study however, was to monitor the effect of the changing nature of numeracy tests given over the period. They found the construction of numeracy tests had not changed.

Boardman (2006) conducted a qualitative study to investigate the impact of age and gender on the academic results of five- and six-year-old students in Tasmanian schools. Evidence of age and gender effects was confirmed from Boardman's (2006) qualitative analysis. Younger children (aged 5.00–5.03 years at the time of the test) within the preparatory cohort performed significantly lower in the areas of mathematics and reading than their peers (cohort of Tasmanians) who were 6 to 11 months older. Girls achieved significantly higher results in reading and in the PIPS[16] total scores than the boys.[17] The method of questionnaire survey and interview adopted (involving preparatory class teachers from 38 schools) were prone to sample selection bias. A quantitative analysis involving a larger representation of students remains an unexplored avenue for further research.

Andrew, Beswick, Swabey, Barrett, Bridge, Louden and Rohl (2005) investigated the effectiveness of learning support on literacy and numeracy development of students with learning difficulties in the early and middle years of schooling in Tasmania. The qualitative study explored the connections between school system and teacher practices

[16] PIPS (Performance Indicators of Primary Schools) is a testing procedure mandated by the Tasmanian Department of Education for all children at the start of their year in Prep.

[17] Male students' mean scores in maths, reading and phonics were 33.73, 44.73 and 11.89. On the other hand, female students' mean scores in maths, reading and phonics were 34.64, 49.28 and 12.31 (Boardman, 2006, p. 6).

on literacy and numeracy.[18] Two sets of best-practice indicators taken for the study were: (i) school-level factors, based on indicators of Tasmania's Supportive school communities initiative (Department of Education, Tasmania [DoE, Tas.], 2002a), and (ii) teacher practices, based on Productive Pedagogies (Education Queensland, 2001) and Flying Start effective teacher practices from Tasmanian professional support materials (DoE, Tas., 2002b). Three key measures to improve literacy and numeracy that Andrew et al. (2005) recognised were: (i) effective school policy and programs implementation, (ii) clear design of organisational system to support into practice the policies and programs, and (iii) effective professional training for teaching staff. The research, however, failed to identify a clear educational input-output relationship, where the role of discretionary and non-discretionary variables remained undefined and quantitatively unmeasured.

I searched widely the extant literature on Tasmanian students' academic achievement and the reviewed studies were the most relevant published research on the issue. From the literature review conducted, to my knowledge, there has been no Tasmanian-based study to analyse students' academic achievement based on an economic modelling framework. Economic models can be used to shed some light on questions such as, what determines students' academic performance, and how efficiently educational inputs have been used. Answers to the questions are important for three reasons: (i) to understand the performance trend as observed in Section 2.2, (ii) to guide policymakers in their efforts to improve students' academic achievement, and (iii) to know whether educational resources have been utilised efficiently. The knowledge is important for a more informed debate on policy intervention in education planning.

[18] The analysis was based on surveys and interviews involving teachers from 49 schools.

2.5 Conclusion

The motivation to conduct this research was sparked by the observations made in Sections 2.2 and 2.3. The analysis of Tasmanian students’ literacy and numeracy performance (in Section 2.2) suggests a declining trend in students’ academic achievement in terms of the national benchmark from 2000 until 2007. This decline in literacy and numeracy performance coincided with the declining trend in real operational expenditure in Tasmanian education. The State Government was however, committed to reduce the class size as shown by a continuous decline in student-teacher ratios (proxy for class size). The observed situation is puzzling for two reasons: (i) if class size reduction is important, then why does student achievement decline? and (ii) what other factors are in play that may explain the worrying trends in student performance? The situation invites a thorough investigation of the factors that explain Tasmanian students’ academic achievement. The extant literature does not begin to answer the questions. From the review, I found that all the studies had approached the issue from an educationist perspective. An economic modelling framework to understand the phenomenon remained an unexplored avenue. In Chapters 3 and 4, economic models based on educational production functions and production frontier analysis will be discussed.

3 An Educational Production Function

3.0 Introduction

A review of the education production function literature is provided in this chapter. The discussion covers two important aspects of research development in the area. First, the various approaches used in the estimation of educational production functions, their strengths and weaknesses, are analysed. The main objective of the exercise is to arrive at a shared understanding of the appropriate approach to modeling primary educational production in Tasmania. Second, the general relationship between the input and the output of education is identified from the extant literature. An identification of the relationship is instrumental in terms of variable selection for the estimation of Tasmanian educational production function in Chapter 5.

The review starts with a discussion of the concept of an educational production function in Section 3.1. The various models of the educational production function found in the extant literature are examined in Section 3.2. Then, in Section 3.3, methodological issues that are often raised in the estimation of an educational production function are discussed. Empirical findings from the reviewed literature follow in Section 3.4. The conclusion of the chapter is presented in Section 3.5.

3.1 The Concept of Educational Production Function

Education can be considered to be analogous to a production process. In Figure 3.1, the process is illustrated. The figure shows the flow of how educational inputs are transformed into educational outputs. The transformation involves teaching and learning processes (education process) that usually takes place in formal institutions, such as schools and universities. The mathematical form of the process is commonly known as an educational production function.[1] It shows the relationship between alternative combinations of educational inputs and educational outputs, given a production technology.

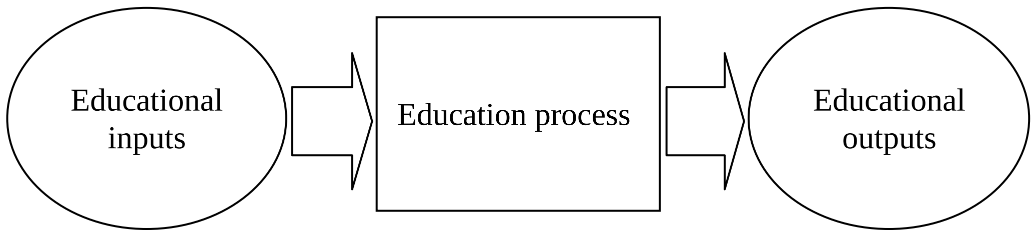
Educational output is typically measured by students' academic performance. Variables such as average test scores, the percentage of an enrolment progressing to the next level of education or the percentage of graduate employment are often employed to represent educational outputs. Educational inputs can be categorised into discretionary and non-discretionary inputs (sometimes referred to as control variables). They can be classified into four major factors namely: student/family background characteristics; peer or community influence; school resources and innate abilities.[2] Discretionary inputs involve variables within the direct control of schools/policymakers such as educational expenditure. Non-discretionary inputs, or also known as environmental factors, involve variables beyond the direct control of schools/policymakers but they may influence the educational output. An example of the non-discretionary input is a helpful peer who assists a student in his study. Within the four factors also, there are certain external variables that need to be control for, such as ethnicity, rural or urban status of schools and gender of a student.

[1] In the economics of education literature, the educational production function is also called the input-output or cost-quality method (Hanushek 1986, p. 1148). The existence of a production function is central to a study and practice of management and administration. A systematic understanding of the transformation of inputs into outputs enables researchers to calculate the level of production that is technically possible under given circumstances and the knowledge enables managers to allocate resources according to a firm's specific objective.

[2] See papers by Houtenville and Karen (2008), Mayston (2003), Monk (1989) and Hanushek (1979) for further elaboration of the relationship between inputs and outputs in educational production function.

Figure 3.1: The Educational Production Function

Educational output = f(educational input)



Schools/universities transform educational inputs into educational outputs

Research to find a statistically robust regression of an educational production function started with Coleman, Campbell, Hobson, McPartland, Mood and Weinfeld's (1966) study.[3] Since then, a considerable amount of research effort has been expended to estimate the parameters of the underlying production functions [see Houtenville and Karen (2008), Mayston (2003), Monk (1989) and Hanushek (1979)]. A few systematic relationships between educational inputs and educational outputs have been confirmed. The findings are discussed in Section 3.3.

3.2 Models of Educational Production Function

I provide a review of models of educational production function in this section. Four empirical models that can be considered central in the extant literature on

[3] The study is known as the Coleman Report. The Report is a national study involving 4,000 public schools in the U.S., which attempts to relate family background (including race and socioeconomic status) and school equity variables (including the integration of white and African-American children) to students' test results and their attitudes towards attending higher education. The Report finds that students' test outcomes are unrelated to the characteristics of schools (for example, the quality of school facilities, programs, and teachers). Instead, the improvement in academic results among minority children is significantly linked to the quality of the family background and students' characteristics—as measured by the proportion of students with encyclopedias in their home and the proportion with high aspirations.

educational production function are: (i) the contemporaneous education production model, (ii) the value-added model, (iii) the linear growth (or the gains) model, and (iv) panel data models. In this section, the models are analysed and their strengths and weaknesses are compared in order to recognise the appropriate method to modeling a Tasmanian educational production function.

A general empirical model of educational production function is presented before the three models are discussed. The general model sets a basic theoretical framework for the estimation of an educational production function. Following the conventional literature of education production,[4] student academic achievement depends on the combinations of current and past educational inputs. The process can be written as:

$$\mathbf{A}_{ijT} = f_T(\mathbf{F}_{ijT} \ldots \mathbf{F}_{ij0},\ \mathbf{P}_{ijT} \ldots \mathbf{P}_{ij0},\ \mathbf{S}_{ijT} \ldots \mathbf{S}_{ij0},\ \mathbf{I}_i) \tag{3.1}$$

where $\mathbf{A}_{ijT}$ represents a measure of achievement for the i^{th} student at school j at time T; capital letter T denotes the current time; small letter $t = 0$ corresponds to the time interval prior to the time the individual enters school, $t = 1$ corresponds to the first year of school, and $t = 2$ to the second year, and so forth. The notation $\mathbf{F}_{ijT}$ represents a vector of family background influences cumulative to time T; $\mathbf{P}_{ijT}$ is a vector of peer (or community) influences cumulative to time T; $\mathbf{S}_{ijT}$ is a vector of school inputs cumulative to time T; $\mathbf{I}_i$ is a vector of unobserved innate abilities.[5]

[4] See Hanushek (1979) for an early review of conceptual and empirical issues of educational production functions; Vignoles, Levacic et al. (2000) for a more recent review; Todd and Wolpin (2003) for methods on model specification of educational production functions; Meyer and Nascimento (2008) for a review on worldwide findings and methodological issues involving educational production functions.

[5] I use the bold type to represent vectors.

Ding and Lehrer (2007)[6] show that equation (3.1) can be estimated as a linear equation:

$$\mathbf{A}_{ijT} = \boldsymbol{\beta}_{0T} + \boldsymbol{\beta}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\beta}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\beta}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\beta}_{IT}\mathbf{I}_{i} + \sum_{t=0}^{T-1}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}) + \boldsymbol{\varepsilon}_{ijT} \quad (3.2)$$

In equation (3.2), betas ($\boldsymbol{\beta}$) represent the parameters to be estimated and $\boldsymbol{\varepsilon}_{ijT}$ is the error term. The independent variables in equation (3.2) can include higher-order terms and interaction terms to capture non-linear relationships. Lagging equation (3.2) by one period yields $\mathbf{A}_{ijT-1}$:

$$\begin{aligned}\mathbf{A}_{ijT-1} = {} & \boldsymbol{\beta}_{0T-1} + \boldsymbol{\beta}_{1T-1}\mathbf{F}_{ijT-1} + \boldsymbol{\beta}_{2T-1}\mathbf{P}_{ijT-1} + \boldsymbol{\beta}_{3T-1}\mathbf{S}_{ijT-1} + \boldsymbol{\beta}_{IT-1}\mathbf{I}_{i} + \\ & \sum_{t=0}^{T-2}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}) + \boldsymbol{\varepsilon}_{ijT-1}\end{aligned} \quad (3.3)$$

Equation (3.3) is important in setting the discussion because some of the terms in the equation will be used in the derivation of the three models of educational production function. Both equations (3.2) and (3.3) represent an ideal case when all the input data are available. Researchers, however, resort to one of the three empirical models (as mentioned earlier) depending on the availability of educational input data (Todd & Wolpin, 2003).[7] The application of each of the models to deal with the problem of missing input data is detailed in Appendix 3.1. Below I describe the underlying theoretical foundation of each of the educational production models.

[6] In their paper, Ding and Lehrer (2007) express the unobservable past inputs with an error term as $\sum_{t=0}^{T-1}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt} + \boldsymbol{\rho}_{t}\boldsymbol{\varepsilon}_{ijt})$. I exclude the term because the term $\boldsymbol{\varepsilon}_{ijT}$ in equation (3.2) is assumed to capture all the past unobservable inputs. In Section 5.1, I discuss how the effects of time-invariant past inputs are accounted for.

[7] Input data, especially on family background and innate abilities are rarely available.

3.2.1 Contemporaneous Educational Production Model

The origin of a contemporaneous educational production function can be traced back to Coleman et al. (1966).[8] Hanushek (1986) notes that early studies on education production included only contemporaneous inputs because data on historical inputs were very limited and often not available.

The contemporaneous educational production function requires two central assumptions, namely:

i) Only contemporaneous inputs[9] matter to the production of current achievement. Accordingly, the effect of past educational inputs and unobserved innate ability in the production process decay immediately, or, $\boldsymbol{\beta}_{it} = 0$ for t = 0, 1, …, T-1 and $\boldsymbol{\beta}_{IT} = 0$.

ii) Contemporaneous inputs are unrelated to unobserved innate ability and unobserved past educational inputs.

The full derivation of the contemporaneous model from equation (3.2) is set out in Appendix 3.1. In essence, the contemporaneous model can be expressed as:

$$\mathbf{A}_{ijT} = \boldsymbol{\alpha}_{0T} + \boldsymbol{\alpha}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\alpha}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\alpha}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\varepsilon}_{ijT}^{c} \tag{3.4}$$

where α's are the parameters to be estimated, and $\boldsymbol{\varepsilon}_{ijT}^{c}$ is the error term. As suggested, the model includes only current measures of educational inputs as explanatory variables.

Unbiased parameter estimates from equation (3.4) require assumption (i) so that unobserved innate abilities and past inputs to the production process have no effect (such that $\boldsymbol{\beta}_{IT} = 0$ and $\boldsymbol{\beta}_{it} = 0$ for t = 0, 1, …, T-1 on the current achievement.

[8] For an early critical appraisal on the method used in the Coleman Report, see Bowles and Levin (1968). A more current review on model specification of educational production function can be found in Todd and Wolpin (2003).
[9] Contemporaneous inputs can be defined as inputs that are close in time to the achievement measure.

3.2.2 Value-added Educational Production Model

The value-added model is the generally acceptable approach among the three models of educational production function (Atkinson, Burgess et al., 2008; Cory, 2008; and Ding & Lehrer, 2007). The model can be expressed as:

$$\mathbf{A}_{ijT} = \boldsymbol{\gamma}_{0T} + \boldsymbol{\gamma}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\gamma}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\gamma}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\lambda}\mathbf{A}_{ijT-1} + \boldsymbol{\varepsilon}_{ijT}^{L} \qquad (3.5)$$

where γ's and λ's are the parameters to be estimated, and $\boldsymbol{\varepsilon}_{ijT}^{L}$ is the error term.

Consistent and unbiased parameter estimates of equation (3.5) require several assumptions to hold (Ding & Lehrer, 2007; Todd & Wolpin, 2003):

i) The effect of observed and unobserved factors in the educational production process should decay over time at the same rate. More specifically, input coefficients must geometrically decline, as measured by time or age, with distance from the achievement measurement (for all *i*), and the rate of decline must be the same for each input). Mathematically, $\boldsymbol{\beta}_{kn} = \boldsymbol{\lambda}\boldsymbol{\beta}_{kn-1}$, where n = 1, 2, …, T and $0 < \boldsymbol{\lambda} < 1$ for *k* = 0, 1, 2, 3, I. And

ii) $\mathbf{A}_{ijT-1}$ is a sufficient measure of all the previous inputs influences, which includes the unobserved endowment of innate abilities, parental, school and community effects.

There are some considerations that should be taken into account before the model is applied. First, the model places strong restrictions on the production technology when it treats the parameters of innate abilities and past educational inputs as non-age/non-time varying (the effects of the inputs are the same across time, or, $\boldsymbol{\beta}_{kT} = \boldsymbol{\beta}_{kT-1} = \ldots = \boldsymbol{\beta}_{k0}$ for *k* = 0, 1, 2, 3, I). In fact, this assumption is important to overcome the issue of data on innate abilities without falling into the problem of endogeneity as discussed in Appendix

3.2. Second, data on a lagged measure of achievement is required, in addition to the need for data on contemporaneous family and peer/community variables that are often lacking.

3.2.3 Linear Growth Educational Production Model

The linear growth model[10] can be dated back to Hanushek (1979). It is expressed as a function of the growth rate in test scores, or mathematically, $\Delta\mathbf{A}_{ijT} = \mathbf{A}_{ijT} - \mathbf{A}_{ijT-1}$.

The model is built upon two central assumptions:

i) The unobserved innate ability, $\mathbf{I}_i$, has a constant effect such that, $\boldsymbol{\beta}_{IT} = \boldsymbol{\beta}_{IT-1} = ... = \boldsymbol{\beta}_{I0} = c$, where c is a constant,

ii) the test score gain, $\Delta\mathbf{A}_{ijT} = \mathbf{A}_{ijT} - \mathbf{A}_{ijT-1}$, removes the need for data on innate ability, and past educational inputs of family, school and community influences.

Given the assumptions, the linear growth model can be expressed as:

$$\Delta\mathbf{A}_{ijT} = \boldsymbol{\tau}_{0T} + \boldsymbol{\tau}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\tau}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\tau}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\varepsilon}^{G}_{ijT} \quad (3.6)$$

where τ's are the parameters of each of the independent variables and $\boldsymbol{\varepsilon}^{G}_{ijT}$ is the error term.

In equation (3.6), the test score gain is explained by contemporaneous inputs. The unbiased and consistent parameter estimates of equation (3.6) rely on the assumption that past inputs have a constant effect on achievement at different points in time.[11] Zimmer and Toma (2000, p. 80) suggest that, adding $\mathbf{I}_i$ to equation (3.6) may improve the

[10] In Appendix 3.1, a derivation of the linear growth model from equations (3.2) and (3.3) is detailed and equation 3.6 is derived.

[11] Note that taking first differences in order to generate equation (3.6) one removes time invariant heterogeneity and the associated problem of endogeneity.

estimation results.[12] Since $\mathbf{I}_i$ is one of the important variables that needs to be considered in explaining students' academic achievement, its omission may result in a model misspecification.[13] Notice that the error term, $\boldsymbol{\varepsilon}_{ijT}^{G}$, includes the difference of current and past level of innate abilities.

With the three empirical models of education production in mind, two points merit further consideration. First, notice that all three models rely on strict assumptions. The three models are different in terms of their assumptions about how the impact of observed historical inputs in each production function decay (Todd & Wolpin, 2003) and how each model captures the impact of unobserved innate abilities.[14] Second, in comparison of the three models discussed, the value-added model is most commonly used (Hanushek, 1997). To capture the confounding effects of educational inputs, the value-added model relates an individual's current performance to the individual's performance at some prior time and to the school, community and family inputs during the intervening time.[15] Empirical studies such as Atkinson, Burgess et al. (2008), Koedel (2008), and Houtenville & Karen (2008), favour the value-added model because it provides the most reliable estimates compared to the other two models of educational production function. Equipped with the presentations of the various models in Section 3.1 and Section 3.2, methodological issues commonly encountered in research designed to estimate an educational production function are discussed in the next section.

[12] Zimmer and Toma's (1999) strategy employs data on innate abilities (**I**) directly, while the original equation (3.6) implicitly captures the effect of innate abilities in the growth rate of test scores.
[13] In the case when one important variable (such as $\mathbf{I}_i$) is omitted and that variable is correlated with any included explanatory variables (for example parental education), then the effect of $\mathbf{I}_i$ is confounded, resulting in an omitted variable bias.
[14] Often data on innate abilities (such as IQ) are not available.
[15] See for example the discussion in Hanushek (2003, 1996) and Krueger (2000).

3.2.4 Panel Data Model

The availability of panel data provides an alternative solution to the problem of data on innate ability. In the following sub-sections, I show how the problem can be solved using panel data. A panel model of an educational production function is expressed as:

$$\mathbf{A}_{ijt} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\mathbf{F}_{ijt} + \boldsymbol{\beta}_2\mathbf{P}_{ijt} + \boldsymbol{\beta}_3\mathbf{S}_{ijt} + \boldsymbol{\beta}_I\mathbf{I}_i + \boldsymbol{\varepsilon}_{ijt} \tag{3.7}$$

where $\mathbf{A}_{ijt}$ represents a measure of students' academic achievement, $\mathbf{F}_{ijt}$ is a vector of student/family background characteristics, $\mathbf{P}_{ijt}$ is a vector of peer background characteristics, $\mathbf{S}_{ijt}$ is a vector of school resources, $\mathbf{I}_i$ is a vector of unobserved individual-specific heterogeneity (such as innate ability) and $\boldsymbol{\varepsilon}$ is the error term. The error term is assumed to be normally distributed with zero mean $E\left(\boldsymbol{\varepsilon}_{ijt}\right) = 0$. It is also assumed to be independently and identically distributed (iid). The subscripts i denotes the i^{th} student (i = 1, …, N), j denotes the j^{th} school (j = 1, …, J) and t denotes the time period (t = 1, …, T). Notice that since innate ability ($\mathbf{I}_i$) is assumed to be time-invariant (constant through time), the vector does not have a time subscript, t.[16]

In many empirical works on education, data on individual-specific heterogeneity such as innate ability is often lacking. Omission of the variable means the effect of innate ability, if any, now appears in the error term component. If $\boldsymbol{\beta}_I\mathbf{I}_i = \alpha_i$, equation (3.7) can now be rewritten as:

$$\mathbf{A}_{ijt} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\mathbf{F}_{ijt} + \boldsymbol{\beta}_2\mathbf{P}_{ijt} + \boldsymbol{\beta}_3\mathbf{S}_{ijt} + \alpha_i + \boldsymbol{\varepsilon}_{ijt} \tag{3.8}$$

where the effect of omitting any time-invariant individual-specific variable now appears as a composite error term, $\alpha_i + \boldsymbol{\varepsilon}_{it}$. A panel data model, the so-called fixed effects (FE) or

[16] The assumption of time-invariant for innate ability (**I**) is common in the literature of returns to education.

within-transformation model avoids the need for data on individual-specific heterogeneity such as innate ability. Before I discuss the fixed effects model, a simplification is made to equation (3.8) for the purpose of notational convenience. Let $\mathbf{X}_{1ijt} = \mathbf{F}_{ijt}$, $\mathbf{X}_{2ijt} = \mathbf{P}_{ijt}$, $\mathbf{X}_{3ijt} = S_{ijt}$ and $\sum_{k=1}^{K} \boldsymbol{\beta}_k \mathbf{X}_{kijt} = \boldsymbol{\beta}_1 \mathbf{F}_{ijt} + \boldsymbol{\beta}_2 \mathbf{P}_{ijt} + \boldsymbol{\beta}_3 \mathbf{S}_{ijt}$, so that equation (3.8) can now be expressed as:

$$\mathbf{A}_{ijt} = \boldsymbol{\beta}_0 + \sum_{k=1}^{K} \boldsymbol{\beta}_k \mathbf{X}_{kijt} + \alpha_i + \boldsymbol{\varepsilon}_{ijt} \tag{3.9}$$

where **X** is a matrix that represents the educational inputs such as student/family background, peer influence, and school resources (except the unobservable individual-specific innate ability). The subscripts k denotes the k^{th} variable (k = 1, …, K). The two major approaches to estimating a model using panel data are the fixed effects (FE) model and random effects (RE) model are now discussed.

a. Fixed Effects (FE) Model

The purpose of this sub-section is to show how the manipulation of panel data under the fixed effects (FE) model resolves the unobserved effect (α_i). An important assumption of such a model is that the individual-specific unobserved effect is time-invariant or constant over time (Wooldridge, 2002, p.459).

To show how the unobserved effect is eliminated, first I average equation (3.9) over time for each student (i) such that $\overline{\mathbf{A}}_{ij} = \frac{1}{T}\sum_t \mathbf{A}_{ijt}$, $\overline{\mathbf{X}}_{kij} = \frac{1}{T}\sum_t \mathbf{X}_{kijt}$ and $\bar{\boldsymbol{\varepsilon}}_{ij} = \frac{1}{T}\sum_t \boldsymbol{\varepsilon}_{ijt}$, thus obtaining:

$$\overline{\mathbf{A}}_{ij} = \boldsymbol{\beta}_0 + \sum_{\mathrm{k=1}}^{\mathrm{K}} \beta_{\mathrm{k}} \overline{\mathbf{X}}_{\mathrm{kij}} + \alpha_i + \bar{\boldsymbol{\varepsilon}}_{ij} \tag{3.10}$$

Since α_i is fixed over time, it still appears in equations (3.9) and (3.10). Now subtract equation (3.10) from equation (3.9), yielding:

$$\left(\mathbf{A}_{ijt} - \overline{\mathbf{A}}_{ij}\right) = \left(\boldsymbol{\beta}_0 - \boldsymbol{\beta}_0\right) + \sum_{k=1}^{K} \boldsymbol{\beta}_k \left(\mathbf{X}_{kijt} - \overline{\mathbf{X}}_{kij}\right) + \left(\alpha_i - \alpha_i\right) + \left(\boldsymbol{\varepsilon}_{ijt} - \bar{\boldsymbol{\varepsilon}}_{ij}\right)$$

$$= \sum_{k=1}^{K} \boldsymbol{\beta}_k \left(\mathbf{X}_{kijt} - \overline{\mathbf{X}}_{kij}\right) + \left(\boldsymbol{\varepsilon}_{ijt} - \bar{\boldsymbol{\varepsilon}}_{ij}\right) \tag{3.11}$$

where $\left(\mathbf{A}_{ijt} - \overline{\mathbf{A}}_{ij}\right)$, $\left(\mathbf{X}_{kijt} - \overline{\mathbf{X}}_{kij}\right)$ and $\left(\boldsymbol{\varepsilon}_{ijt} - \bar{\boldsymbol{\varepsilon}}_{ij}\right)$ are termed time-demeaned variables. Note that the time-invariant individual-specific unobserved effect, α_i, is no longer present in equation (3.11). A regression based on equation (3.11) explains the variation around the mean of the dependent variable in terms of the variations around the means of the explanatory variables for the group of observations relating to a given individual (or also referred as ‘within‘ estimation).[17]

An advantage of OLS regression based on equation (3.11) is that the problem of unobserved heterogeneity bias is explicitly ruled out. The disadvantage of the model is that any explanatory variable that is constant for each individual (*i*) will be also dropped out of the model. The ensuing loss of being able to use a constant regressors such as using a dummy variable to represent, for example, the gender or indigenous status of a

[17] Estimators based on the time-demeaning approach in equation (3.11) are similar to the first-differencing approach of the data when T < 3 (Wooldridge, 2002). In a case when panel data is not available, the value-added and the linear growth models of education production function, as described in Appendix 3.2, are often employed. The intuition behind all these models is to eliminate the need for data on unobserved individual specific heterogeneity.

student, may reduce the explanatory power of the model. A solution to this problem is to use the random effects model.

b. Random Effects (RE) Model

An alternative approach to the FE model is a random effects (RE) model. The RE model avoids the problem of eliminating constant variables as is the case under the FE model because it assumes that the unobserved variables are drawn randomly from a given distribution. In other words, all unobserved individual effects come from a common distribution with a constant mean, $E(\boldsymbol{\alpha}) = 0$, and a constant, finite variance, $\boldsymbol{\sigma}_{\alpha}^{2}$. With the assumption, equation (3.9) can be rewritten alternatively as:

$$\mathbf{A}_{ijt} = \boldsymbol{\beta}_0 + \sum_{k=1}^{K} \boldsymbol{\beta}_k \mathbf{X}_{kijt} + \mathbf{u}_{ijt} \tag{3.12}$$

where $\mathbf{u}_{ijt} = \boldsymbol{\alpha}_i + \boldsymbol{\varepsilon}_{ijt}$. The unobserved effect, α_i, is placed in the disturbance term, $\mathbf{u}_{ijt}$ — made possible by the assumption that α_i is a random variable (hence the name of the RE model).

Another crucial assumption of the RE model is that the unobserved effects, α_i, are uncorrelated with the regressors, $\operatorname{cov}\left(\mathbf{X}_{ijt}, \alpha_i\right) = 0$. Violation of this assumption means the random effects coefficients will be biased and inconsistent. If both assumptions are met, equation (3.12) can be used as a regression specification.

An estimation based on pooled OLS for equation (3.12), however, suffers a problem of serial correlation in the errors. Since α_i is in the composite error, $\mathbf{u}_{ijt} = \alpha_i + \boldsymbol{\varepsilon}_{ijt}$, in each time period, the $\mathbf{u}_{ijt}$ is serially correlated across time (Wooldridge, 2002, p. 450). As Wooldridge shows, the positive serial correlation is evident from the non-zero covariance between the disturbance term of an individual *i* in school *j* at time *t*, $\mathbf{u}_{ijt}$, and the disturbance term of the same individual at any other period *t-s*, $\mathbf{u}_{ijt-s}$:

$$\operatorname{cov}\left(\mathbf{u}_{ijt},\mathbf{u}_{ijt-s}\right)=\operatorname{cov}\left[\left(\alpha_i+\boldsymbol{\varepsilon}_{ijt}\right),\left(\alpha_i+\boldsymbol{\varepsilon}_{ijt-s}\right)\right]$$

$$=\operatorname{var}\left(\alpha_i\right)=\boldsymbol{\sigma}_\alpha^2\neq 0 \qquad (3.13)$$

The correlation coefficient between any two errors is

$\operatorname{cor}\left(\mathbf{u}_{ijt},\mathbf{u}_{ijt-s}\right)=\dfrac{\operatorname{cov}\left(\mathbf{u}_{ijt},\mathbf{u}_{ijt-s}\right)}{\sqrt{\operatorname{var}\left(\mathbf{u}_{ijt}\right)\operatorname{var}\left(\mathbf{u}_{ijt-s}\right)}}$. Given that $\boldsymbol{\sigma}_\alpha^2=\operatorname{var}\left(\alpha_i\right)$ and $\boldsymbol{\sigma}_u^2=\operatorname{var}\left(\mathbf{u}_{ijt}\right)$, then after some manipulation, the correlation coefficient can be expressed as:

$$\operatorname{cor}\left(\mathbf{u}_{ijt},\mathbf{u}_{ijt-s}\right)=\frac{\boldsymbol{\sigma}_\alpha^2}{\boldsymbol{\sigma}_\alpha^2+\boldsymbol{\sigma}_\varepsilon^2}\ \text{ for any } s\neq t \qquad (3.14)$$

One way to estimate a model with autoregressive serial correlation is to use a generalised least squares (GLS) estimation. A GLS transforms the RE model so that the error term is not serially correlated. To show the transformation, first a scalar, $\boldsymbol{\theta}$, is defined as:

$$\boldsymbol{\theta}=1-\sqrt{\frac{\boldsymbol{\sigma}_\varepsilon^2}{\boldsymbol{\sigma}_\varepsilon^2+T\boldsymbol{\sigma}_\alpha^2}} \qquad (3.15)$$

where $\boldsymbol{\theta}$ is always between zero and one. All observations in equation (3.12) are then averaged over time [as shown in equation (3.10)], multiplied by $\boldsymbol{\theta}$, and the derived equation is subtracted from equation (3.12).

$$\left(\mathbf{A}_{ijt}-\boldsymbol{\theta}\overline{\mathbf{A}}_{ij}\right)=\boldsymbol{\beta}_0\left(1-\boldsymbol{\theta}\right)+\sum_{k=1}^{K}\boldsymbol{\beta}_k\left(\mathbf{X}_{kijt}-\boldsymbol{\theta}\overline{\mathbf{X}}_{kij}\right)+\left(\mathbf{u}_{ijt}-\boldsymbol{\theta}\overline{\mathbf{u}}_{ij}\right) \qquad (3.16)$$

where $\left(\mathbf{A}_{ijt} - \boldsymbol{\theta}\overline{\mathbf{A}}_{ij}\right)$, $\left(\mathbf{X}_{kijt} - \boldsymbol{\theta}\overline{\mathbf{X}}_{kij}\right)$ and $\left(\mathbf{u}_{ijt} - \boldsymbol{\theta}\overline{\mathbf{u}}_{ij}\right)$ are the quasi-demeaned data on each variable.[18] The GLS estimation is performed by running OLS on the quasi-demeaned data (Wooldridge, 2002, p. 450).

The choice between the FE and the RE models depends on the validity of the assumption whether the unobserved individual-specific effect, α_i, is uncorrelated with the regressors. Hausman (1978) provides a statistical test based on the consistency and efficiency of the estimators obtained from the two models to determine whether the assumption holds. As shown in Table 3.1, the first column shows the correlation between the unobserved individual effect and the regressors, and the second and third columns show the effects of the correlation to the estimates of RE and FE. If the assumption that the unobserved individual-specific effect, α_i, is uncorrelated with the regressors is satisfied, then the RE model is the preferred model of choice. In that case, the RE model is consistent and efficient while the FE model is only consistent. In a case when the assumption is not satisfied, the FE model is favoured against the RE model because the estimates are consistent while the estimates of the RE model are inconsistent.

Table 3.1: The Basis of the Hausman Test

Assumption	**Random Effects**	**Fixed Effects**
$\mathrm{cov}\left(\mathbf{X}_{kijt}, \alpha_i\right) = 0$ for $k = 1, \ldots, K$	Consistent & efficient	Consistent
$\mathrm{cov}\left(\mathbf{X}_{kijt}, \alpha_i\right) \neq 0$ for $k = 1, \ldots, K$	Inconsistent	Consistent

The Hausman test, as described above, proceeds by testing the null hypothesis (H_o) that $\mathrm{cov}\left(\mathbf{X}_{kijt}, \alpha_i\right) = 0$ for all *k*, against the alternative hypothesis (H_a) that

[18] The transformation process that yield equation (3.16) does not subtract the entire individual mean but rather subtracts some fraction of the mean, as defined by $\boldsymbol{\theta}$.

$\text{cov}\left(\mathbf{X}_{kijt},\alpha_i\right)\neq 0$ for all *k*. The test compares the difference between the FE and RE estimates, β_{FE} and β_{RE}. Hausman's test statistic (for a case where *K*=1) is given by:

$$H=\frac{\left(\beta_{FE}-\beta_{RE}\right)^2}{\text{var}\left(\beta_{FE}\right)-\text{var}\left(\beta_{RE}\right)}\sim\chi_1^2 \tag{3.17}$$

In the case when the Hausman test points to the FE model as the most appropriate, the coefficient parameters for the variables that have no within variation are lost—recall that the FE model drops any variable with no within variation such as gender and indigenous status of students. To capture the effects of the dropped variables, alternative estimation strategies need to be considered. Consequently, two other regression estimations that I run are the between effects (BE) model and the pooled GLS model. The two models are discussed in the next sub-section.

c. Between Effects (BE) Model

The between effects (BE) model captures the average effects of the variables across individual students. A mathematical expression of the BE model is given by:

$$\overline{\mathbf{A}}_{ij}=\boldsymbol{\beta}_0+\sum_{k=1}^{K}\boldsymbol{\beta}_k\overline{\mathbf{X}}_{kij}+\overline{\mathbf{u}}_{ij},\ \text{where}\ \overline{\mathbf{u}}_{ij}=\alpha_i+\overline{\boldsymbol{\varepsilon}}_{ij} \tag{3.18}$$

In equation (3.18), the student-specific means of test scores overtime ($\overline{\mathbf{A}}_i$) are regressed on the student-specific means of the explanatory variables—as in the case of equation (3.10). Equation (3.18) is regressed using OLS in terms of a cross-sectional estimation of *N* observations. The model ignores all the individual-specific variation as in the case of the FE model. The model instead replaces all observations for a given individual with their mean. As a result, the BE model is less efficient than the RE model since the BE model has less observations as compared to the RE model. Caution needs to be exercised when interpreting estimation results from the BE model. If α_i is correlated with the explanatory variables, $\text{cov}\left(\overline{\mathbf{X}}_{kij}, \alpha_i\right) \neq 0$, the zero-mean conditional assumption does not hold, $E\left(\overline{\mathbf{u}}_{ij} \mid \overline{\mathbf{X}}_{kij} \neq 0\right)$. The consequence is that estimates based on the BE model will risk omitted variables bias.

d. Pooled GLS Model

For pooled data, the data is pooled together like in panel analysis but observations over time for the same unit are treated as if they are not the same unit over time. The structure of a dataset with a cross-section of *N* units and *T* time periods is combined to produce a pooled dataset of *N* x *T* observations. The reason for employing a pooled data estimation in this study is to capture the effects of gender, indigenous status of students, and parental education and occupation, which are all dropped in the FE model.

One advantage of pooled data is the large number of observations available for estimation purposes. Two major problems, however, may arise when pooled data is estimated using OLS regression. First, if the unobserved individual-specific error term is correlated with the regressors, $\text{cov}\left(\overline{\mathbf{X}}_{kij}, \alpha_i\right) \neq 0$, the estimates from the regression will be biased. Second, there is a problem of serial correlation. Since there is a composite error term, $\mathbf{u}_{ijt} = \alpha_i + \boldsymbol{\varepsilon}_{ijt}$, the term α_i is serially correlated in each time period—as explained in relation to equation (3.13). The consequence of serial correlation is that OLS is no longer the most efficient method of estimation. A Generalised Least Square (GLS) estimation is one solution to the problem.

Given a panel data of N x T (for student i = 1, …, N and time t = 1, …, T) and by stacking the data over i and t to create a NT observations, a pooled GLS model is expressed as:

$$\mathbf{A}_{ij} = \boldsymbol{\beta}_0 + \sum_{k=1}^{K} \boldsymbol{\beta}_k \mathbf{X}_{kij} + \mathbf{u}_{ij} \tag{3.19}$$

where now i = 1, …, NT. The dimensions of $\mathbf{A}$ amd $\mathbf{u}$ are both NT x 1 vectors, **X** is a NT x K matrix, $\boldsymbol{\beta}_k$ is a K x 1 vector of the parameters to be estimated and $\boldsymbol{\beta}_0$ is the intercept. For the pooled GLS estimation, I assume that the unobserved individual-specific heterogeneity to be zero. $\alpha_i = 0$. It is also assumed that $E(\mathbf{u} \mid \mathbf{X}) = 0$, where $\mathbf{X}$ is the matrix of $\mathbf{X}_{kij}$), so that errors are strictly exogenous and $\boldsymbol{\Omega} = E(\mathbf{uu}' \mid \mathbf{X})$. The pooled GLS estimator is given by $(\mathbf{X}'\boldsymbol{\Omega}^{-1}\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{\Omega}\mathbf{A}$ and the variance matrix is $(\mathbf{X}'\boldsymbol{\Omega}^{-1}\mathbf{X})^{-1}$. The pooled GLS is consistent and efficient if $\boldsymbol{\Omega}$ is a consistent estimator for $\boldsymbol{\Omega}$ (Cameron & Trivedi, 2005, pp. 702-721).

3.3 Methodological Issues

The aim of this section is to review the methodological issues commonly encountered in empirical works of estimating an educational production function. For convenience of presentation, the discussion that follows is broken into sub-sections.

3.3.1 Levels of Analysis

In the context of estimating an educational production function, the appropriate level of data to be employed is the key to achieve a better understanding of the determinants of students' academic performance. Most studies that estimate educational production function use aggregate data at the district and school levels. The drawback of using school or district level data is that the analysis focuses on the identification of the determinants of school or district educational performance,[19] instead of individual student performance. Most studies use aggregate level data due to serious data limitations on student/family background characteristics and peer background characteristics at the individual level (see Levacic & Vignoles, 2002).

3.3.2 Omitted Variables

Many educational production function studies suffer from inadequate measures of students' innate ability,[20] peer effect, school context and processes (teaching methods, teacher quality and school management). Omission of any of these variables may result in biased estimates, particularly when one or more omitted variable is correlated with the included independent variables.[21]

One solution to the problem is to employ a panel data. The richness of panel data obviates the need for data that may be difficult to obtain. In Section 5.1-a, I show how a panel data analysis obviates the need for such data.[22]

3.3.3 Functional Form

One area of research that has received less attention in the study of educational production functions is in the identification of the appropriate functional form for the production technology. Most empirical work in the literature assumes a linear or Cobb-Douglas functional form (Figlio, 1999, p. 242). A more cautious approach to identifying

[19] Data aggregation may result in misleading conclusions regarding the economic behaviour of students.
[20] In the case of this type of research, data on individual-specific heterogeneity on student innate ability and motivation are often unobservable.
[21] Hanushek (1986), for example, states that since innate ability is correlated with a positive family background, then omitting the innate ability variable will cause the estimate of family background to be biased upward.
[22] For this research, I employ a panel dataset obtained from the Department of Education, Tasmania (DoE, Tas).

the appropriate functional form prevails in the Stochastic Frontier Analysis literature (see the discussion in Section 4.3.1 and Chapter 6).

3.3.4 Endogeneity

An endogeneity problem is one issue commonly encountered when estimating an educational production function. The endogeneity problem exists when:

i) Any of the independent variables is jointly determined.[23] As a result, the independent variable is correlated with the error term ($\mathrm{Cov}\,(\boldsymbol{\varepsilon}, \mathbf{X}) \neq 0$) in a regression. Or

ii) the dependent variable (student academic achievement) influences the independent variables (educational inputs). In other words, the problem occurs when factors that are supposed to affect a particular outcome, depend themselves on that outcome. If, for example, a budget allocation to a school is influenced by the school's performance, then care should be taken when incorporating the education spending variable to capture the school's performance since it is endogenous.[24] Or

iii) past achievement, $\mathbf{A}_{ijT-1}$, is taken as one of the explanatory variables in estimating the educational production function (see Appendix 3.2). In other words, the problem of endogeneity arises when a lag of the dependent variable is employed as one of the explanatory variables. It may be possible by manipulating the equation to remove the endogeneity problem.

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[23] Resources available to schools are a consequence of factors such as financing rules, school performance and parental choices.

[24] Resources available to schools, for example, are a consequence of factors such as student performance, financing rules and parental choices. Parents of high performing students may choose schools which are well equipped. This act of parental choice may result in a positive correlation between performance and school resource.

Without addressing the endogeneity problem, a serious methodological shortcoming arises. The consequence is that estimation results can no longer be interpreted with confidence (Glewwe, 2002, p. 445). The problem can be solved by four main strategies that are elaborated below:

a. Randomised Experiments

One way to eliminate the problem of endogeneity is by having randomised or experimental data. To conduct a randomised experiment, students are assigned to a treatment and a comparison group randomly. The random assignment ensures probabilistic equivalence, where any difference between the treatment and comparison groups is due to chance. The endogeneity problem is eliminated because the randomisation establishes that the intended treatment or program works. In other words, the randomisation provides the assurance (in probability) that the groups are the same before the treatment (program or intervention), and that any difference is due to the treatment. Experimental data, however, is very rare in education. The Tennessee's Student Teacher Achievement Ratio (STAR) project in the US is one of a kind and the scope of the experiment is just on the effect of class size. The experiment involved 11,600 Tennessee kindergarten students and teachers that began in 1985. Students and teachers were randomly assigned to one of the three types of classes: (i) small classes (13-17 students), (ii) regular-size classes (22-25 students) and (iii) regular teacher's aide classes (22-25 students). Krueger (1999) employed the Project STAR data and found a positive effect of small classes on students’ academic achievement, particularly for students in the early years of schooling and minority students.

Cook (2007) argues that having this kind of experiment is expensive and may raise ethical issues. Furthermore, Hawthorne effects may prevail since participants may be aware of the experiment and set their behaviour to meet the intended objectives of it (Hoxby, 1998).[25] Krueger (1999) however, notes that the positive effect of smaller classes found in his analysis is free from Hawthorne effects.

b. Simultaneous Equation Models

According to Mayston (1996, p. 131), the number of researchers using simultaneous equation models to estimate an educational production function is small. One difficulty in employing the technique is that a clear understanding of resource allocation process to schools is required. The determinants of school input allocation need to be identified and modelled first. The purpose of that exercise is to make the structural relationships explicit, so that the structural associations between the multiple inputs and outputs of education are untangled (Vignoles et al., 2000). Researchers therefore, need to obtain information on how resources are allocated to schools and this exercise adds another complexity to the task.

c. Instrumental Variables (IV)

The instrumental variable (IV) approach is the more common[26] technique used in the extant literature to deal with the endogenous school resources variable(s). The condition of the IV is that it must be correlated with the endogenous variable and uncorrelated with the error term (the instrument works indirectly through its role as a predictor of the endogenous variable). In the study of school resources based on educational production function, the problem of using the IV approach is the

[25] Students perform better just because they are the subject of an experiment, rather than due to the educational intervention itself. Since the experiment may lead to a policy recommendation (smaller classes), the interested parties involved have the incentive for the experiment to work (Hoxby, 1998).
[26] As compared to the simultaneous equation approach, data required for the IV approach is less demanding. Researchers only need to employ a suitable instrument under the IV approach. Under the simultaneous equation approach, however, a set of data that explains, for example, how resources are allocated to schools is needed. Such information may not be available.

identification of the instruments that influence the allocation of school resources among students but the instruments must not affect the learning outcomes.

Angrist and Lavy (1999) and Figlio (1997) have used the IV approach to evaluate the effect of school resources on students' academic performance. Angrist and Lavy (1999) estimate the effect of class size on student achievement using instruments constructed from Maimonides' rule, a bureaucratic ceiling on class size that induces differences in average class size in Israeli schools. Figlio (1997) uses the tax revenue raising limits that have been imposed in certain US states to identify the random change in educational expenditure.

d. Panel Data Approach

A panel data analysis (the approach that I employ in Chapter 5) addresses some of the endogeneity by eliminating the effects of unobserved variables (see Section 3.2.4). If unobserved traits such as innate ability and motivation are assumed to be time-invariant, then any change in achievement level over time can be regressed on change in school inputs and other observable factors. As such, a clean estimate of the effect of the observable factors on students' academic achievement can be achieved since a panel data approach avoids any contamination by students'/schools' unobserved traits in the regression analysis (Kingdon, 2006, p. 4).

Caution is however, required when employing panel data, particularly in the following cases: (i) when students' unobserved traits change over time. Since panel data models eliminate the effect of unobserved heterogeneity, the change is not accounted for in the model; and (ii) when the cohort of students changes over time due to sample attrition. If students have dropped out of their studies, for example, then the data may comprise only motivated/ambitious/able students (Kingdon, 2006, p. 4).

3.4 Empirical Evidence

In this section, findings from the extant literature of educational production function are discussed. The aim is to identify which variables are important in determining educational output. The main purpose is to identify how standard educational inputs are represented so that the estimation of Tasmanian educational production function can be undertaken in light of the standard empirical practice. Factors that affect academic achievement, such as family backgrounds, peer influence, school resources and innate abilities, as described in equation (3.1), are presented in separate sub-sections.[27]

3.4.1 Family Background and Student Performance

In the literature of educational production function, family background is one important variable found to consistently affect students' academic performance. The effect of positive family backgrounds[28] on a child's academic performance is confirmed in many studies [Houtenville and Karen (2008), McIntosh and Martin (2007), Ammermueller (2007), Rangvid (2007), Woessmann (2004), Henderson & Berla (1994), Nyirongo et al. (1988) and Coleman et al. (1966)]. Okagaki (2001) provides an explanation for this observed phenomenon, stating that a positive family background is usually associated with high familial support.[29]

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[27] See Fuchs and Wossmann (2007) for international educational production estimates and Alvarez et al. (2007) for state educational production estimates based on Mexico.

[28] Positive family backgrounds refer to a conducive physical, mental and emotional environment within a family that stimulate positive child's growth, such as living with both parents, good parental education and income, home library and good parental support and encouragement.

[29] Okagaki (2001) suggests that parental involvement influences student achievement via both direct and indirect pathways. The direct pathways involve literal parental engagement with both student homework as well as their involvement in intellectually stimulating activities. This help can be effective depending on the parent's own level of education and self-efficacy. The indirect pathways involve an observation of parental behaviours (positive or negative) by children. A positive/negative spillover effect of the parental behavious is an outcome of assimilation process by the children of their parental positive/negative behavious.

Factors such as parental education (Burnhill et al., 1990), family wealth (Deon & Pritchett, 2001), and family structure[30] (Pong, 1997 and Krein, 1986) are some of the conventional variables used to analyse the effect of family backgrounds on students' test scores. These variables are considered to fall within the 'home production' side of the educational production function.

Often a set of family variables is used to capture the effect of familial background when estimating an educational production function. Parental education and income are two variables commonly employed [Rivkin et al. (2005), Schiller et al. (2002), Goldhaber & Brewer (1996), Ferguson & Ladd (1996), Ehrenberg & Brewer (1994), Hanushek (1992), and Mumane et al. (1981)]. Burnhill et al. (1990), for example, used the number of parents' schooling years and fathers' occupational groups to measure the level of parental education and the level of family incomes, in their estimation of Scotland's educational production function.

Rangvid (2007) employed conventional family variables such as parental education, occupation, wealth and family structure (a student lives with both natural parents) in quantile regressions of Denmark's educational production function. She also included parental academic interest, home educational resources, and cultural possessions in her estimation. Rangvid (2007) argued some of the complex relationships between familial settings and achievement were untangled by adding more family background variables. She found the coefficients on parental education and occupation[31], parental

[30] For example, parental marital status, teen motherhood, single-parent households, and a child's birth order in a family.

[31] The reference group contained the unemployed, and those not looking for work. Positive coefficients were found for unskilled and skilled manual workers (0.881 for male students, 0.370 for female students) and for the managerial, professional, and independent or self-employed entrepreneurs (1.258 for male students, 1.029 for female students).

academic interest, educational resources in the home, cultural possessions, ethnicity (being a native Dane) and living with both parents to be positive and significant.

In a study based on Germany's schools, Ammermueller (2007) investigated the determinants of German students' achievement vis-à-vis immigrant students' achievement in PISA examination (in Germany). Ammermueller used dummy variables for parental education and father's unemployment. The other variables that he employed were the number of books at home, number of siblings and language spoken at home. He found significant positive effects of parental education and number of books at home, and negative effects of speaking other than German on students' academic achievement for both categories of students.

McIntosh and Martin (2007) investigated the determinants of educational achievement of Danish students who were 14 years old in 1968, based on the Danish Longitudinal Survey of Youth. Family background variables were found to affect Danish students' achievement. Father's occupation[32] was found to have the largest positive impact on the cohort's achievement. Other variables like parental education[33] (positive), the number of siblings (negative), disrupted childhoods (negative), attitudes towards school (positive), and household income (positive) were also significant.

A recent study by Houtenville and Karen (2008) further confirmed the importance of family background variables.[34] They also found that parental efforts in supporting a child's learning progress were significant and had a strong positive effect on

[32] Father's occupations were categorised into: (1) the reference group, which contained the unemployed, those not looking for work, and others, (2) unskilled and skilled manual workers, and (3) managerial, professional, and independent or self-employed entrepreneurs.
[33] Parental education was categorised into: (1) the reference group, containing no education beyond compulsory schooling, (2) vocational or apprenticeship, (3) intermediate levels of education leading to white-collar qualifications, and (4) higher levels of education, like universities.
[34] The study was based on a value-added educational production function. Data from the National Education Longitudinal Study (NELS) of USA were employed.

achievement. According to them, parental efforts, however, were not captured by the family background variables employed such as mother's education, father's education (number of years in school), number of siblings, total family income, and percentage of children with a single mother or a single father.[35] Instead, the variable for parental efforts was derived from a ninth-grade student survey that asked how frequently parents; (1) discussed activities or events of particular interest with the child, (2) discussed things the child studied in class, (3) the selection of courses or programs at school, (4) attended a school meeting, and (5) volunteered at the child's school. Note that the data from the survey, in essence, measured the level of familial supports and according to Okagaki (2001), the effectiveness of familial support depends on the parents' level of education and self-efficacy.[36] Since such data on parental efforts, as employed by Houtenville and Karen (2008), are often lacking, parents' level of education remains one variable commonly available to capture the effects of parental effort.

In brief, extant research has confirmed the systematic relationship between family background and students' academic achievement. A set of family background variables that represents parents' education, family income, family structure, and parental effort is crucial to the design of an educational production function. This set of variables captures the main underlying role of familial setting in a child's academic achievement.

[35] The implication of Houtenville and Karen's (2008) study was that, if parental effort was an important variable and was not captured by the common family background variables, then omitting the parental effort variable could result in biased estimations.

[36] Okagaki's (2001) work was reviewed at the beginning of the current section.

3.4.2 Peer/Community Influence and Student Performance

In this section, the effect of peers, community or social influence on students' academic achievement is reviewed. [37] Peer effect is a change in an individual's behaviour or motivation, caused by the influence of a social group. Researchers separate peer effects into contextual and behavioural effects (Hanushek et al., 2003; Boozer & Cacciola, 2001; Manski, 1993). The contextual effect includes variables that represent group characteristics, such as socio-economic status or race. The behavioural effect refers to a case when an individual outcome is affected by some aspects of the reference group outcomes (for example, achievement of a student may be influenced by a similar achievement of peers). In light of the two effects, analyses on how a student's achievement are affected by the influence of peer academic achievement (Rangvid, 2003; Hanushek et al., 2003; Michael & Stephen, 2001), peer race/ethnicity (Ream, 2003), peer socio-economic status, gender (Whitmore, 2005) and peer behaviour (Kirk, 2000) are common in the literature of educational production function.

Empirical findings based on the contextual and behavioural effects are outlined below. To evaluate the contextual effect, the standard practice in the extant literature is to include several peer contextual variables based on race/ethnicity, socio-economic status and gender of peers. Many studies have found a modest negative peer effect based on a racial composition variable[38] (Ream, 2003; Datnow et al., 2003; Bankston & Caldas, 2000). An early study by Hanushek (1972) based on US data found that white students' test scores were negatively affected when the peer group had a very high proportion (greater than 45 percent) of blacks. Further, a study by Angrist and Lang (2004) on a

[37] For convenience, I will call the community or social influence as peer effect/influence henceforth.
[38] Racial composition also reflects the socio-economic status of peers when there is a clear economic gap between races.

desegregation programme[39] in Boston discovered that mixing black with white students modestly reduced the test scores in the receiving districts.

Another common contextual variable employed is the gender of students. Whitmore (2005) employed the Project STAR data to show the effect of being in a predominantly female class on a student's test score. The independent variable used to capture the gender effect was the proportion of female students in a class room. After disentangling the impact of girls and the impact of higher scoring peers (to separate the effect of induced variations in gender composition and peer quality), Whitmore (2005) found supporting evidence of gender (female) per se on test scores. The estimation result was that having a class predominated by female students had a 1.3 point increase in a student's test score, *ceteris paribus*.[40]

One issue needs consideration when dealing with the contextual variables because the variables tend to be related to parental choice of residential area and/or parental selection of preferred school (for example, public versus private, gender mixed or gender-isolated schools). This selection issue (by parents) may lead to biased estimates.[41] To solve the selection problem, an instrumental variable (IV) for the peer group, assumed to be exogenous, is usually employed. Credible IV that captures the peer effect, however, is difficult to find. Feinstein and Symons (1999) used dummy variables, assigned according to the proportion of parents' occupational status in the local authority area, to instrument for peer groups. The instrument proved to be valid, but no test of strength was reported.

[39] The desegregation programme sends black students from Boston schools to more affluent suburbs (higher numbers of white students).

[40] Whitmore (2005) also found that being exposed to higher-quality peers improved a student's test score by 0.6 point for every one point rises in average peer scores.

[41] Certain schools are good in ways as observed by parents (for example, some parents may perceive that a gender-isolated school is not good for their child's social development and therefore, send their child to a gender-mixed school) and this unobserved factor may result in biased estimates.

Other suggested instrumental variables for the peer group are regional indicators; urbanicity indicators and student body characteristics (Argys, Rees & Brewer, 1996); the percentage of black students in the school and the percentage of students who received full US federal lunch assistance at the school (Betts & Shkolnik, 2000).

With regard to the behavioural peer effect, variables that represent peer quality, such as peer intellectual level[42] and peer behaviour have been employed in the extant literature of educational production function. Hanushek et al. (2003) and Zimmer and Toma (2000) used peer mean test scores to capture the effect of peer intellectual level on students' academic achievement. Zimmer and Toma (2000) reported a robust positive influence of higher achieving peers,[43] where raising the average peer academic level in a group of students could increase an individual student achievement. The findings of Zimmer and Toma (2000) confirmed Summers and Wolfe's (1977) earlier finding that peer effect due to ability grouping was stronger in affecting the achievement level of low-ability students as compared to high-ability students.

In an empirical peer effect study based on Denmark's PISA 2003 data, Rangvid (2003) avoided using peer average test scores as a proxy for peer ability, claiming the potential problem of reverse causality.[44] Instead, Rangvid (2003) employed the average years of schooling of the classmates' mothers, arguing that a large part of a child's

[42] Ability grouping is another topic of research that has received great scrutiny. Ability grouping is the practice of dividing students for instruction on the basis of their perceived capacities for learning. Hollifield (1987) argued that ability grouping increased student achievement by reducing the disparity in student ability levels. The advantage of ability grouping was that a teacher could provide instruction based on his students' pace of learning.

[43] Zimmer and Toma (2000) conducted a study involving five countries: the US, Belgium, New Zealand, Canada and France.

[44] A peer affects his peers and is affected by peers. This interaction may have reverse causality, which may cause a standard regression estimates to be biased (Rangvid, 2003, p. 16). An instrumental variables (IV) approach is one strategy to solve the problem. The strategy is to use a third variable (instrumental variable) to extract variation in the variable of interest that is unrelated to the causality problem, and to use this variation to estimate its causal effect on an outcome measure.

academic performance was influenced by the educational level of parents, especially the mother. Rangvid (2003) found strong positive effects of attending school for peers with better educated parents based on OLS results (mean effects). In addition, the quantile regression (median effects) analysis conducted, also showed that peer group effects were stronger at the lower end of the test score distribution. The conclusion based on Rangvid's (2003) quantile regression confirmed further the findings by Zimmer & Toma (2000) and Summers & Wolfe (1977) that low achievers were dependent learners (highly influenced by the achievement of their peers).

Kirk (2000) conducted a behavioural peer effect study based on peer behaviour. He examined the effect of peers' attitude towards their classmates' effort based on the 1998 National Assessment of Educational Progress database of USA for students in fourth and eighth grades. The variable for the peer behaviour was derived from a question in the survey that asked the child to strongly agree, agree, disagree, or strongly disagree with the following statement: "My friends make fun of people who try to do well in school." A negative peer effect was found with a coefficient of 12.26 (negative) in reading test for the fourth grade and 7.003 (negative) for the eighth grade. Kirk (2000) also found that peer behaviour was independent of other factors such as race, gender and income variables.

In summary, the effect of peers on student academic achievement is significant but modest. An empirical analysis to separate peer effects from other confounding influences is econometrically difficult because of the simultaneous nature of peer interactions.[45] Researchers need to identify and obtain data on the salient characteristics of the relevant peer group in order to separate the investigated peer effect from other

[45] Simultaneous interaction is when a student may affect his/her peers or is affected by peers.

confounding influences. Any study therefore, must carefully address the endogenous choice of neighbourhood and schools so that the effect of peers on performance can be captured accurately (Moffitt, 2001; Manski 2000).

3.4.3 School Resources and Student Performance

School resources are another important factor that affects students' academic achievement. Class size, teacher quality, and educational expenditure are the common variables investigated under this topic. These variables are discretionary variables of school because they are under a direct control of policymakers (Hanushek, 1986). The main hypothesis under this topic is that greater school resources should have positive effects on students’ academic achievement. A review of each of the variables and their impact on students’ academic achievement is discussed below.

a. Class size

Evidence from extant literature suggests that class size does affect students’ academic achievement in an inverse relationship, especially for students in early years of schooling (Wilby, 2008; Rivkin et al., 2005; Finn et al., 2003; Nye et al., 2002). The range of optimal class size varies across studies from 17 to 25 students per class.[46] Student-teacher ratio and average number of students per class are the variables usually employed to measure the effect of class size on achievement (Rivkin et al., 2005).

The explanation of how class size affects students’ academic achievement is explained in Lazear’s (2001) analysis of Catholic vis-à-vis public schools in the US. Lazear found an inverse relationship between class size and students’ academic achievement. The argument for the inverse relationship was that students in a larger class

[46] For example, in 2003/2004, Alberta's Commission on Learning of Canada had identified 17 to be the ideal number of students for kindergarten, 23 for primary school, 25 for junior high school, and 27 for senior high school classes.

had less teacher's attention on an individual student and more distraction from other students, resulting in a shorter attention span on a subject being taught as compared to students in a smaller class.

b. Teacher quality

With regard to teacher quality, the level of teacher's education (having Master or PhD) and experience are two variables commonly employed. In many studies, teacher quality is found as a major determinant of students' academic achievement (Rivkin et al., 2005; Rice, 2003; Linda, 2000; Hanushek et al., 1998). In a review of US studies, Rice (2003) summarised the empirical evidence of teacher quality on students' academic achievement as follows:

i) Teacher experience – Evidence of a positive effect of teacher experience on students' academic achievement was found. The largest effect occurs in the first five years of a teacher's career (1 to 5 years).

ii) Teacher preparation programs and degrees - The prestige of the institution a teacher attended had a positive effect on students' achievement, particularly at the secondary level. Teachers who held advanced degrees had a positive impact on high school students' mathematics and science achievement when the degrees earned were in these subjects.

The significant effects of teacher quality on students' academic achievement, as summarised by Rice (2003) above, was confirmed by several recent studies—see Rivkin et al. (2005), Nye et al. (2004), Wayne & Youngs (2003).

Clotfelter et al. (2006) and Nye et al. (2004) cautioned the potential problem of biased estimates of teacher quality when better trained and more experienced teachers were assigned to teach students of greater ability and with fewer discipline problems. In such a case, there was an upward bias for the estimate of teacher effect because of the positive matching[47] between good students and better teacher quality.[48]

c. Educational expenditure

A survey of literature by Hanushek (1989, 1996) involving 187 studies that had been conducted in the US since 1966 concluded that there was no systematic relationship between educational expenditure and student performance. This conclusion sparked heated debates between him and several other researchers who found a positive effect of educational expenditure on students' academic achievement. Ferguson and Ladd (1996) and Hedges et al. (1994), for example, found that educational expenditure was significant in affecting students' academic performance. Hanushek's ((1989, 1996) method of aggregating results by counting t-statistics in coming to such a bold conclusion was unsatisfactory, according to his opponents.[49] The appropriate method of combining the results of many studies was not to count the significant t-statistics as Hanushek had done, but to use the tools of meta-analysis, as described by Hedges and Olkin (1980, 1985).[50] Hedges et al. (1994a, 1994b) performed such a meta-analysis and found that taken

[47] Negative matching, on the other hand, could occur when students with low academic achievement were matched with low performing teachers. In such a case, there was a downward bias for the estimate of teacher effect.

[48] To overcome the positive matching between better trained and experienced teachers with high ability students, an experimental dataset, formulated based on a random allocation of teachers and students (such as the popular Project STAR data) was one solution.

[49] From the 187 previous studies, Hanushek (1989, 1996) counted the percentage of statistically significant evidence of school expenditure variables on student performance with positive and negative signs. Hanushek (1987, 1996) also counted the percentage of statistically insignificant evidence of school expenditure variables on student performance. His conclusion was based on the net outcome between the studies that recorded significant (positive/negative) effects versus the studies that recorded insignificant (positive/negative) effects of school expenditure variables on students' academic achievement.

[50] Meta-analysis is a statistical technique for combining the findings from many independent studies. Meta-analysis technique gives due weight to the size of the different studies included. The validity of the meta-analysis depends on the quality of the systematic review on which it is based. A good meta-analysis should be based on a complete coverage of all relevant studies, look for the presence of heterogeneity, and explore the robustness of the main findings using sensitivity analysis (Hedges & Olkin, 1980, 1985).

collectively, the studies surveyed by Hanushek imply the existence of a positive and statistically significant relationship between test scores and expenditure per student.

Jacques and Brorsen (2002) employed school-district data from the Oklahoma Department of Education to investigate the impact of specific categories of expenditure on test scores. They employed 11 expenditure categories[51] as independent variables.[52] They found institutional, student support and transportation expenditures (3 out of 11 expenditure categories) had a statistically significant relationship on students' test scores. The reported magnitude for instructional and transportation expenditures were positive while for student support expenditure was negative.

In summary, the effect of school resources on students' academic achievement is significant. Since school resources are the discretionary variables, results from estimation exercises are important in guiding policymakers to formulate educational policy that aims at improving students' academic achievement.

3.4.4 Innate Ability and Student Performance

Innate ability is the presence of special talents, attributes or natural aptitudes in an individual. The hypothesis of research on innate ability is that the likelihood of an individual to becoming exceptionally competent in certain fields depends on his/her

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[51] The categories of the expenditures were: (i) instructional expenditures that deal directly with teacher-student interactions, including salaries and benefits for teachers, teacher's aides, clerks, tutors, etc; (ii) instructional support expenditures that assist instructional staff with content and provide tools that enhance the learning process; (iii) student support expenditures on attendance, social work services, guidance services, health services and speech pathology; (iv) school administration expenditures in general supervision of school operations (including staff such as school principals, assistant principals, secretaries and clerks); (v) general administration and business; (vi) student transportation expenditures; (vii) operations, maintenance, child nutrition, and community service operations; (viii) facilities acquisition and construction expenditures; (ix) other outlays such as debt service, a clearing account, and funds transfer; (x) scholarships; and (xi) repayment.

[52] They applied maximum likelihood estimation (MLE) to determine the relationship of the expenditure categories to achievement test scores, controlling for school size, educational attainment of parents, and percentage of students on free/reduced lunch, student race/ethnicity, and proportion of students in special education.

innate ability.[53] Since innate ability is a non-discretionary variable[54], it is not the main policy variable targeted for an improvement in the achievement of schools (Hanushek, 1986). In estimating an educational production function, however, innate ability is part of an individual student characteristic that should not be omitted, unless a careful model specification adjustment is made (see Appendix 3.1). Omission of the variable without a careful model specification can cause biased estimates of an educational production function. Hanushek (1986) stated that since innate ability was correlated with a positive family background, then omitting the innate ability variable would cause the estimate of family background to be biased upward.

Data on innate ability, nevertheless, is lacking. The value-added and the linear growth models of educational production function, as explained in Section 3.2, employ a lagged test score as a sufficient measure for all heritable endowments and historical inputs to overcome the deficiency in data on innate ability, family and community characteristics (Ding & Lehrer, 2007; Woesman, 2006; Todd & Wolpin, 2003; Huang 2002; Hanushek, 1997, 1986).[55] In the value-added model, the implication of employing a lagged test score as an independent variable to represent innate ability can cause an endogeneity problem as I have shown mathematically in Appendix 3.2. In Section 5.1, I explain how the use of panel data can eliminate the need for data on innate ability.

In brief, estimating the effect of innate ability on performance remains an open area for further research especially in the application of educational production function. Unless data of higher quality is available, estimating the effects of innate ability will

[53] Just to cite one influential argument on the presence of innate ability; in one British survey, over three-quarters of the educators who decided which young people were to receive instruction (in music) believed that children could not perform well unless they had special innate gifts (Davis, 1994).
[54] Innate ability is not directly amenable to adjustment through economic policy.
[55] The models treat pasted individual characteristics as unobservable and invoked assumptions so that the unobservable could be eliminated or ignored (see Appendix 1).

remain elusive due to the simplifying assumptions required and the complications of the econometric technical exercise.

3.5 Conclusion

In this chapter, I have reviewed the concept of education as a production process based on the framework of educational production function. Under the framework, educational output, frequently measured in terms of students' academic achievement, is expressed as a function of educational inputs. In doing so, the output depends on past and present educational inputs: (i) student/family background characteristics, (ii) peers/community influences, (iii) school resources, and (iv) innate ability.

From the review, I found that the estimation of an educational production function is critically susceptible to the problems of data limitation and multi-dimensional interactions of the input-output variables. As a consequence, a pertinent problem of endogeneity must not be ignored. The implication of neglecting the problem is that one ends up with biased estimates of the educational production model. With that in mind, empirical findings from the literature of educational production functions should be interpreted with caution.

I also found from the literature review conducted that the availability of data often influenced the type of analysis to be undertaken. The empirical research reviewed varied from a local-level (individual students, schools, or districts level) to a country-level (cross-countries) analysis. Estimations based on the local-level dataset were usually constrained by serious data limitation, particularly the data on student characteristics, family characteristics and peer characteristics. To undertake a country-level analysis, however, data aggregation problems must be considered. In a case of a country-level analysis, data aggregation could result in misleading conclusions regarding the economic behaviour of individuals.[56]

In the next chapter, I review SPF and DEA, particularly in their applications to measure schools' efficiency. The discussion continues with the literature review on SPF and DEA in order to keep readers aware of how the concept of education as a production process has evolved in research in economics of education. Based on the concept, SPF and DEA have been applied in education to measure schools' technical efficiency. Equiped with the understanding derived from the literature review in Chapters 3 and 4, I then estimate the educational production function (Chapter 5) and technical efficiency of schools (Chapter 6) based on Tasmanian dataset.

[56] See Garrett, Thomas A. "Aggregated Vs. Disaggregated Data in Regression Analysis: Implications for Inference." In Working Paper 2002-024B: Federal Reserve Bank of St. Louis, 2002.

Appendix 3.1: A Derivation of the Educational Production Functions

The purpose of this appendix is to derive the three models of educational production function. Based on the assumptions as outlined in Todd and Wolpin (2003), I use the general forms of the educational production function (equations 3.2 and 3.3), as given in Ding and Lehrer (2007), to derive the contemporaneous, value-added and linear growth models. Recall equation (3.2):

$$\mathbf{A}_{ijT} = \boldsymbol{\beta}_{0T} + \boldsymbol{\beta}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\beta}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\beta}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\beta}_{IT}\mathbf{I}_{i} + \sum_{t=0}^{T-1}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}) + \boldsymbol{\varepsilon}_{ijT}$$

and equation (3.3):

$$\mathbf{A}_{ijT-1} = \boldsymbol{\beta}_{0T-1} + \boldsymbol{\beta}_{1T-1}\mathbf{F}_{ijT-1} + \boldsymbol{\beta}_{2T-1}\mathbf{P}_{ijT-1} + \boldsymbol{\beta}_{3T-1}\mathbf{S}_{ijT-1} + \boldsymbol{\beta}_{IT-1}\mathbf{I}_{i} + \sum_{t=0}^{T-2}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}) + \boldsymbol{\varepsilon}_{ijT-1}$$

<u>Deriving the contemporaneous educational production model</u>

Since data on innate ability and past educational inputs are rarely available, the following assumptions are invoked:

i) Only contemporaneous inputs[57] matter to the production of current achievement, in which the effect of past educational inputs and unobserved innate ability in the production process decay immediately, or, $\boldsymbol{\beta}_{it} = 0$ for t = 0, 1, …, T-1 and $\boldsymbol{\beta}_{IT} = 0$.

ii) Contemporaneous inputs are unrelated to unobserved innate ability and unobserved past educational inputs.

[57] Contemporaneous inputs can be defined as inputs that are close in time to the achievement measure.

Assumption (i) eliminates the terms $\boldsymbol{\beta}_{IT}\mathbf{I}_i + \sum_{t=0}^{T-1}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt})$ in equation (3.2). Thus, if the assumptions hold, then $\boldsymbol{\varepsilon}_{ijT}^{c} = \sum_{t=0}^{T-1}\boldsymbol{\varepsilon}_{ijt}$. However, if the assumptions of the contemporaneous model do not hold, then the unobserved variables in the terms $\boldsymbol{\beta}_{IT}\mathbf{I}_i + \sum_{t=0}^{T-1}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt})$ now appear in the error term component of the following model—the contemporaneous educational production model:

$$\mathbf{A}_{i\,jT} = \boldsymbol{\alpha}_{0T} + \boldsymbol{\alpha}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\alpha}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\alpha}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\varepsilon}_{ijT}^{c} \tag{3.4}$$

where

$$\boldsymbol{\varepsilon}_{ijT}^{c} = \boldsymbol{\beta}_{IT}\mathbf{I}_i + \sum_{t=0}^{T-1}\left(\boldsymbol{\beta}_{ot} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}\right) + \boldsymbol{\varepsilon}_{ijT} \,.$$

<u>Deriving the value-added educational production model</u>

In a case when data on innate ability and past educational inputs are not available, let us assume:

i) the effect of observed and unobserved factors in the educational production process should decay over time at the same rate. More specifically, input coefficients must geometrically decline, as measured by time or age, with distance, from the achievement measurement (for all *j*, and the rate of decline must be the same for each input). Mathematically, $\boldsymbol{\beta}_{kn} = \boldsymbol{\lambda}\boldsymbol{\beta}_{kn-1}$, where n = 1, 2, …, T and $0 < \boldsymbol{\lambda} < 1$ for k = 0, 1, 2, 3, I. And

ii) $\mathbf{A}_{i\,jT-1}$ is a sufficient measure of all the previous inputs influences, which includes the unobserved endowment of innate abilities, parental, school and community effects.

Recall equation (3.2):

$$\mathbf{A}_{ijT} = \boldsymbol{\beta}_{0T} + \boldsymbol{\beta}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\beta}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\beta}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\beta}_{IT}\mathbf{I}_{i} + \sum_{t=0}^{T-1}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}) + \boldsymbol{\varepsilon}_{ijT}$$

Lagging equation (3.2) by one period gives equation (3.3):

$$\mathbf{A}_{ijT-1} = \boldsymbol{\beta}_{0T-1} + \boldsymbol{\beta}_{1T-1}\mathbf{F}_{ijT-1} + \boldsymbol{\beta}_{2T-1}\mathbf{P}_{ijT-1} + \boldsymbol{\beta}_{3T-1}\mathbf{S}_{ijT-1} + \boldsymbol{\beta}_{IT-1}\mathbf{I}_{i} + \sum_{t=0}^{T-2}(\boldsymbol{\beta}_{ot} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}) + \boldsymbol{\varepsilon}_{ijT-1}$$

Multiplying both sides of equation (3.3) by $\boldsymbol{\lambda}$ yields:

$$\begin{aligned}\boldsymbol{\lambda}\mathbf{A}_{ijT-1} &= \boldsymbol{\lambda}\boldsymbol{\beta}_{0T-1} + \boldsymbol{\beta}_{1T-1}\boldsymbol{\lambda}\mathbf{F}_{ijT-1} + \boldsymbol{\beta}_{2T-1}\boldsymbol{\lambda}\mathbf{P}_{ijT-1} + \boldsymbol{\beta}_{3T-1}\boldsymbol{\lambda}\mathbf{S}_{ijT-1} + \boldsymbol{\beta}_{IT-1}\boldsymbol{\lambda}\mathbf{I}_{i} + \\ &\sum_{t=0}^{T-2}(\boldsymbol{\lambda}\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\boldsymbol{\lambda}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\boldsymbol{\lambda}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\boldsymbol{\lambda}\mathbf{S}_{ijt} +) + \boldsymbol{\lambda}\boldsymbol{\varepsilon}_{ijT-1}\end{aligned} \tag{A3.1}$$

Subtracting (A3.1) from equation (3.2) gives:

$$\begin{aligned}\mathbf{A}_{ijT} - \boldsymbol{\lambda}\mathbf{A}_{ijT-1} &= (\boldsymbol{\beta}_{0T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{0T-1}) + (\boldsymbol{\beta}_{1T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{1T-1})\mathbf{F}_{ijT} + (\boldsymbol{\beta}_{2T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{2T-1})\mathbf{P}_{ijT} + (\boldsymbol{\beta}_{3T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{3T-1})\mathbf{S}_{ijT} + (\boldsymbol{\beta}_{IT} - \boldsymbol{\lambda}\boldsymbol{\beta}_{IT-1})\mathbf{I}_{i} + \\ &\sum_{t=0}^{T-1}\left[(\boldsymbol{\beta}_{0t} - \boldsymbol{\lambda}\boldsymbol{\beta}_{0t}) + (\boldsymbol{\beta}_{1t} - \boldsymbol{\lambda}\boldsymbol{\beta}_{it})\mathbf{F}_{ijt} + (\boldsymbol{\beta}_{2t} - \boldsymbol{\lambda}\boldsymbol{\beta}_{2t})\mathbf{P}_{ijt} + (\boldsymbol{\beta}_{3t} - \boldsymbol{\lambda}\boldsymbol{\beta}_{3t})\mathbf{S}_{ijt}\right] + \boldsymbol{\varepsilon}\end{aligned} \tag{A3.2}$$

Taking the term $\boldsymbol{\lambda}\mathbf{A}_{ijT-1}$ to the right-hand side of equation (A3.2) yields:

$$\begin{aligned}\mathbf{A}_{ijT} &= (\boldsymbol{\beta}_{0T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{0T-1}) + (\boldsymbol{\beta}_{1T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{1T-1})\mathbf{F}_{ijT} + (\boldsymbol{\beta}_{2T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{2T-1})\mathbf{P}_{ijT} + (\boldsymbol{\beta}_{3T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{3T-1})\mathbf{S}_{ijT} + \boldsymbol{\lambda}\mathbf{A}_{ijT-1} \\ &+ (\boldsymbol{\beta}_{IT} - \boldsymbol{\lambda}\boldsymbol{\beta}_{IT-1})\mathbf{I}_{i} + \sum_{t=0}^{T-1}\left[(\boldsymbol{\beta}_{0t} - \boldsymbol{\lambda}\boldsymbol{\beta}_{0t}) + (\boldsymbol{\beta}_{1t} - \boldsymbol{\lambda}\boldsymbol{\beta}_{it})\mathbf{F}_{ijt} + (\boldsymbol{\beta}_{2t} - \boldsymbol{\lambda}\boldsymbol{\beta}_{2t})\mathbf{P}_{ijt} + (\boldsymbol{\beta}_{3t} - \boldsymbol{\lambda}\boldsymbol{\beta}_{3t})\mathbf{S}_{ijt}\right] + \boldsymbol{\varepsilon}_{ijT}\end{aligned} \tag{A3.3}$$

And gathering some terms yields:

$$\begin{aligned}\mathbf{A}_{ijT} &= (\boldsymbol{\beta}_{0T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{0T-1}) + (\boldsymbol{\beta}_{1T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{1T-1})\mathbf{F}_{ijT} + (\boldsymbol{\beta}_{2T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{2T-1})\mathbf{P}_{ijT} + (\boldsymbol{\beta}_{3T} - \boldsymbol{\lambda}\boldsymbol{\beta}_{3T-1})\mathbf{S}_{ijT} + \boldsymbol{\lambda}\mathbf{A}_{ijT-1} + \\ &(\boldsymbol{\beta}_{IT} - \boldsymbol{\lambda}\boldsymbol{\beta}_{IT-1})\mathbf{I}_{i} + \sum_{t=0}^{T-1}\left[(1-\boldsymbol{\lambda})\boldsymbol{\beta}_{0t} + (1-\boldsymbol{\lambda})\boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + (1-\boldsymbol{\lambda})\boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + (1-\boldsymbol{\lambda})\boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}\right] + \boldsymbol{\varepsilon}_{ijT}\end{aligned} \tag{A3.4}$$

Re-expressing equation (A3.4) gives the value-added educational production model:

$$\mathbf{A}_{ijT} = \boldsymbol{\gamma}_{0T} + \boldsymbol{\gamma}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\gamma}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\gamma}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\lambda}\mathbf{A}_{ijT-1} + \boldsymbol{\varepsilon}_{ijT}^{L} \tag{3.5}$$

where if the assumptions of the model hold, then $\boldsymbol{\varepsilon}_{ijT}^{L} = \boldsymbol{\varepsilon}_{ijT}$. However, if the assumptions do not hold, then the terms

$$\left(\boldsymbol{\beta}_{IT} - \boldsymbol{\lambda}\boldsymbol{\beta}_{IT}\right)\mathbf{I}_i + \sum_{t=0}^{T-1}\left[\left(1-\boldsymbol{\lambda}\right)\boldsymbol{\beta}_{ot} + \left(1-\boldsymbol{\lambda}\right)\boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \left(1-\boldsymbol{\lambda}\right)\boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \left(1-\boldsymbol{\lambda}\right)\boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}\right]$$

now appear in the error term component of the model, such that:

$$\boldsymbol{\varepsilon}_{ijT}^{L} = \left(\boldsymbol{\beta}_{IT} - \boldsymbol{\lambda}\boldsymbol{\beta}_{IT}\right)\mathbf{I}_i + \sum_{t=0}^{T-1}\left[\left(1-\boldsymbol{\lambda}\right)\boldsymbol{\beta}_{ot} + \left(1-\boldsymbol{\lambda}\right)\boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \left(1-\boldsymbol{\lambda}\right)\boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \left(1-\boldsymbol{\lambda}\right)\boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}\right] + \boldsymbol{\varepsilon}_{ijT}$$

Deriving the linear growth educational production model

The following assumptions are made when data on innate ability and past educational inputs are not available.

i) The unobserved innate ability, $\mathbf{I}_i$, has a constant effect such that, $\boldsymbol{\beta}_{IT} = \boldsymbol{\beta}_{IT-1} = \ldots = \boldsymbol{\beta}_{I0} = c$, where c is a constant.

ii) The test score gain, $\Delta\mathbf{A}_{ijT} = \mathbf{A}_{ijT} - \mathbf{A}_{ijT-1}$, removes the need for data on innate ability, and past educational inputs of family, school and community influences.

Given the assumptions, the linear growth model is derived by:

$\Delta\mathbf{A}_{ijT} = \mathbf{A}_{ijT} - \mathbf{A}_{ijT-1}$ = [Equation (3.2)] – [Equation (3.3)]

$$\Delta\mathbf{A}_{ijT} = \left[\boldsymbol{\beta}_{0T} + \boldsymbol{\beta}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\beta}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\beta}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\beta}_{IT}\mathbf{I}_i + \sum_{t=0}^{T-1}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}) + \boldsymbol{\varepsilon}_{ijT}\right] -$$
$$\left[\boldsymbol{\beta}_{0T-1} + \boldsymbol{\beta}_{1T-1}\mathbf{F}_{ijT-1} + \boldsymbol{\beta}_{2T-1}\mathbf{P}_{ijT-1} + \boldsymbol{\beta}_{3T-1}\mathbf{S}_{ijT-1} + \boldsymbol{\beta}_{IT-1}\mathbf{I}_i + \sum_{t=0}^{T-2}(\boldsymbol{\beta}_{0t} + \boldsymbol{\beta}_{1t}\mathbf{F}_{ijt} + \boldsymbol{\beta}_{2t}\mathbf{P}_{ijt} + \boldsymbol{\beta}_{3t}\mathbf{S}_{ijt}) + \boldsymbol{\varepsilon}_{ijT-1}\right]$$

Simplifying the above equation yields:

$$\Delta\mathbf{A}_{ijT} = \left(\boldsymbol{\beta}_{0T} - \boldsymbol{\beta}_{0T-1}\right) + \left(\boldsymbol{\beta}_{1T} - \boldsymbol{\beta}_{1T-1}\right)\mathbf{F}_{ijT} + \left(\boldsymbol{\beta}_{2T} - \boldsymbol{\beta}_{2T-1}\right)\mathbf{P}_{ijT} + \left(\boldsymbol{\beta}_{3T}\boldsymbol{\beta}_{3T-1}\right)\mathbf{S}_{ijT} + \left(\boldsymbol{\beta}_{IT} - \boldsymbol{\beta}_{IT-1}\right)\mathbf{I}_i + \boldsymbol{\varepsilon}_{ijT}$$

Given assumption (i) that $\boldsymbol{\beta}_{IT} = \boldsymbol{\beta}_{IT-1} = \boldsymbol{\beta}_{IT-2} = \dots = \boldsymbol{\beta}_{IT-m} = c$, then,

$$\Delta\mathbf{A}_{ijT} = (\boldsymbol{\beta}_{0T} - \boldsymbol{\beta}_{0T-1}) + (\boldsymbol{\beta}_{1T} - \boldsymbol{\beta}_{1T-1})\mathbf{F}_{ijT} + (\boldsymbol{\beta}_{2T} - \boldsymbol{\beta}_{2T-1})\mathbf{P}_{ijT} + (\boldsymbol{\beta}_{3T}\boldsymbol{\beta}_{3T-1})\mathbf{S}_{ijT} + \boldsymbol{\varepsilon}_{ijT}$$

Re-expressing the above equation, yields—the linear growth educational production model:

$$\Delta\mathbf{A}_{ijT} = \boldsymbol{\tau}_{0T} + \boldsymbol{\tau}_{1T}\mathbf{F}_{ijT} + \boldsymbol{\tau}_{2T}\mathbf{P}_{ijT} + \boldsymbol{\tau}_{3T}\mathbf{S}_{ijT} + \boldsymbol{\varepsilon}_{ijT}^{G} \qquad (3.6)$$

where if the assumptions of the model hold, then $\boldsymbol{\varepsilon}_{ijT}^{G} = \boldsymbol{\varepsilon}_{ijT}$. However, if the assumptions do not hold, then the error term is given by $\boldsymbol{\varepsilon}_{ijT}^{G} = \boldsymbol{\varepsilon}_{ijT} + (\boldsymbol{\beta}_{IT} - \boldsymbol{\beta}_{IT-1})\mathbf{I}_{i}$.

Appendix 3.2: Endogeneity Problem when a Lagged Test Score is Used as One of the Independent Variables

The purpose of this appendix is to prove the existence of an endogeneity problem when a lagged test score is used as one of the independent variables in the value-added educational production model. I prove the problem based on a manipulation of equations (3.2) and (3.3). A simplification is made to equations (3.2) and (3.3) for notational convenience. The intercept and all the educational inputs, except **I,** are replaced by $\mathbf{X}_{ijt}$, such that $\mathbf{X}_{ijt} = \left[1\,\mathbf{F}_{ijt}\;\mathbf{P}_{ijt}\;\mathbf{S}_{ijt}\;\right]$, for t = 0, 1, 2, 3, …, T.

Given the simplification, equation (3.2) can now be expressed as:

$$\mathbf{A}_{ijT} = \boldsymbol{\beta}_T\mathbf{X}_{ijT} + \boldsymbol{\beta}_{IT}\mathbf{I}_i + \sum_{t=0}^{T-1}\left(\boldsymbol{\beta}_t\mathbf{X}_{ijt}\right) + \boldsymbol{\varepsilon}_{ijT} \qquad \text{(A3.5)}$$

while equation (3.3) can be written as:

$$\mathbf{A}_{ijT-1} = \boldsymbol{\beta}_{T-1}\mathbf{X}_{ijT-1} + \boldsymbol{\beta}_{IT-1}\mathbf{I}_i + \sum_{t=0}^{T-2}\left(\boldsymbol{\beta}_t\mathbf{X}_{ijt}\right) + \boldsymbol{\varepsilon}_{ijT-1} \qquad \text{(A3.6)}$$

From equation (A3.6), re-expressing the equation in terms of unobserved innate abilities yields:

$$\mathbf{I}_i = \frac{1}{\boldsymbol{\beta}_{IT-1}}\left[\mathbf{A}_{ijT-1} - \boldsymbol{\beta}_{T-1}\mathbf{X}_{ijT-1} - \sum_{t=0}^{T-2}\left(\boldsymbol{\beta}_t\mathbf{X}_{ijt}\right) - \boldsymbol{\varepsilon}_{ijT-1}\right] \qquad \text{(A3.7)}$$

Substituting equation (A3.7) into equation (A3.5) gives:

$$\mathbf{A}_{ijT} = \boldsymbol{\beta}_T\mathbf{X}_{ijT} + \frac{\boldsymbol{\beta}_{IT}}{\boldsymbol{\beta}_{IT-1}}\left[\mathbf{A}_{ijT-1} - \boldsymbol{\beta}_{T-1}\mathbf{X}_{ijT-1} - \sum_{t=0}^{T-2}\left(\boldsymbol{\beta}_t\mathbf{X}_{ijt}\right) - \boldsymbol{\varepsilon}_{ijT-1}\right] + \sum_{t=0}^{T-1}\left(\boldsymbol{\beta}_t\mathbf{X}_{ijt}\right) + \boldsymbol{\varepsilon}_{ijT} \qquad \text{(A3.8)}$$

Expanding equation (A3.8) yields:

$$\mathbf{A}_{ijT} = \boldsymbol{\beta}_T \mathbf{X}_{ijT} + \frac{\boldsymbol{\beta}_{IT}}{\boldsymbol{\beta}_{IT-1}} \mathbf{A}_{ijT-1} - \frac{\boldsymbol{\beta}_{IT}}{\boldsymbol{\beta}_{IT-1}} \boldsymbol{\beta}_{T-1} \mathbf{X}_{ijT-1} - \frac{\boldsymbol{\beta}_{IT}}{\boldsymbol{\beta}_{IT-1}} \sum_{t=0}^{T-2} \left(\boldsymbol{\beta}_t \mathbf{X}_{ijt} \right) - \frac{\boldsymbol{\beta}_{IT}}{\boldsymbol{\beta}_{IT-1}} \boldsymbol{\varepsilon}_{ijT-1} + \sum_{t=0}^{T-1} \left(\boldsymbol{\beta}_t \mathbf{X}_{ijt} \right) + \boldsymbol{\varepsilon}_{ijT} \tag{A3.9}$$

In equation (A3.9), let $\boldsymbol{\upsilon}_{i\,jT} = -\frac{\boldsymbol{\beta}_{IT}}{\boldsymbol{\beta}_{IT-1}} \left[\boldsymbol{\beta}_{T-1} \mathbf{X}_{ijT-1} + \sum_{t=0}^{T-2} \left(\boldsymbol{\beta}_t \mathbf{X}_{ijt} \right) + \boldsymbol{\varepsilon}_{ijT-1} \right] + \boldsymbol{\varepsilon}_{ijT}$ (A3.10)

Considering (A3.10), then, equation (A3.8) can be re-written as:

$$\mathbf{A}_{ijT} = \boldsymbol{\beta}_T \mathbf{X}_{ijT} + \frac{\boldsymbol{\beta}_{IT}}{\boldsymbol{\beta}_{IT-1}} \mathbf{A}_{ijT-1} + \sum_{t=0}^{T-1} \left(\boldsymbol{\beta}_t \mathbf{X}_{ijt} + \boldsymbol{\varepsilon}_{ijt} \right) + \boldsymbol{\upsilon}_{i\,jT} \tag{A3.11}$$

Hence, there is an endogeneity problem since $\mathbf{A}_{ijT-1}$ is correlated with $\boldsymbol{\upsilon}_{i\,jT}$, which contains $\boldsymbol{\varepsilon}_{ijT-1}$, a component of $\mathbf{A}_{ijT-1}$. Estimating equation (A3.11) using an OLS procedure may result in biased estimates.

4 Concepts and Measures of Efficiency and their Application in the Education Sector

4.0 Introduction

A review of the literature on frontier efficiency measurement is provided in this chapter. Both the parametric and non-parametric techniques of efficiency measurement will be assessed, namely, the Stochastic Production Frontier (a parametric approach) and Data Envelopment Analysis (a non-parametric approach). The main objective of this chapter is to identify the key methodological issues present when school efficiency is measured based on the two techniques. The review is crucial to the work at hand. It sets proper lines of inquiry, hypotheses and choice of methods for a study of Tasmanian schools' technical efficiency.

The underlying theory for both the parametric and non-parametric techniques is based on the economic production model as established under the educational production function. The difference between the reviews in this chapter as compared to Chapter 3 (and later between the estimations undertaken in Chapters 5 and 6) resides on the level of aggregation. The review in Chapter 3 and the estimation of educational production function in Chapter 5 are based on student-cohort level data while the review in this chapter and the estimation of efficiency in Chapter 6 is based on school-level data.

The presentation of the chapter is as follows. The concepts of efficiency and productivity in an educational sector are first discussed in Section 4.1. The section is crucial because it provides a perspective on how the concepts of school efficiency and productivity, as they are viewed by economists, can be understood. A review of the empirical findings based on the two approaches is then offered in Section 4.2. The strengths and weaknesses of both techniques are compared in the section. Some concluding remarks are presented in Section 4.3.

4.1 The Concepts of Productivity and Efficiency in Education

According to Worthington (2001, p. 252), technical efficiency in education deals with the best use of educational inputs, such as school resources, in order to improve students' academic achievement. Allocative efficiency, he states (p. 253), concerns the optimal combinations of educational inputs needed (for example, teacher instruction and computer-aided learning), in order to produce a given level of educational output at minimal cost. In other words, allocative efficiency is about choosing the right combination of educational inputs and must take into account the relative costs of the inputs employed, assuming outputs are constant.[1]

Productivity in education, according to Rolle (2004, p. 32), is related to the issues of how to achieve the efficient production of educational outcomes. Rolle (2004, p. 54) states that in the context of public education institutions, educational productivity debates cover the issues of how to: minimise costs; maximise the utilisation of available resources; meet increased and diversified educational objectives and how to become accountable to the public for the expenditure of resources.

In order to apply the concepts of productivity and efficiency to the field of education, Duyar et al. (2006) emphasise the need to establish the relationship between educational inputs and outputs. One way to understand that relationship is by estimating an educational production function. Once the relationship is clear, a production frontier of the best-practice schools can be estimated, where the estimated frontier stands as the

[1] In Appendix 4.1, the various concepts of efficiency in microeconomics are detailed using some diagrams.

benchmark in the process of evaluating the efficiency (relative) of other schools. Consequently, in order to assess the level of efficiency of schools in Tasmania, I first estimate the Tasmanian educational production function (the literature review on educational production function is offered in Chapter 3 and the estimation results are provided in Chapter 5). Economists have applied the frontier production approaches to measure technical efficiency, allocative efficiency and cost efficiency of schools. The research here will only evaluate the level of technical efficiency of schools in Tasmania. Technical efficiency alone is estimated because in order to estimate allocative efficiency, data on educational resource prices are required and those data are not available. In Appendix 4.1, I review the models of frontier production literature that have been used to measure school technical efficiency.

4.2 Empirical Evidence and Issues

4.2.1 Stochastic Production Frontier (SPF)

I provide a review of the empirical evidence of the Stochastic Production Frontier (SPF) in relation to measuring schools' technical efficiency in this section. The purpose of the review is to investigate the common variables employed, empirical strategies applied and the main findings obtained from the various studies of school efficiency measurement. This review is important to arrive at a standard application of SPF in measuring the level of school technical efficiency.

Limited studies to estimate technical efficiency of schools based on SPF have been undertaken. An empirical survey by Worthington (2001) on frontier efficiency measurement techniques found that most studies had applied DEA to measure school efficiency.[2] The reason for the limited application of SPF lies in the requirement to assume a specific functional form for the production technology and the need to assume a certain distributional assumption for the inefficiency term (*U*) of the error component. Those requirements make the application of SPF more complex than DEA.

In Table 4.1, a summary of research on school technical efficiency based on SPF is presented. In the table, information on the authors, the publication year, the input-output variables used, the functional form and distributional assumptions made and the main findings of each study are provided.

The discussion of Table 4.1 starts with a paper by Adkins and Moomaw (2007) who estimated a translog production frontier for 418 school districts in the state of Oklahoma. The output and input variables employed in the study are detailed in Table 4.1. For the SPF estimation, Adkins and Moomaw (2007) employed a model as introduced by Battese and Coelli (1995).[3] The model was based on a translog production function and assumed a truncated distribution for the inefficiency term (*U*). Adkins and Moomaw (2007) justified the application of a translog functional form because of its flexibility in specifying the input-output relationship of education.

The flexibility in the translog model, according to Adkins and Moomaw (2007, p. 4), lies in the second-order approximation to the unknown, but true, functional form of an educational process. From their study, Adkins and Moomaw (2007) found a significant but small effect of instructional and non-instructional expenditures on students' academic achievement. Their estimates of technical efficiency of school

[2] Out of 24 papers reviewed and presented in a table by Worthington (2001, pp. 253-259), only 3 papers employed SPF while the rest evaluated schools' technical efficiency using DEA.
[3] The model is usually known as Battese and Coelli (1995) model. Details of the model are available in a manual of Frontier 4.1 (a software)—see Coelli (1996a). The software allows the estimation of the SPF based on a maximum likelihood procedure to be undertaken.

districts in Oklahoma found that the highest median technical efficiency score was 0.938 for grade 11 while the lowest was 0.865 for grade 3. In addition, their investigation of the determinants of school efficiency found that school district size (larger educational districts were technically more efficient than smaller educational districts), teacher education and experience, and teacher salary were all significant in explaining the technical efficiency of school districts in Oklahoma.

Tarja (2007) estimated a Cobb-Douglas production frontier for a panel data of 436 Finnish upper-secondary schools.[4] Five different panel stochastic frontier models, namely: pooled panel data model; random effects model; fixed effects model; true random effects model and true fixed effects model were estimated.[5] To determine the appropriate distributional assumption for the inefficiency term (U), Tarja (2007, p. 7) conducted a one-sided likelihood ratio test, introduced by Coelli (1995). The test was to analyse the skewness of the inefficiency term so that an appropriate distributional assumption could be assigned. From the test, a half-normal distribution for the inefficiency term (u) was found appropriate for all the models.

[4] Tarja (2007, p. 2) did not mention any specific justification for assuming a Cobb-Douglas functional form except merely stating the common application of the form in many studies.

[5] For a great length of elaboration on panel data production frontier models, see Kumbhakar and Lovell (2000, pp. 95-130).

Table 4.1: Stochastic Production Frontier Applications in Education

Author	Data	Variables	Functional Form & Distributional Assumption	Findings
Adkins & Moomaw (2007)	418 Oklahoma school districts; year 1990-91 and 1994-95	Output; results in percentiles of the Iowa Test of Basic Skills (ITBS) for grades 3 (IT3) and 7 (IT7), and the Test of Achievement and Proficiency (TAP) for grades 9 (TAP9) and 11 (TAP11). Inputs; district enrolment, instructional expenditures per student , administration expenditures, average teacher salary, years of experience, percentage of teaching staff with an advanced degree (Master's degree or higher), percentage of Oklahoma students eligible for federally funded or reduced payment lunch in the school, percent of non-white students (e.g., American Indian, black, Hispanic, Asian) in the district.	Translog production frontier, assuming truncated distribution.	Larger districts had greater degree of technical efficiency. The optimal size of number of students per district was in the range of 18,000 to 22,000 to achieve technical efficiency.
Tarja (2007)	436 Finnish upper secondary, school-level panel data, year 2000-2004.	Output; grades in matriculation examination. Inputs; comprehensive school GPA, parents' socio economic background (education, occupational and marital status), gender, share of Swedish speaking students, school expenditures, student-teacher ratio, heterogeneity of student body, average length of studies, average participation in examination periods, school size, curriculum specialisation, private/state/municipality, location of the school (urban/rural)..	Cobb-Douglas production frontier with half-normal distribution.	Efficiency rankings were different between models. No relation between the ranking of random effect and true random effect models, and fixed effect and true fixed effect models.
Chakraborty, Biswas & Lewis (2001)	40 Utah school districts.	Output; average test score in the 11th grade. Inputs; (a) School inputs - student-teacher ratio, percentage of teachers with an advanced degree, percentage of	Cobb-Douglas production frontier with half-normal and	Measures of technical efficiency differ between half-normal and exponential distributions, but the

		teachers with more than 15 years of experience. (b) Nonschool inputs - percentage of students who qualified for Aid to Families with Dependent Children (AFDC) subsidised lunch, percentage of district population having completed high school, net assessed value per student.	exponential distributions.	rankings were almost similar (the correlation coefficient for the two rankings was 0.976). The mean efficiency was 0.858 for the half-normal estimates and 0.897 for the exponential function. The most and the least efficient schools based on the half-normal distribution technical efficiency scores were 0.991 and 0.625 while the scores were 0.981 and 0.672 for the exponential distribution.
Manuel & Sara (2007)	502 Portugal's public and private schools, school-level data, year 2003/04 and 2004/05, involve both cross-sectional and panel data analyses.	Output; average score in the 12th grade national examination. Inputs; number of teachers per 100 student, share of the student population in "ensino recorrente", school size, private school dummy, average teacher age, average wage of teachers, proportion of teachers with university education, purchase power index by municipality, average years of schooling by municipality, health status index by municipality, average household electricity consumption by municipality.	Cobb-Douglas production frontier with truncated distribution.	The estimated technical inefficiency was between 90% and 80%. Quality of teachers (proxied by seniority) was found to have larger effects on output than quantity (proxied by teachers per student).
Mizala, Romaguera & Farren (2002)	2000 Chile's schools, year 1996.	Output; average test score (fourth grade). Inputs; (a) Student characteristics - socioeconomic level, vulnerability index. (b) School characteristics - types of school, geographical index, school size: number of students, pupil-teacher ratio, dummy on whether or not pre-school education is provided, gender (boys' schools, girls' schools, coeducational schools). (c) Teacher characteristics - average experience.	Linear production frontier with half-normal distribution.	Average school technical efficiency was 93.18%. Technical efficiency of the most efficient school was 98.19% and the least efficient school was 73.04%. Private fee-paying schools performed better than private-subsidised and public schools.

Tarja (2007) found that students' innate ability (comprehensive school GPA) had the largest positive effect on students' academic achievement (matriculation examinations), where a one-tenth growth in school's GPA leads to 0.3% increase in grades. Other variables with positive effects were parental education and occupation, the proportion of female students and the proportion of Swedish speaking students. No systematic effects on matriculation examinations were found for single parents, school size, school specialisation, school location and private/public schools. Tarja (2007) also found that efficiency rankings were different depending on the panel data production frontier models employed. The random effects and fixed effects models produced high estimates of inefficiency because the models considered all time-constant school heterogeneity[6] as an inefficiency. True random and true fixed effects models, on the other hand, provided lower estimates of inefficiency because the models considered the time-constant school heterogeneity to be separated from inefficiency.[7]

Chakraborty, Biswas and Lewis (2001) conducted a research to measure the technical efficiency of 40 Utah school districts based on Stochastic Production Frontier (SPF) and Data Envelopment Analysis (DEA). In this section, I only provide a review of the study based on the SPF analysis. Their analysis based on DEA will be discussed in the next section. I detail the variables used for their SPF analysis in Table 4.1.

The application of SPF by Chakraborty et al., (2001) assumed a Cobb-Douglas production frontier. Chakraborty et al., (2001) stated that due to insufficient data, more

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[6] In panel data analysis, inefficiency might vary through time. One reason for the variation was due to school-specific heterogeneity. Tarja (2007) confined the heterogeneity by looking at the heterogeneity of students, measured by the standard deviation of their grades in compulsory subjects in matriculation examinations.

[7] In true random and true fixed effects models, school heterogeneity was allowed by dividing the school specific inefficiency term into two; (i) unmeasured heterogeneity, assumed as constant through time, and (ii) measured heterogeneity that varied through time (Tarja, 2007).

flexible functions, such as a translog production function, were not viable for testing due to a limited number of degrees of freedom. Chakraborty et al., (2001) did not provide any reason for the selection of half-normal and exponential distributional assumptions for the inefficiency term (*u*). They, however, provided a comparison of efficiency estimates obtained based on the two distributional assumptions employed. Their findings suggested that each distribution gave a different measure of technical efficiency, but efficiency rankings of school districts were very similar (the correlation coefficient for the two rankings was 0.976). The estimated mean efficiency was 0.858 for the half-normal assumption and 0.897 for the exponential assumption. For the half-normal distribution, scores of the most and the least technically efficient school districts were 0.991 and 0.625, while for the exponential distribution, the scores were 0.981 and 0.672.

An efficiency study based on Portuguese secondary schools was undertaken by Manuel and Sara (2007). The study involved both a cross-sectional and a panel data analysis. A Cobb-Douglas functional form was assumed for the production frontier in both analyses. To determine the appropriate distributional assumption for the inefficiency term, Manuel and Sara (2007) applied a one-sided likelihood ratio test as introduced by Coelli (1995). Based on the test, they employed a half-normal distribution for the cross-sectional analysis, and a truncated distribution for the panel data analysis. In Table 4.1, I provide the variables employed in their study. No variables on family background of students were included in their analysis. Consequently, the authors cautioned that both the cross-sectional and panel data estimates of the variables were prone to measurement error. From the study, quality of teachers (proxied by seniority) was found to have larger effects on output than quantity (proxied by teachers per student). Manuel and Sara (2007) also found that had the schools been technically efficient, students' academic achievement would have been on average about 10% to 20% higher given the current level of resources.

Mizala, Romaguera and Farren (2002) investigated the level of technical efficiency of 2000 schools in Chile using SPF and DEA. A discussion of SPF is offered here while the discussion of DEA will be presented in the next section. In Table 4.1, the variables employed in the study are listed. The estimation of SPF by Mizala et al. (2002) was based on a linear production function with a half-normal distribution was assumed for the inefficiency component (U). The results from the frontier estimation showed that socio-economic status (higher income and higher parental education) was significant in explaining students' academic achievement in Chile. Other significant variables that affect students' academic achievement were: (i) girls' schools performed better than boys' and mixed schools, (ii) private schools performed better than public schools, and (iii) larger class had negative effects on students' performance. From the study, the estimated average school efficiency was 93.18%. The most efficient school's score was 98.19% and the least efficient school's score was 73.04%.

4.2.2 Data Envelopment Analysis (DEA)

In this section I provide a review of the application of Data Envelopment Analysis (DEA) to measure schools' technical efficiency. The aim of the review is to arrive at a shared understanding of DEA application to the measurement of school technical efficiency. A summary of the reviewed papers is shown in Table 4.2. In the table, the author, publication year, description of the sample and variables employed, and major findings of each study are shown. The selection of papers, as shown in Table 4.2, starts from 1998 until 2006. Studies prior to 1998 can be found in Worthington's

(2001) survey of the literature.[8] The survey by Worthington (2001, p. 223) traces the literature from 1981, with the work of Charnes et al. (1981) until 1997, to the work of Duncombe et al. (1997).[9]

The discussion of Table 4.2 starts with a study by Noulas and Ketkar (1998) who investigated the technical efficiency of 100 school districts in New Jersey. They employed a two-stage procedure, where a DEA estimation was conducted in the first stage, and a Tobit regression was conducted in the second stage. The two-stage procedure was normally employed in DEA to account for exogenous influences on efficiency. In the first stage, the DEA model was estimated using variables that were controlled by schools (endogenous variables). The application of a Tobit regression in the second stage employed the DEA technical efficiency scores (obtained from the first-stage estimation) as a dependent variable and socio-economic (non-discretionary) variables as the independent variables. The Tobit regression was undertaken to identify the socio-economic variables that might explain technical efficiency. In Table 4.2, I provide a detail description of variables used in Noulas and Ketkar's (1998) study.

Noulas and Ketkar (1998) found that the average technical efficiency of school districts in New Jersey was 0.8093 (or 80.93% technically efficient). The highest technical efficiency score was 86.79% while the lowest score was 69.29%. From the

[8] My review of the literature starts from 1998 onwards is to avoid repetition of the comprehensive review of the literature prior to 1998 by Worthington (2001). Worthington (2001) reviewed works based on frontier efficiency measurement techniques to measure the efficiency of primary schools, secondary schools and universities. Worthington found that Data Envelopment Analysis (DEA) was more popular than Stochastic Frontier Analysis (SFA) in works to measure education efficiency. The approach under DEA was straightforward, as described in Section 4.2.2. The SFA, in contrast, required a prior determination of the functional form of the production function and the distributional assumption for the inefficiency component of the error term. Worthington also pointed out that the main issue in works to identify the determinants of education efficiency was on disentangling the effect of the uncontrollable inputs (namely, students' socio-economic status) from efficiency scores. Worthington (2001) identified that the two-stage estimation procedure (DEA in the first-stage and Tobit regression in the second-stage) was the common approach used to deal with the issue.

[9] Worthington (2001) included all studies involving primary, secondary and tertiary education levels. My focus for this review only considers studies involving primary and secondary education.

Tobit regression conducted, technical efficiency of school districts in New Jersey was positively affected by the value of house (proxy for family income). By way of contrast, crime rate, poverty level and percentage of minority students had a significant negative effect on school district efficiency.

Another study based on the United States of America case was undertaken by Ruggiero (2000). The study involved 556 New York State school districts—details of the variables employed are provided in Table 4.2. Ruggiero (2000) estimated a variable returns to scale (VRS) DEA model. The author emphasised the importance of controlling for environmental factors when estimating public sector performance such as the performance of schools. Ruggiero (2000) argued that public sector production was characterised by a strong influence of environmental factors on its service outcomes, leading to the problem of multiple frontiers (such as the DEA frontier for rural schools and another frontier for urban schools). Failure to control for the multiple frontiers could cause point estimates of efficiency and returns to scale to be biased (Ruggiero, 2000, p. 908).

To control for differences in the production environment, Ruggiero, (2000) discriminated between the school districts according to the percentage of adults graduating from college (proxy for parental education). The selection of the variable was based on a finding by Gyimah-Brempong and Gyapong (1991) that the education of the adult population was the only variable appropriate to represent all exogenous community characteristics influencing educational production in the case of New York schools. Ruggiero (2000) found that 80% of the school districts were technically inefficient. The disadvantage in socio-economic conditions of the environment under which the school operated had a negative effect on efficiency.[10] Ruggiero (2000) estimated that due to disadvantages in socio-economic environment (25% of the school districts were considered socio-economically disadvantaged), the identified school districts required on average 11% more of all inputs to achieve the same level of services (as produced by the educational districts operating under a favourable environment).

The study by Maragos and Despotis (2003) involved 60 high schools in Greece—see Table 4.2 for additional details of the variables employed. Before applying a VRS-DEA model, Maragos and Despotis (2003) clustered the schools according to the socio-economic environment[11] in which the schools operated. They clustered the schools so that the impact of socio-economic background on schools' efficiency could be accounted for. Maragos and Despotis (2003) found that the schools operating in non-privileged areas performed, on average better than the schools in privileged areas. They however, did not provide any comment on the findings.[12]

Stupnytskyy (2004) estimated efficiency of secondary schools in the Czech Republic using both constant (CRS) and variable returns to scale (VRS) DEA models. The robustness of the DEA analysis conducted was checked using a jackknife procedure.[13] Variables employed in the study are listed in Table 4.2. Under the CRS assumption, the estimated average technical efficiency was 83% and under the VRS assumption, it was 87%. Stupnytskyy (2004) then related the efficiency scores to school and teacher characteristics variables (see Table 4.2) using a Tobit regression model.

[10] A harsher environment was characterised by high rates of poverty and single-parent families.

[11] The clustering was set in reference to parental education and occupation status, and housing category.

[12] In my opinion, more technical help by the government to schools in the non-privileged areas could be one reason to explain the results.

[13] The jackknife procedure was performed by dropping one efficient point at a time. A new DEA estimate was obtained for each round with the rest of the sample. If the new results were similar to the old one then the point which was dropped had no significant effect on the estimated efficiency. The results were considered robust against outliers at the frontier. The correlation computed by the jackknife method ranges from 0.93 to 0.99—showing that the results were robust (Stupnytskyy, 2004, p. 10).

From the second stage analysis conducted, he found that teacher-student ratio was significant with a negative effect on efficiency. Variables with positive and significant effects were cooperation with other schools and ability sorting of students.[14] Stupnytskyy however, found no significant effects on efficiency for the variables that represented teacher age, the percentage of female teachers, and change in school headmasters.

Borge and Linn (2005) employed a two-stage-procedure to measure schools' technical efficiency and to identify the determinants of efficiency of Norwegian schools —see Table 4.2 for details. In order to clean the data of outliers[15], they adjusted the test score (output) according to student and family background characteristics. To check whether the DEA results were robust to measurement errors and outliers, they performed a jackknife procedure.[16] They found that the strategy of adjusting the test score to socio-economic influence was effective to overcome the effect of outliers (Borge and Linn, 2005, p. 13). The estimated average technical efficiency of the schools was 86%. The analysis of the determinants of efficiency found that a high level of municipal revenue, a high degree of party fragmentation, and a high share of socialists in the local council were associated with low technical efficiency. The study by Borge and Linn (2005) also

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[14] Students at proximate ability levels within a school curriculum are put together for instruction based on prior achievement levels (Van Tassel-Baska, 1992, p. 68).

[15] Outliers refer to the existence of extreme observations that includes the sample maximum or sample minimum, or both, and they are unusually far from other observations. In DEA, outliers with high levels of output and/or low input affect the position of the frontier and thereby reduce the efficiency score of other units. Inclusion of outliers means allowing over stated data to be included in the reference set. Since the framework of DEA (non-parametric) does not consider measurement error when constructing a frontier, the inclusion of outliers causes the efficiency estimate to be biased. As such, outlier detection in a DEA framework is important (Borge & Linn, 2005, p. 8).

[16] To conduct the jackknife procedure, Borge and Linn (2005) left out each efficient school district one at a time. They then ran a new DEA analysis in each case. From the exercise, they found 19 efficient school districts, implying 19 additional DEA analyses were undertaken. When one efficient unit was left out, the mean efficiency score of the remaining units increased. Robustness from outliers was checked in reference to by how much the mean efficiency had increased. They found the benchmark efficiency scores were very robust to outliers since mean efficiency increased by one percentage point or less in 17 out of the 19 cases.

found negative associations between the share of socialists and party fragmentation with higher resource consumption and lower student performance.

Smith and Andrew (2006) analysed the performance of 2,928 English secondary schools. Based on the data as reported in Table 4.2, they provided estimates for both the input-oriented and output-oriented approaches of DEA. For schools with 6^{th} forms (grade 13), the average technical efficiency under the input-oriented DEA was 88.4% (for schools without 6^{th} forms it was 89.9%) while the average technical efficiency under the output-oriented DEA was 90.7% (for schools without 6^{th} forms, it was 91.1%). All the results based on the output-oriented approach of DEA gave higher estimations as compared to the input-oriented approach of DEA.

Jeon and Shields (2006) applied a two-stage procedure in the investigation of efficiency of public education in the Upper Peninsula of Michigan. Variables employed for the analysis are listed in Table 4.2. The problem of input and output selection in the DEA analysis were handled by using extreme-bound analysis[17] and thick modeling[18], where various combinations of outputs and inputs were dropped in several model specifications (Jeon & Shields, 2006, p. 604-607).[19] The authors ran 12 different model

[17] Extreme-bound analysis is a sensitivity analysis that is usually applied in the process of variable selection in a linear regression. Suppose one is interested in measuring the effect of class size on students' academic performance. Extreme-bound analysis starts with a general model of educational production that includes class size (focus variable), as well as other variables (control variables). The general model can be formulated in various ways, for example by excluding one or more explanatory variables. Extreme-bound analysis is concerned with the largest and smallest values of the estimates of the class size coefficient when various 'simplified' models are estimated. If the estimated coefficient of class size varies greatly over the range of the simplified models, inference concerning the coefficient is then said to be unreliable. The reason is the coefficient estimate obtained appears to be sensitive to the precise specification of the model used. Based on a simple rule, however, the estimation is said to be robust if the parameter estimates of the focus variable are significantly of the same sign—regardless of any alteration in the control variable specification (Leamer, 2008).

[18] Thick modeling is applied in order to avoid model-mining. Granger & Jeon (2004) suggested a thick modeling approach, based on trimming to eliminate the *k*% worst performing forecasts and then taking a simple average of the remaining forecasts.

[19] The standard approach in DEA is to consider just a single specification and then discuss efficiency scores. This practice implies that any information in the alternative specifications is not being used. Since

specifications in the extreme-bound analysis in which technical efficiency scores were computed. The maximum and the minimum efficiency scores obtained from the 12 model specifications were taken out for each district in the thick modeling calculation[20] (Jeon & Shields, 2006, p. 607). Their thick modeling results showed that 14 school districts were fully efficient (100%), whereas 21 out of 49 school districts were less than 90% efficient. The average level of technical efficiency was 89% and its median was 91.3% with minimum efficiency of 50.2%. From the second-stage analysis conducted, they found that family income was the most important explanatory variable in explaining technical efficiency of the school districts.

A recent study by Cherchye et al. (2008) was based on student-cohort level data of Flemish primary schools (see Table 4.2). Their main research objective was to evaluate the level of technical efficiency between private and public schools by taking into account the differences in inputs and environment factors.[21] From the study, the environmental variables (average parental education level, average parental professional status and total family income) were found to have a positive effect on technical efficiency. They suggested that in order to avoid any misleading interpretation of efficiency results, school performance comparison should be made on the basis of environment corrected efficiency scores. Since schools' performance was sensitive to students' equity considerations, environment-corrected efficiency scores were the appropriate measure to be used when making efficiency comparison.

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many specifications are possible, extreme-bound analysis and thick modeling provide a basis for selection of the best specification.

[20] Based on Granger and Jeon's (2004) thick modeling procedure, Jeon and Shields (2006) deleted the maximum and minimum efficiency scores in each school district in order to obtain the trimmed-mean.

[21] The departing point of the research was based on a belief that private schools in Flanders performed better although they received less teaching inputs because of the advantageous condition of the student population.

Table 4.2: Data Envelopment Analysis Applications in Education

Author	Data	Variables	Findings
Noulas & Ketkar (1998)	100 New Jersey's school districts (high schools)	DEA - Output; percentage of students that pass the ninth-grade level High School Proficiency Test (HSPT) for the 1990/91. Inputs; students-to-teacher ratio, students-to-administrator ratio; students-to-educational support servicespersonnel (such as counselors and students-to non-certificate staff ratio). Regression analysis – Dependent variable: efficiency levels from DEA estimate. Independent variables; median value of homes, crime rate, percentage of population below poverty level and percentage of minority students.	The average technical efficiency score is 0.8093. The highest technical efficiency score is 0.8679 while the lowest is 0.6929. The value of home is positive and significant, while the crime rate, the poverty level and the percentage of minority students have a significant negative effect on the technical efficiency of schools.
Ruggiero (2000)	556 New York State school districts for the year 1990/91	VRS DEA - Output; average test scores in Pupil Evaluation Program and dropout rate. Discretionary inputs; teacher salary expenditures, instructional expenditures, other expenditures, books and computers. Environmental input; percentage of adults with college education.	80 per cent of the educational districts are inefficient. Increasing technical returns to scale is found for 162 districts out of 556 educational districts analysed.
Maragos & Despotis (2003)	60 high schools in the Greater Athens Area (GAA), Greece for the academic year 2000-2001	VRS DEA - Output; percentage of university entrants and upper level graduates. Inputs; percentage of full time teachers, students-to-teachers ratio.	Schools operating in non-privileged areas perform, on average, better than the schools in privileged areas.
Stupnytskyy (2004)	Secondary schools in the Czech Republic	DEA - Output; school average scores in test in mathematics, Czech language and number of students admitted to university. Inputs; average grade of students at completion of primary schools, classrooms per student ratio, school facility index. Tobit regression analysis - dummy of efficient schools. Dependent variable; Independent variables; teacher-student ratio, average age of teachers, per cent of fulltime teachers, per cent of female teachers, years the school's director in service, per cent of male students, existence of career advise centre or not.	Technical efficiency is 0.83 for CRS-model and 0.87 for VRS-model. The Tobit regression shows that teacher age, per cent of female teachers, fluctuation of teachers and years of service of the current school director have no significant effects on efficiency. Variables with significant effects are teacher-student ratio, per cent of fulltime teachers, existence of students career advice centre, percentage of male students in class, cooperation with foreign schools and sorting of students.

Borge & Linn (2005)	426 Norway's lower-secondary schools, 2001/02 & 2002/03	DEA- Outputs; adjusted grade of 10th grade students in Norwegian, mathematics, English and the average grade of the remaining subjects. Inputs; total number of teacher hours and the fraction of certified teachers. Tobit regression; Dependent variable - efficiency score from the DEA analysis. Independent variables - level of education in the municipality, share of minority students, share of students with special needs, average school size, school size squared, municipal revenue, Herfindahl-index of (the inverse) of party fragmentation, share of socialists in the local council, population size, share of the population living in rural areas, centralised budgetary procedure.	The average school districts could reduce inputs by 22 percent without reducing measured output. 19 out of 426 municipalities come out as efficient (with an efficiency score of 1), whereas the lowest efficiency score is 0.42. Around 25 percent of the municipalities come out with an efficiency score below 0.71, and other 25 percent have efficiency score above 0.87.
Smith & Andrew (2006)	2928 English secondary schools	DEA - Output; GCSE scores. Inputs; number of teachers per 1000 pupils, number of learning support staff per 1000 pupils, number of administrative and clerical staff per 1000 pupils, expenditure on learning and ICT resources per 1000 pupils, percentage pupils not eligible for free school meals, percentage pupils without special education needs, percentage pupils with English as additional language.	For schools with 6th forms (grade 13), the mean for the input-oriented technical efficiency is 0.884 (for schools without 6th forms it is 0.899) while the mean for the output-oriented technical efficiency is 0.907 (for schools without 6th forms, it is 0.911).
Jeon & Shields (2006)	School Districts of Upper Peninsula of Michigan	DEA - Output; results of students in grade 11 in Michigan Educational Achievement Program. Inputs; state fund per student, average teacher salary, teacher to student ratio and proportion of students who do not qualify for subsidised or free student lunches. Regression analysis - Dependent variable; efficiency scores. Independent variables; per cent of the school district's population living in urban areas, the median value of housing in the district, and median household income in the district, per cent of students enrolled in private schools	14 school districts are fully efficient (100%), whereas 21 out of 49 school districts are less than 90% efficient. The average level of efficiency is 0.890 and its median is 0.913 with minimum efficiency of 0.502. The second-stage analysis finds that family income is the most important explanatory variable, whereas the median value of housing is found to be insignificant.
Cherchye et al., (2008)	Student-cohort level data of Flemish (Belgium) students - 3143 students in second year primary schools	DEA - Outputs; test scores in mathematics, technical reading and writing. Inputs; number of instruction units assigned to a particular pupil, average parental education level, average parental professional status and total family income.	The environmental characteristics (parental education, professional status and family income) are found to have a positive effect on the educational output. The authors suggest that in order to avoid misleading interpretation of the DEA results, school performance comparisons should be made on the basis of environment-corrected efficiency scores.

Chakraborty et al. (2001) and Mizala et al. (2002) applied both SPF and DEA to measure schools' efficiency. Details of their SPF analysis were discussed in Section 4.5.1. Their analyses based on DEA are discussed here together with the comparative findings from both their applications of SPF and DEA analyses.

Chakraborty et al.'s (2001) analysis of Utah school districts was based on a two-stage output-oriented DEA.[22] After adjusting for the differences in socio-economic environment, they found that the order of school district rankings from the SPF and DEA was quite similar, where rankings for the most and the least efficient school districts were the same across both models. The two-stage DEA model indicated that socioeconomic and factors had a strong influence on technical efficiency success. Two points from their work are worth emphasising:

Caution needs to be exercised when an analysis involves data aggregation (such as to obtain data on school district). Chakraborty et al. (2001) cautioned against the potential problem of specification error that could be transmitted to the estimation of efficiency score in both the SPF and DEA models. The problem happened because decisions regarding controllable inputs were often made at the school level rather than the district level. As a consequence, aggregation of inputs and outputs at the district level might overlook strategic decisions by an individual school.

If fixed factors in the environmental variables were carefully controlled, Chakraborty et al. (2001) pointed out that researchers could select any of the parametric and the nonparametric methods without great concern for the choice of models having a large influence on the empirical results.

[22] Descriptions of the variables are given in Table 4.1.

The findings by Chakraborty et al. (2001) were confirmed by Mizala et al. (2002) who employed a VRS-DEA model in the analysis of 2,000 Chilean schools. Results obtained from their analysis also led to the conclusion that the SPF and DEA approaches gave almost a similar efficiency ranking of schools. Schools in Chile displayed an average technical efficiency of 93% (ranging from 73% to 98%) as measured by the SPF, while the DEA results showed an average efficiency of 95% (ranging from 53% to 100%).

4.3 Conclusions

In this chapter, I have provided a review of the theoretical and empirical literature on techniques used to measure technical efficiency, with special reference to the primary and secondary levels of education. Extant literature based on Stochastic Production Frontier (SPF) and Data Envelopment Analysis (DEA) has been reviewed.

In general, the application of DEA has been found to be more popular than SPF. In the application of SPF, care needs to be taken when choosing a functional form for the production technology and specifying a distributional assumption for the inefficiency term of the error component. The application of DEA, in contrast, is more straightforward than SPF because DEA requires no specific functional form and no measurement error to be assigned in constructing its piecewise production frontier.

The applications of SPF and DEA to the educational sector both require careful treatment of the environmental factors. Failure to control the environmental factors can cause point estimates of efficiency to be biased. According to Chakraborty et al. (2001) and Mizala et al. (2002), once the socio-economic and environmental factors have been controlled, researchers can select any of the parametric and the nonparametric methods without great concern that the choice of models is having a large influence on the empirical results.

The literature review as discussed in Chapters 3 and 4 provides a detailed overview of contemporary research on efficiency and productivity in the education sector. The reviewed studies involve several OECD countries but there has been no published study based on an Australian case. The next two chapters will use this literature review to form an analytical framework for analysis of educational production functions and the technical efficiency of Tasmanian primary schools.

Appendix 4.1: A Theoretical Review of Literature on Technical Efficiency in Educational Production

To measure technical efficiency of schools, two popular approaches have emerged: (i) the econometric (parametric) approach, based on Stochastic Production Frontier (SPF), and (ii) the linear programming (non-parametric) approach, based on Data Envelopment Analysis (DEA). In this appendix, a theoretical review of both approaches is reviewed within the context of the education sector..

Stochastic Production Frontier (SPF)

One approach to measure technical efficiency is the application of Stochastic Production Frontier (SPF) analysis. The development of the approach can be traced back to Aigner et al., (1977) and Meesen and van den Broek (1977). The authors estimated a regression model by introducing a two-part error term. The first part of the error term represents the ordinary statistical noise and the second part captures inefficiency. To facilitate the discussion of SPF in the context of an educational sector, let us assume that school j is maximising its output[23] (test score) with N inputs. A Cobb-Douglas SPF model for a panel dataset takes the form:

$$\ln \mathbf{A}_{jt} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \ln \mathbf{X}_{jt} + \mathbf{V}_{jt} - \mathbf{U}_{jt} \quad \text{or}$$

$$\mathbf{A}_{jt} = \exp\left(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \ln \mathbf{X}_{jt} + \mathbf{V}_{jt} - \mathbf{U}_{jt}\right) \quad \text{or}$$

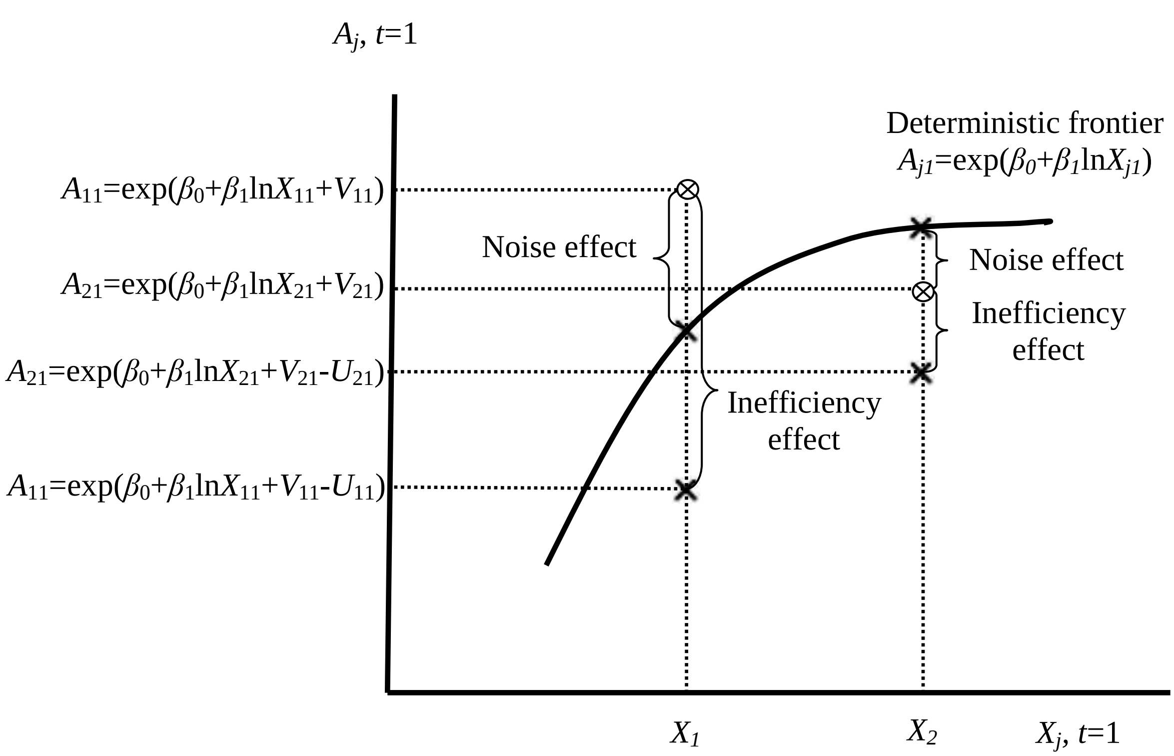
$$\mathbf{A}_{jt} = \underbrace{\exp\left(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \ln \mathbf{X}_{jt}\right)}_{\text{Deterministic component}} \cdot \underbrace{\exp\left(\mathbf{V}_{jt}\right)}_{\text{Noise}} \cdot \underbrace{\exp\left(-\mathbf{U}_{jt}\right)}_{\text{Inefficiency}} \qquad \text{(A4.1)}$$

where $\mathbf{A}_{jt}$ is the scalar output of school j, $j = 1, \ldots, J$, and time t, $t = 1, \ldots, T$; $\mathbf{X}_{jt}$ is a vector of N inputs used by school j in time t; $\boldsymbol{\beta}$ is a vector of parameters to be estimated;

[23] The description here proximates a case of an educational production process, where the single-output is a test score and there are multiple inputs in the production process.

$\left(\mathbf{V}_{jt} - \mathbf{U}_{jt}\right)$ is a composite error term, where $\mathbf{V}_{jt}$ represents statistical noise that is assumed to be independent, identically distributed (iid), symmetric and independent of $\mathbf{U}_{jt}$, and $\mathbf{U}_{jt}$ is a non-negative term that represents technical inefficiency ($\mathbf{U}_{jt} \geq 0$). Note that the term $\mathbf{A}_{jt}$ used is to represent school-level data instead of student-cohort level data as used in Chapter 3 (the term $\mathbf{A}_{ijt}$ represents student- level data with the subscript *i* denotes student *i*).

Figure 4.1: Stochastic Production Frontier



* Source: Based on Coelli et al., (2005, p.244)

In Figure 4.1, I provide an illustration of SPF involving two firms, 1 and 2 at time t =1 [the time t is included to be consistent with the panel data SPF model in equation (A4.1)]. In a case when there is no technical inefficiency ($U_{11} = 0$ and $U_{21} = 0$), the so-called frontier output is given by $A_{11} = \exp\left(\beta_0 + \beta_1 \ln X_{11} + V_{11}\right)$ and $A_{21} = \exp\left(\beta_0 + \beta_1 \ln X_{21} + V_{21}\right)$, where the points are depicted by $\otimes$ in Figure 4.1. For firm 1, its frontier output, $A_{11} = \exp\left(\beta_0 + \beta_1 \ln X_{11} + V_{11}\right)$, lies above the deterministic part of the production frontier [as given by $A_{j1} = \exp\left(\beta_0 + \beta_1 \ln X_{j1}\right)$] because its noise effect is positive ($V_{11} > 0$). The observed output for firm 1 [as given by $A_{11} = \exp\left(\beta_0 + \beta_1 \ln X_{11} + V_{11} - U_{11}\right)$], however, lies below the deterministic frontier because the sum of the noise and inefficiency effects is negative, or $V_{11} + \left(-U_{11}\right) < 0$. The frontier output for firm 2, on the other hand, lies below the deterministic part of the production frontier because its noise effect is negative ($V_{21} < 0$). Firm 2's observed output, $A_{21} = \exp\left(\beta_0 + \beta_1 \ln X_{21} + V_{21} - U_{21}\right)$, also lies below the deterministic frontier because the sum of the noise and inefficiency effects is negative, or $V_{21} + \left(-U_{21}\right) < 0$.

The measure of technical efficiency of firm *j* at time *t* (TE_{jt}) can be obtained by re-arranging equation (A4.1), and is given by:

$$\mathrm{TE}_{jt} = \frac{\mathbf{A}_{jt}}{\exp\left(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \ln \mathbf{X}_{jt} + \mathbf{V}_{jt}\right)} = \frac{\exp\left(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \ln \mathbf{X}_{jt} + \mathbf{V}_{jt} - \mathbf{U}_{jt}\right)}{\exp\left(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \ln \mathbf{X}_{jt} + \mathbf{V}_{jt}\right)} = \exp\left(-\mathbf{U}_{jt}\right) \quad \text{(A4.2)}$$

where technical efficiency is defined as a ratio of observed output and the maximum feasible output conditional on $\exp\left(\mathbf{V}_{ji}\right)$. The measure of technical efficiency is between zero and one, $0 < \mathrm{TE}_{jt} < 1$. A technical efficiency score of one, $\mathrm{TE}_{jt} = 1$, means the firm (or school) *j* achieves the maximum feasible output. In a case where technical efficiency is between zero and 1, $0 < TE_{jt} < 1$, equation (A4.1) provides a measure of the shortfall of observed output from the maximum feasible output conditional on $\exp\left(\mathbf{V}_{jt}\right)$. In Section 4.2.1, I further discuss the application of the SPF to studies involving school efficiency.

Data Envelopment Analysis (DEA)

In this section, an analysis of the concept and models of Data Envelopment Analysis (DEA) is discussed. Particular attention is given to the application of DEA to the measurement of schools' technical efficiency, in order to set the standard DEA methodology to be followed when I evaluate the technical efficiency of Tasmanian schools.

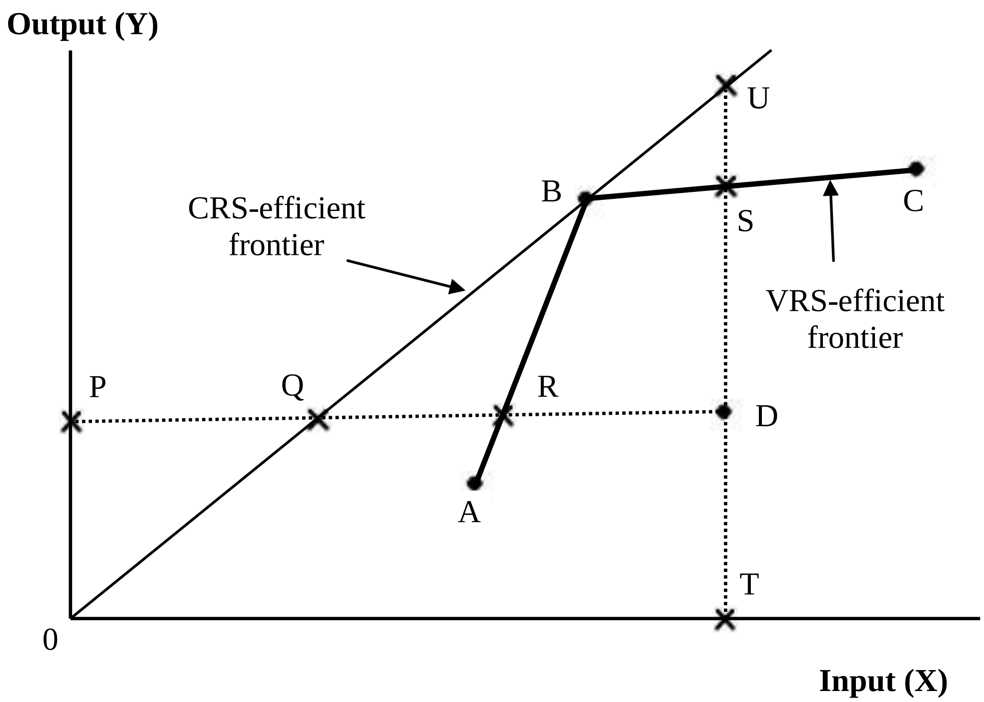
Charnes et al. (1978) first introduced DEA to the evaluation of public education sector based on Farrell's (1957) measure of technical efficiency (refer to Appendix 4.2). The work of Charnes et al. (1978) extended Farrell's measure of efficiency from a single-input, single-output case to a multiple-input, multiple-output case. The explanation of DEA models in this section follows the same presentation, where first a single-input, single-output case is discussed and then a multiple-input, multiple-output case is introduced.

a. Theoretical framework of DEA

The calculation of DEA is based on a mathematical linear programming method. Performance of each decision making unit (referred as DMU henceforth) is calculated based on a ratio of weighted outputs produced to weighted inputs used with a condition that the ratio for all DMUs' is less than or equal to one. Efficient DMUs have a ratio equal to unity and inefficient DMUs have a ratio less than one. The identified best-practice DMUs form the frontier, and the performance of other DMUs is compared to the frontier (Charnes et al., 1994).

Two basic DEA models have been widely applied: (i) the constant returns to scale (CRS) model of Charnes, Cooper and Rhodes (1978), and (ii) the variable returns to scale (VRS) model of Banker, Charnes and Cooper (1984).

Figure 4.2: The Best-Practice Reference Frontier



* Source: Based on Coelli et al. (2005, p. 174)

In Figure 4.2, I illustrate the theoretical idea behind the two principal approaches to DEA frontier analysis and the derivation of technical efficiency measures based on the DEA frontier. The figure is constructed based on a single-input, single-output case. The simplification enables the production process to be described in a simple two-dimensional diagram.

In Figure 4.2points *A*, *B*, *C* and *D* represent the observed performance of four DMUs (such as schools), given their level of input and output and production technology. The CRS model is represented by the thin line extending from the origin of Figure 4.2 through point *B*, where the DMU *B* is chosen to maximise the angle of the ray. The thin line is the production frontier as identified under the CRS model. Based on the CRS model, the DMU *B* is identified as the most efficient DMU since it lies on the frontier. Point *B* is therefore, CRS-efficient. Other DMUs (*A*, *C* and *D*), which lie below the frontier, are inefficient under the CRS model.

Still referring to Figure 4.2, the VRS model is illustrated by the solid thick lines that connect points *A* and *B*, and *B* and *C*. The solid lines depict the so-called VRS production frontier. The VRS model has its production frontier spanned by the convex hull of the DMUs (from point *A* to *B*, and *B* to *C*). The frontier is piecewise linear and concave. The VRS-frontier assumes variable returns to scale where: (i) increasing returns to scale occurs in the first solid line (*AB*) segment, and (ii) decreasing returns to scale in the second segment (*BC*) (Cooper et al., 2006, pp. 119-126). Note that points *A*, *B* and *C* are on the frontier and are therefore VRS-efficient. Point *D*, on the other hand, is the inefficient DMU because it lies below the frontier (Cooper et al., 2000).

b. DEA projection paths

Given the CRS-efficient and VRS-efficient frontiers, an inefficient DMU has two major projection paths to improve its performance, namely, (i) an input-oriented path, and (ii) an output-oriented path (Cooper et al., 2000). The input-oriented path aims at reducing the input amounts by as much as possible while keeping the present output levels unchanged. The output-oriented path aims at maximising output levels under the given input consumption.

The input-oriented path is discussed first with the aid of Figure 4.2. The input-oriented path identifies technical inefficiency as a proportional reduction in input usage for a given level of output. Recall that under the VRS model, only the DMU *D* is found to be inefficient. Accordingly, under the input-oriented path, DMU *D* can improve its performance by a movement to reduce inputs to point *R*. Notice that point *R* falls on the efficient frontier as identified by the VRS model. The input-oriented path requires DMU *D* to reduce its input consumption to produce the same amount of output as it presently produces. The VRS-technical efficiency of *D* under an input-oriented path (ITE_{VRS}) is given by:

$$ITE_{VRS} = PR/PD \tag{A4.3}$$

On the other hand, the input-oriented path under the CRS model requires the DMU *D* to move to point *Q* because point *Q* falls on the CRS efficiency frontier. The CRS technical efficiency of *D* under an input-oriented path (ITE_{CRS}), therefore, is given by:

$$ITE_{CRS} = PQ/PD \tag{A4.4}$$

Again, referring to Figure 4.2, the output-oriented model identifies technical efficiency as a proportional augmentation of output for a given level of input. Under the VRS model, the inefficient DMU *D* can improve its performance by a movement to point *S*. The movement to point *S* means DMU *D* needs to increase its output level given the amount of inputs it has. As such, the VRS technical efficiency of DMU *D* under the output-oriented path (OTE_{VRS}) is given by:

$$OTE_{VRS} = SD/ST \tag{A4.5}$$

Conversely, the output-oriented path under the CRS model requires DMU *D* to move to point *U* in order to improve its performance (point *U* falls on the CRS-efficient frontier). The CRS technical efficiency of DMU *D* under an output-oriented path (OTE_{CRS}), therefore, is given by:

$$\mathrm{OTE}_{\mathrm{CRS}} = UD/UT \tag{A4.6}$$

With the understanding of the theoretical concept of DEA in mind, I discuss the mathematical linear programming of DEA in the next sub-section.

c. Linear programming of DEA

A case of multiple-input and multiple-output of DEA is now discussed. I start the discussion by defining some notation to be used in this section. The dataset is assumed to consist of J DMUs (j=1, …, J). Each DMU j employs x_n inputs (for n = 1, …, N) in order to produce y_m outputs (for m = 1, …, M). Based on a simple productivity measure (productivity = output/input), the ratio form of DEA can be expressed as $\sum_{m=1}^{M} u_m y_{mj} \Big/ \sum_{n=1}^{N} v_n x_{nj}$, where u_m are the output weights and v_n are the input weights. The weights for outputs and inputs are estimated as the best advantage for each DMU to maximise its relative efficiency. The mathematical programming problem to solve for the optimal value of the weights is set out as:

$$\text{For each } j;\ \max_{u,v} \frac{\sum_{m=1}^{M} u_m y_{mj}}{\sum_{n=1}^{N} v_n x_{nj}} \tag{A4.7}$$

subject to:

$$\frac{\sum_{m=1}^{M} u_m y_{mj}}{\sum_{n=1}^{N} v_n x_{nj}} \le 1, \text{ for each } j = 1, \ ..., J$$

$$u_m, v_n \ge 0,\ m = 1, \ ..., M;\ n = 1, \ ..., N$$

where in finding the values of u and v, the first constraint sets the maximum efficiency value of the j^{th} DMU to be less than or equal to one, and 1 signifies the most efficient score. The second constraint is to indicate that the input and output weights are non-negative. The problem with equation (A4.7) is that it has an infinite number of solutions. If (u^*, v^*) is one solution, then $(\alpha u^*, \alpha v^*)$ is another solution, and so on (Coelli, 1996b, p. 11). The problem can be solved by adding another constraint, $\sum_{n=1}^{N} v_n x_{nj} = 1$, which yields:

$$\text{For each } j,\ \max_{\mu,\upsilon} \sum_{m=1}^{M} \mu_m y_{mj} \tag{A4.8}$$

subject to:

$$\sum_{n=1}^{N} \upsilon_n x_{nj} = 1$$

$$\sum_{m=1}^{M} \mu_m y_{mj} - \sum_{n=1}^{N} \upsilon_n x_{nj} \leq 0, \text{ for } j = 1, \ldots, J$$

$$\mu_m, \upsilon_n \geq 0$$

where the change in notation from u and v to μ and υ is designed to reflect the transformation of the linear programming from the ratio form to the so-called multiplier form[24] (Coelli, 1996b, p. 11). The objective of equation (A4.8) is to maximise the weighted output of the j^{th} DMU subject to the constraint that the sum of input weights of the j^{th} DMU must equal one. At the same time, the objective function maintains the condition that the output weights must not exceed the input weights. Note also that the linear programming in equation (A4.8) must be solved J times, once for each DMU in

[24] Refer to Appendix 4.3 for a description of the multiplier form in the linear programming of DEA.

the sample. Equation (A4.8) is an output-oriented linear programming problem under constant returns to scale (CRS) assumption.

A duality[25] in the linear programming of DEA means that the maximised value of the objective function in the multiplier form [as given by equation (A4.8)] can also be written as the minimised value of the objective function in the so-called an envelopment form, as given below:

$$\text{For each } j,\ \min_{\theta_j, \boldsymbol{\lambda}}\ \theta_j \tag{A4.9}$$

subject to

$$\sum_{j=1}^{J} \lambda_j y_{mj} \geq y_{mj},\ \text{for } m = 1, ..., M$$

$$\theta_j x_{nj} - \sum_{j=1}^{J} \lambda_j x_{nj} \geq 0,\ \text{for } n = 1, ..., N$$

$$\lambda_1,\ ...,\ \lambda_J \geq 0$$

where θ_j is the technical efficiency of the j^{th} DMU and $\boldsymbol{\lambda}$ is the vector of weights assigned to each DMU ($\boldsymbol{\lambda}$ also is known as peer weights). Note that the linear programming in equation (A4.9) must be solved J times, once for each DMU in the sample. As such, a different set of $\boldsymbol{\lambda}$ is obtained for each j^{th} solution of the linear programming. The un-bold λ's refer to the value of weights for each DMU under the solution of the j^{th} linear programming. The first constraint implies that the output produced by the observed DMU j must be less than or equal to the sum of output weights of all the DMUs. The second constraint puts the condition that the inputs used by the observed DMU j minus the sum of inputs weights of all the DMUs must be more

[25] I provide an example using hypothetical data to describe the duality (the difference between the multiplier and envelopment forms) in the linear programming of DEA in Appendix 4.3.

than or equal to zero. The last constraint is to ensure that the value of λ is non-negative. Equation (A4.9) is an input-oriented linear programming of DEA under constant returns to scale (CRS) assumption.

By adding a convexity constraint, $\sum_{j=1}^{J}\lambda_j = 1$, to equation (A4.9), the CRS linear programming is now modified to a variable returns to scale (VRS) linear programming as set out below:

$$\text{For each } j,\ \min_{\theta_j,\lambda}\ \theta_j \qquad \text{(A4.10)}$$

subject to

$$\sum_{j=1}^{J}\lambda_j y_{mj} \geq y_{mj},\ \text{for } m = 1, ..., M$$

$$\theta_j x_{nj} - \sum_{j=1}^{J}\lambda_j x_{nj} \geq 0,\ \text{for } n = 1, ..., N$$

$$\sum_{j=1}^{J}\lambda_j = 1$$

$$\lambda_1,\ ...,\ \lambda_J \geq 0$$

where the purpose of the convexity constraint, according to Coelli et al., 2005, p. 172), is to "… form a convexity hull of intersecting planes that envelope the data point more tightly than the CRS conical hull and thus provides technical efficiency scores that are greater than or equal to those obtained using the CRS model…". The convexity constraint also ensures that each DMU is only benchmarked or compared with DMUs of relatively similar scale. If the j^{th} DMU is technically efficient (θ_j is equal to one), the weights of its λ_j is one while the weights of λ's for the other DMUs are zero. In a case when the observed j^{th} DMU is technically inefficient, the weights of λ's for any (or some) of the other DMUs (known as peers to the j^{th} DMU) must be positive—a peer with higher value of λ signifies a greater position as an exemplar (relative to the other peers) to DMU j.[26]

The envelopment form of an output-oriented VRS DEA, on the other hand, is given by:

$$\text{For each } j,\ \max_{\phi_j,\boldsymbol{\lambda}}\ \phi_j \tag{A4.11}$$

subject to:

$$-\phi_j y_{mj} + \sum_{j=1}^{J} \lambda_j y_{mj} \geq 0, \text{ for } m = 1, ..., M$$

$$x_{nj} - \sum_{j=1}^{J} \lambda_j x_{nj} \geq 0, \text{ for } n = 1, ..., N$$

$$\sum_{j=1}^{J} \lambda_j = 1$$

$$\lambda_1, ..., \lambda_J \geq 0$$

where ϕ_j is the output weight of the j^{th} DMU to be maximised and $\boldsymbol{\lambda}$ (bold) and λ's (un-bold) are as defined above. The value of ϕ_j is $1 \leq \phi_j < \infty$. The measure of technical efficiency for the j^{th} DMU is given by $1/\phi_j$ [Coelli (1996b, p. 23)]. To maximise ϕ_j, the first constraint puts the condition that the weighted outputs of the observed DMU j must be less than or equal to the sum of output weights of all the DMUs. The second constraint states that the inputs of the observed DMU j minus the sum of input weights

[26] Refer to Example 4 in Appendix 4.3 for a comparison of DEA linear programming under the CRS assumption (without the convexity constraint) and under the VRS assumption (with the convexity constraint). In the appendix, I show how the convexity constraint affects the value of $\boldsymbol{\lambda}$, using hypothetical data.

of all the DMUs must be greater than or equal to zero. The third constraint implies that the sum of all the peer weights must equal one and the last constraint is to ensure that the value of λ is non-negative.

Further, the values of λ (peer weights) can be used to calculate the input and output targets for DMU *j*. The measures of input and output targets for DMU *j* are calculated as:

m^{th} output target: $\lambda_1 y_{m1} + ... + \lambda_J y_{mJ}$, for $m = 1, \ldots, M$,

n^{th} input target: $\lambda_1 x_{n1} + ... + \lambda_J x_{nJ}$, for $n = 1, \ldots, N$ (A4.12)

The input and output targets can be used by DMU *j* to improve its efficiency. With the knowledge of how to calculate the CRS and VRS technical efficiencies in mind, I explain the calculation of scale efficiency in the next sub-section.

d. Calculation of scale efficiency

Scale efficiency for each DMU can be calculated when both the CRS and the VRS technical efficiencies are obtained. A difference between the CRS and VRS technical efficiency scores for a particular DMU indicates that the DMU has scale inefficiency.

To describe the concept of scale efficiency, Figure 4.2 is once again employed for expositional purposes (the CRS and VRS frontiers are illustrated in the figure). Notice that the distance *PQ* gives the input technical efficiency under constant returns to scale for DMU *D*. Under the VRS model, however, the input oriented technical efficiency for DMU *D* is given by the distance *PR*. The difference between the two distances, *QR*, is due to scale inefficiency. A ratio efficiency expression for scale efficiency (*SE*) based on Figure 4.2 is given by:

$$SE = PQ/PR \qquad \text{(A4.13)}$$

where the measure is bounded between zero and one. Scale inefficiency therefore is given by one less *SE*:

$$\text{Scale inefficiency} = 1 - SE = QR/PR \qquad \text{(4.14)}$$

Another way to calculate scale efficiency is given by.

$$TE_{CRS} = TE_{VRS} \text{ x } SE \qquad \text{(A4.15)}$$

because

$$\frac{PQ}{PD} = \left(\frac{PR}{PD}\right)\left(\frac{PQ}{PR}\right) \qquad \text{(A4.16)}$$

From equation (A4.16), the CRS technical efficiency can be decomposed into two parts: (i) the VRS technical efficiency (which is also known as ‘pure’ technical efficiency), and (ii) the scale efficiency (Coelli et al., 2005, p. 173). With the understanding of the theoretical framework and calculations of technical and scale efficiencies of DEA in mind, the application of DEA within the scope of school efficiency literature is further discussed in Section 4.2.2.

Appendix 4.2: Microeconomic Concepts of Efficiency

The purpose of this appendix is to outline the various concepts of efficiencies found in microeconomics, namely technical efficiency, allocative efficiency and productive efficiency. The discussion in this appendix is important in providing readers with the theoretical basis of each of the efficiency concepts found in frontier evaluation technique before the discussion goes further into the application of technical efficiency in education.

Efficiency and productivity do not represent the same concept (Coelli et al., 1998). Productivity is the rate at which outputs are produced (for example output per unit of labour). Efficiency, on the other hand, deals with the best possible way to produce and the least amount of inputs required to achieve production in a specific process. As such, a firm is efficient by producing a greater amount of outputs from a given level of inputs, or, by using a minimum amount of inputs to produce a given level of outputs (Coelli et al., 1998).[27]

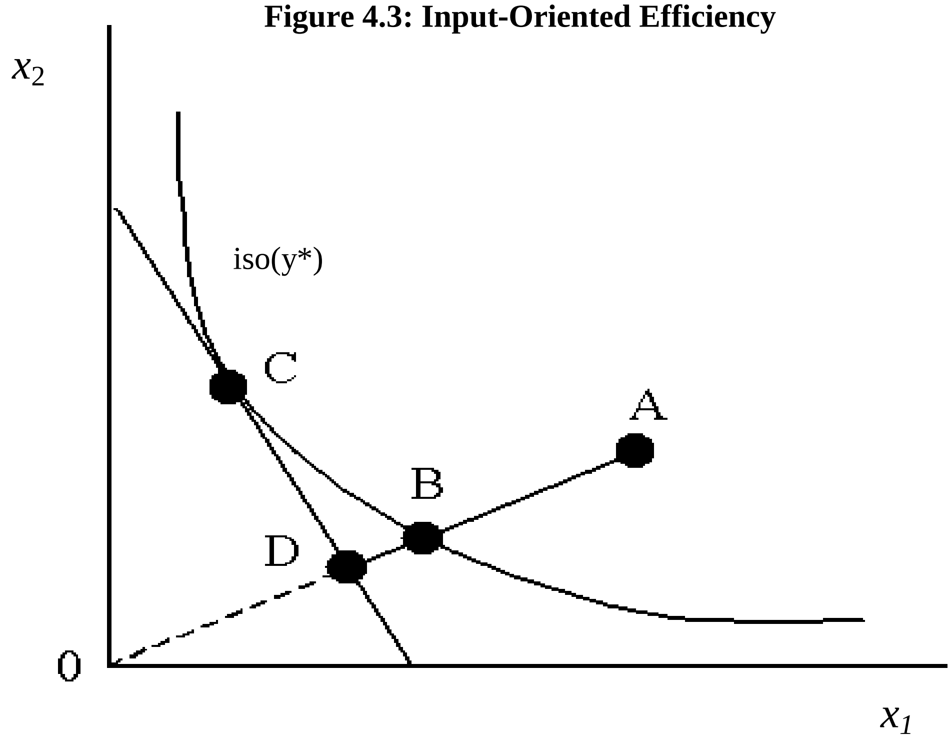
In economics, there are three main concepts of efficiency, namely, technical efficiency, allocative efficiency and productive (or total economic) efficiency. The three efficiency concepts originate from the work of Farrell (1957).[28] Technical efficiency is defined as the production of maximum outputs possible from a given set of inputs. To achieve technical efficiency requires the use of productive resources in the most technologically efficient manner. Allocative efficiency is achieved when a firm uses its

[27] Given certain amount of inputs and technology, the term efficiency in economics refers to the idea of how a production system proceeds to produce the desired outcomes, with a minimum amount of waste and/or maximum amount of output. Therefore, efficiency is improved if the amount of waste is reduced; or, by producing the most output from a given amount of inputs; or, when production proceeds at the lowest possible per unit cost.

[28] Farrell's (1957) conceptual framework of technical efficiency has led to the development of methods for estimating the relative technical efficiencies of firms.

available inputs in an optimal proportion, given the input prices and the production technology it has at hand. Productive efficiency is achieved when allocative efficiency and technical efficiency are both realised. I further discuss the concepts of efficiency based on Figure 4.3 and Figure 4.4 below.

Figure 4.3: Input-Oriented Efficiency

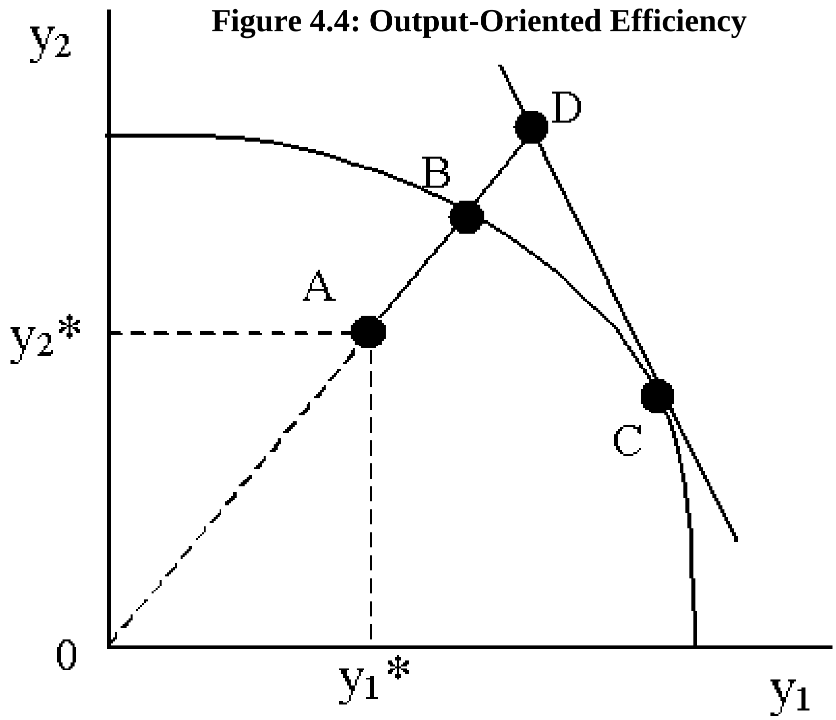


An input-oriented approach to efficiency is first described with the aid of Figure 4.3, followed by the explanation of an output-oriented approach. An input-oriented approach considers the optimal combination of inputs required in order to achieve a given level of output. In Figure 4.3, a production process with two inputs (x_1, x_2), where the input prices are represented by (w_1, w_2) and a single output (y) is shown. The isoquant, iso(y^*), indicates the set of all possible input combinations that could produce the output (y^*). The input combination, as represented by point *A*, is not technically efficient in the production of the given level of output. The same level of output can be produced by radially contracting the use of both inputs back to point *B*. A movement from point A to point B illustrates an input-oriented approach to technical efficiency. The input-oriented level of technical efficiency, $TE_I(y,x_1,x_2)$, is given by $0B/0A$.

At point C, the least-cost combination of inputs to produce (y^*) is achieved where the isocost line is tangent to the isoquant iso(y^*). Point C is where the marginal rate of technical substitution is equal to the input price ratio w_1/w_2. If cost efficiency, $CE(y,x,w)$, is the main concern of the firm, the input combination employed needs to be adjusted to point C. Since all points on the isocost provide the same level of cost, the cost at point C is equivalent to the cost incurred at point D. The measure of cost efficiency, $CE(y,x,w)$, is given by $0D/0A$. Although production at point D is possible, it is not efficient since point D lies below the isoquant iso(y^*). Given the cost efficiency condition, the input allocative efficiency, $AE_I(y,x,w)$, is achieved by adjusting the use of both inputs from point B to the cost-minimising input combination (point C). Input allocative efficiency is given by $0D/0B$, or, $CE(y,x,w)/TE_I(y,x)$ (Kumbhaker & Lovell, 2000, pp. 51-54).

An output-oriented approach of efficiency is now described based on Figure 4.4. An output-oriented approach considers the optimal combination of outputs that can be produced given the level of inputs. The concave curve in Figure 4.4 shows the possible output combinations (y_1, y_2) given a set of inputs (x). The straight line that connects points C and D is the price ratio line with prices (p_1, p_2). At point A, the firm is not efficient. Production can be expanded to point B if the set of inputs (x) employed by the firm are used technically efficiently. The output-oriented measure of technical efficiency, $TE_O(y,x)$, is given by $0A/0B$ (current output divided by potential output).

Figure 4.4: Output-Oriented Efficiency



At point C, the marginal rate of transformation is equal to the price ratio line p_1/p_2, where the price-ratio line is tangent to the frontier. If revenue efficiency, RE(y,x,p), is the main concern of the firm, the output produced needs to be adjusted to point C. Since all points on the price-ratio line provide the same level of revenue, the revenue at point C is equivalent to the revenue earned at point D. The revenue efficiency, RE(y,x,p), is given by $0A/0D$ (current revenue divided by potential maximum revenue). Given the revenue efficiency condition, as illustrated by the tangential line, the output allocative efficiency, $AE_o(y,x,p)$, is achieved by adjusting the production of both outputs from point B to the revenue-maximising output combinations at point C. Hence, the output allocative efficiency is given by $0B/0D$, or, $RE(y,x,w)/TE_o(y,x)$ (Kumbhaker & Lovell, 2000, pp. 54-57).

Based on the ideas represented in Figures 4.4 and 4.5, the foundation of efficiency measurements used in Stochastic Frontier Analysis (SFA)[29] and DEA are developed. The application of the frontier analysis in the derivation of technical efficiency measurement based on a Stochastic Production Frontier is provided in Section 4.2.1 with the help of Figure 4.2. In Section 4.2.2-a, the application of the frontier analysis to the derivation of technical efficiency measurement in DEA is presented based on Figure 4.3. Both SFA and DEA are based on extremal observations from a set of data, where a production frontier under both approaches is made up of the best-practice firms (Lewin & Lovell, 1990).

[29] Efficiency analysis based on Stochastoc Frontier Analysis (SFA) can be divided into Stochastic Production Frontier (SPF) and Stochastic Cost Frontier (SCF).

Appendix 4.3: On the Duality in DEA Linear Programming

The purpose of this appendix is to offer a simple and straightforward account of the multiplier and envelopment forms used in the linear programming of DEA (duality). In doing so, the essential features of the various approaches will be readily apparent.

The description is based on the hypothetical data of 4 schools, as shown in Table 4.3. Each school, as shown in the table, produces one output (test score) using two inputs (books and educational budget).

Table 4.3: A School Case—Hypothetical Data

School	Test score	Books in library	Educational budget ($)
S1	200	200	600
S2	300	600	1200
S3	210	600	300
S4	100	500	800

Based on the data in Table 4.3, examples of the application of the general equations (4.8), (4.9), (4.10) and (4.11) are now presented.

<u>Example 1: An output-oriented CRS model</u>

The multiplier form of the DEA problem for school S1 [based on equation (4.8)] can be written as:

For school S1, $\max_{\mu_1, \boldsymbol{\upsilon}} \ 200\mu_1$

subject to:

$$200\upsilon_1 + 600\upsilon_2 = 1$$

$$200\mu_1 - 200\upsilon_1 - 600\upsilon_2 \leq 0$$

$$300\mu_1 - 600\upsilon_1 - 1200\upsilon_2 \leq 0$$

$$210\mu_1 - 600\upsilon_1 - 300\upsilon_2 \leq 0$$

$$100\mu_1 - 500\upsilon_1 - 800\upsilon_2 \leq 0$$

$$\mu_1, \upsilon_1, \upsilon_2 \geq 0$$

Note that the linear programming problem needs to be solved 4 times since there are 4 DMUs (S1, S2, S3 and S4). Specifically, there will be one set of equations–the objective function and six sets of constraints–for each school.

As shown in example 1, the constraints in the multiplier form are set out by reading the cells in Table 4.3 horizontally. In the case of S1, for example, to maximise μ_1, the first constraint sets the weighted inputs of S1 to one. The next constraint depends on the value of *J*. Since there are only 4 schools (*J* = 4), there is a constraint for each school. The last constraint ensures that the output and input weights are non-negative. The disadvantage of the multiplier form is that, in research work, the number of *J*'s (number of DMUs) is usually large. Accordingly, the constraints for each linear programming of the j^{th} DMU will be large. The consequence of adding more constraints in linear programming is that finding a solution for such a mathematical problem may become more difficult. To overcome the disadvantage in the multiplier form, the mathematical linear programming of DEA can be set out in the so-called envelopment form, as shown in Examples 2, 3 and 4 below.

Example 2: An input-oriented CRS model

The envelopment form of the DEA problem for school S1 [as given by equation (4.9)] can be written as:

For school S1, $\min_{\theta_1, \lambda} \ \theta_1$

subject to:

$$200\lambda_1 + 300\lambda_2 + 210\lambda_3 + 100\lambda_4 \geq 200$$

$$200\theta_1 - 200\lambda_1 - 600\lambda_2 - 600\lambda_3 - 500\lambda_4 \geq 0$$

$$600\theta_1 - 600\lambda_1 - 1200\lambda_2 - 300\lambda_3 - 800\lambda_4 \geq 0$$

$$\lambda_1,\ ...,\ \lambda_4 \geq 0$$

Note that the envelopment form of the linear programming also needs to be solved 4 times, one for each DMU S1, S2, S3 and S4. Specifically, there will be one set of equations–the objective function and four sets of constraints–for each school

Notice that the constraints in the linear programming under the envelopment form are set out by reading the cells in Table 4.3 vertically. With such approach, fewer constraints need to be considered when solving the mathematical linear programming for each j^{th} DMU. The number of constraints now depends on the size of inputs (N) and outputs (M). In Example 2, since M = 1, there is only once constraint corresponding to the output. The second and third constraints in Example 2 correspond to the two inputs (N = 2). The last constraint acts to ensure that the value of peer weights is non-negative.

Example 3: An input-oriented VRS model

The CRS linear programming (as shown in Example 2) can be modified to a VRS linear programming by adding the convexity constraint, $\sum_{j=1}^{J} \lambda_j = 1$, to the envelopment form. By adding the convexity constraint, the envelopment form of the DEA problem for school S1 is now given by [refer to equation (4.10)]:

For school S1, $\min_{\theta_1, \lambda}\ \theta_1$

subject to:

$$200\lambda_1 + 300\lambda_2 + 210\lambda_3 + 100\lambda_4 \geq 200$$

$$200\theta_1 - 200\lambda_1 - 600\lambda_2 - 600\lambda_3 - 500\lambda_4 \geq 0$$

$$600\theta_1 - 600\lambda_1 - 1200\lambda_2 - 300\lambda_3 - 800\lambda_4 \geq 0$$

$$\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1$$

$$\lambda_1,\ ...,\ \lambda_4 \geq 0$$

Note that the envelopment form of the linear programming also needs to be solved 4 times–one solution for each of the four schools.

<u>Example 4: An output-oriented VRS model</u>

The envelopment form of the DEA problem for school S1 under an output-oriented VRS assumption can be written as [refer to equation (4.11)]:

For school S1, $\max_{\phi_1,\lambda}\ \phi_1$

subject to:

$$-200\phi_1 + 200\lambda_1 + 300\lambda_2 + 210\lambda_3 + 100\lambda_4 \geq 0$$

$$200 - 200\lambda_1 - 600\lambda_2 - 600\lambda_3 - 500\lambda_4 \geq 0$$

$$600 - 600\lambda_1 - 1200\lambda_2 - 300\lambda_3 - 800\lambda_4 \geq 0$$

$$\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1$$

$$\lambda_1,\ ...,\ \lambda_4 \geq 0$$

Note that the envelopment form of the linear programming also needs to be solved 4 times as there are four schools.

Without the convexity constraint, the linear programming problem is the envelopment form of an output-oriented CRS model. The solution to the linear programming of an output-oriented CRS model (without the convexity constraint) for all schools is given in Table 4.4.

As shown in Table 4.4, S1 and S3 are 100% technically efficient under the CRS assumption. The level of technical efficiency for S2, on the other hand, is 67.6% while for S4, it is 31.4%. In order for S2 and S4 to improve their technical efficiency, they should learn from the two schools, S1 and S3. Based on the solution of the linear programming for school S2, for example, it is found that the value of λ (peer weights) for S1 is larger than S3 (1.8 > 0.4), implying that S1 is the benchmark school and not S3. In other words, S2 would need to look at S1 more closely than S3 in order to improve its efficiency. In the case of S4, the value of λ (peer weights) for S1 is also larger than S3 (1.1 > 0.467). To improve its technical efficiency, school S4 should also look to S1 more closely than S3.

In Figure 4.5, I plot the positions of S1, S2, S3 and S4 based on a single-output (the test score on the vertical axis) and a single-input (the index of school inputs on the horizontal axis) case—recall Figure 4.3 and the discussion on the theoretical framework of DEA in Section 4.2.2. The CRS-frontier is constructed by extending the points from the origin through the coordinates of S1 and S3. Under the CRS assumption, schools S2 and S4 fall below the CRS-frontier. The dashed line, in the figure, extending from S4 to point *A* shows the output projection path for S4. Point *A* is the projected output (test score) level for S4 under the CRS model. The projected output for S4 at point *A* can be computed using equation (4.12), which is 1.1(200) + 0.467(210) = 318 points.

Table 4.4: Peer Weights and Technical Efficiency Scores—Solutions to the Output-oriented CRS Linear Programming Problem based on the Hypothetical Data

Schools	λ_1	λ_2	λ_3	λ_4	ϕ_j
S1	1	0	0	0	1
S2	1.8	0	0.4	0	0.676
S3	0	0	1	0	1
S4	1.1	0	0.467	0	0.314

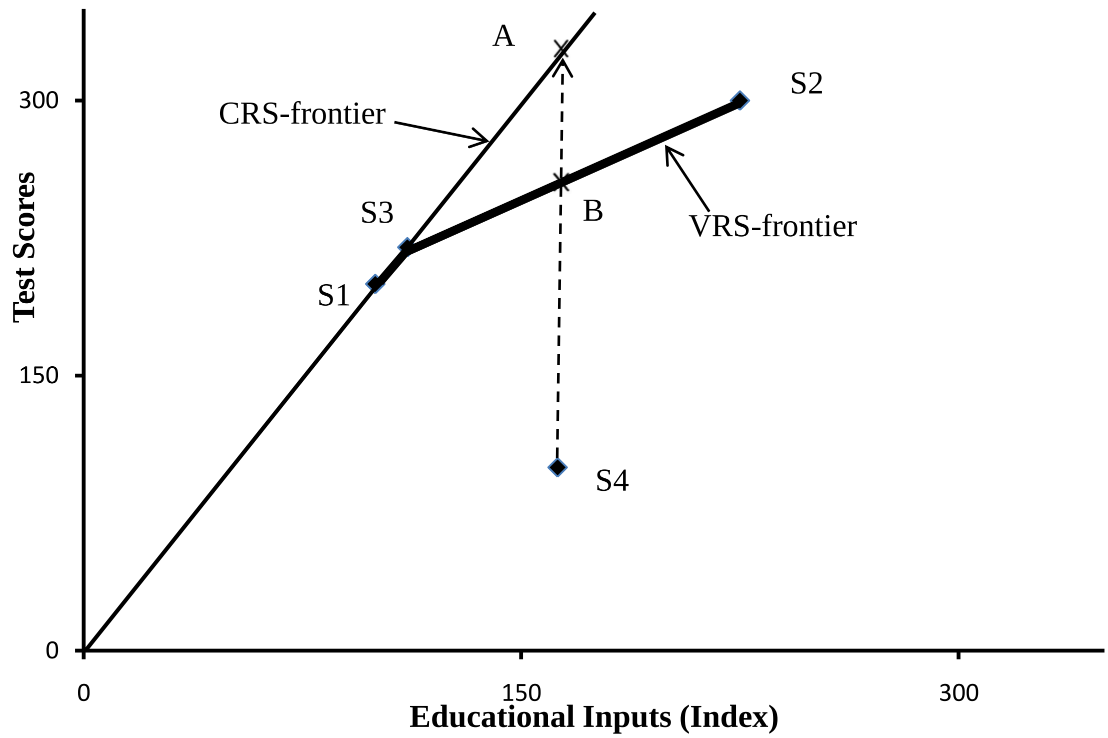
The solution to the linear programming of an output-oriented VRS model (with the convexity constraint) for all schools, on the other hand, is given in Table 4.5. Under the VRS assumption, schools S1, S2 and S3 are 100% technically efficient. The three schools form the VRS-frontier, as shown by the thick solid line in Figure 4.5. The effect of the convexity constraint is that the value of λ is normalised to one. The level of technical efficiency for school S4, on the other hand, is only 40%. As shown in Figure 4.5, the position of S4 is below the VRS-frontier. In order for S4 to improve its technical efficiency, S4 should learn from the three schools, S1, S2 and S3. The solution of linear programming for school S4 shows that the value of λ (peer weights) for S2 (0.472) is the largest as compared to S1 (0.25) and S3 (0.278). In other words, S4 would need to look at S2 more closely (in proportion to the weights) than S1 and S3 in order to improve its efficiency.

The dashed line, as shown in Figure 4.5, extending from S4 to point *B* shows the output projection path for S4 under the VRS model. The projected output for S4 at point *B* can be computed using equation (4.12), which is 0.25(200) + 0.472(300) + 0.278(210) = 250 points.

Table 4.5: Peer Weights and Technical Efficiency Scores—Solutions to the Output-oriented VRS Linear Programming Problem based on the Hypothetical Data

Schools	λ_1	λ_2	λ_3	λ_4	ϕ_j
S1	1	0	0	0	1
S2	0	1	0	0	1
S3	0	0	1	0	1
S4	0.250	0.472	0.278	0	0.4

Figure 4.5: CRS and VRS Output-oriented DEA Frontiers—An Example based on the Hypothetical Data



From the exercise, one can only see that the dual in the linear program of DEA implies that the maximised value of the objective function in the multiplier form can be expressed as the minimised value of the objective function in the envelopment form. The envelopment form of DEA is favoured as compared to the multiplier form because under the envelopment form, there are fewer constraints to deal with as compared to the multiplier form. The inclusion of the convexity constraint in the envelopment form of the DEA linear programming problem results in a normalised value of peer weights (λ). By setting the convexity constraint to one, the DEA linear programming problem is set under the assumption of variable returns to scale (VRS) assumption. Without the convexity constraint, the DEA linear programming problem proceeds under the assumption of constant returns to scale (CRS) assumption.

5 An Estimation of Educational Production Functions: The Case of Tasmanian Public Schools

5.0 Introduction

In this chapter, I estimate educational production functions for reading, writing and numeracy tests based on panel data of Tasmanian students in public schools. Central to the estimation is the evaluation of the effect of educational expenditure on students' academic achievement. As pointed out in Section 2.2—Public Investment in Tasmanian Education—the State Government has made a commitment to educational expenditure as the central approach to improving students' academic achievement. The analysis in this chapter provides crucial background information for an informed policy debate by addressing two key questions: (i) whether educational expenditure significantly affects students' academic achievement? and (ii) if so, what is the effects of the public dollars spent on reading, writing and numeracy performance of Tasmanian students?

The analysis in this chapter is based on the models of educational production function reviewed in Chapter 3. On the basis of the review, the value-added model is considered to be relatively better than the contemporaneous and linear growth models in dealing with the lack of data on students' innate abilities. The comparative advantage of that model does not apply here because I have access to panel data, which is a unique feature of this thesis. The approach is unique because an estimation of educational production function based on panel data is rare in education. In addition, the panel data approach also can deal with the issue of students' innate abilities, as shown in Section 3.2.4.

An outline of this chapter is as follows. In Section 5.1, the data and sample for the analyses are described. In Section 5.2, the results of the analysis are presented and discussed. Section 5.3 offers some concluding remarks.

5.1 Data and Sample Description

This section on the dataset is important in providing explanations of the sample and the variables I employ in the estimations of RE, FE, BE and pooled GLS models.

5.1.1 Source of the Data

The dataset used for the estimation of educational production functions in this chapter is provided by the Department of Education, Tasmania (DoE, Tas). The Department has a rich dataset on student and school background characteristics. The data collected by the Department include students' test scores in literacy and numeracy, attendance rates, gender and indigenous status of the student. Information on students' family characteristics includes parental education and occupation status, and language spoken at home.[1] The data are disaggregated for each student and are traceable to a student and school by unique identifiers.[2] The data on school characteristics consist of information on financial provisions to schools, number of indigenous students, number of students with severe disability and suspension rates. All the data are available on request to the DoE, Tas. [3]

[1] A manual, entitled *Data Implementation Manual for Enrolments for the 2005 and 2006 School Years*, provides a guideline to assist schools in a systematic process of a standard data collection and storage processes. The manual contains the information required for reporting student performance based on the nationally agreed background variables.

[2] For reasons of confidentiality, the data were presented in terms of identifiers. I did not have access to personal information of students as such.

[3] Details on application procedures and forms to be downloaded for any educational research and data request to the DoE, Tas are available at http://www.education.tas.gov.au/dept/reports. For my research, it took approximately six months (from May 2009 to November 2009) to get the requested data.

5.1.2 Sample

The estimations of educational production functions in this chapter are based on a panel data. The construction of the panel data is based on the cohort of students who were in Year 3 in 2003, Year 5 in 2005 and Year 7 in 2007. The cohort of students in Years 3, 5 and 7 has been selected because the national evaluation of students' performance is conducted in those Years. School calendar years 2003, 2005 and 2007 have been chosen because the dataset offers recent information and is therefore relevant to the current debate. The data for the years comprises comprehensive information without many missing cells.

The cross-section of the panel data constructed consists of 4,072 (N = 4,072) students. Since the time-series part of the panel involves three school calendar years, T = 3, the overall number of observations (N x T = M) is M = 12,216. Due to some missing data in one or more of the variables employed[4], 329 observations were not able to be included in all of the time periods. These observations are dropped in order to construct a balanced panel with the actual overall number of observations of 11,887.

5.1.3 Description of the Variables

The notation and description for the variables used in the study is listed in Table 5.1. The student/family background variables are in the form of the student-cohort level data. The school resource and peer background variables, on the other hand, are in the form of school-level data.

The test score variables (**A**) are the dependent variables, involving reading, writing and numeracy test scores. The independent variables are categorised into three

[4] Data on the i^{th} student may be missing, for example, in the case where a student dies or moves to other schools out of Tasmania.

groups, one based on student/family background characteristics (**F**); a second involving peer background characteristics (**P**) and the third deals with school background characteristics (**S**). Based on Table 5.1, I now explain each of the variables in each category.

Table 5.1: Variable Descriptions

Variable		Description
Test Score Variables (**A**)	$read_i$	Student *i*'s score in reading tests
	$write_i$	Student *i*'s score in writing tests
	$numer_i$	Student *i*'s score in numeracy tests
Student/Family Background Variables (**F**)	$absent_i$	Student *i*'s number of days absent per 100 schooling days from school per year
	d_male_i	Dummy of student *i*'s gender (M = 1, F = 0)
	d_indig_i	Dummy of student *i*'s indigenous status (1 if Aboriginal or both Aboriginal and Torres Strait Islander, 0 if not Aboriginal or not stated)
	d_dadedu_i	Dummy of student *i*'s father's maximum education. 1 if the father obtains tertiary education; 0 if otherwise. Tertiary education includes certificate I to IV (including trade certificate), advanced diploma/diploma and bachelor degree or above
	d_mumedu_i	Dummy of student *i*'s mother's maximum education. 1 if the mother obtains tertiary education; 0 if otherwise. Tertiary education includes certificate I to IV (including trade certificate), advanced diploma/diploma and bachelor degree or above
	$d\_dadwork_i$	Dummy of student *i*'s father's occupation. 1 if the father works in senior management in large business organisation, government administration and defence, and qualified professionals (type 1 occupation); 0 if otherwise
	$d\_mumwork_i$	Dummy of student *i*'s mother's occupation. 1 if the mother works in senior management in large business organisation, government administration and defence, and qualified professionals (type 1 occupation); 0 if otherwise
Peer Background Variables (**P**)	$atsi_j$	Percentage of Aboriginal and Torres Strait Islander (ATSI) students in the j^{th} school. ATSI students are those self-identified at the time of enrolment. The numbers are calculated from August 2003, 2005 and 2007 census data
	esl_j	Percentage of students who were involved in the English as a Second Language (ESL) Program in the j^{th} school
	$disable_j$	Percentage of students on the Severe Disabilities Register/the High Needs Register in the j^{th} school
	$susprate_j$	The average number of suspensions for every 100 Full Time Equivalent (FTE) students in the j^{th} school each year
School Resource Variables (**S**)	srp_perstu_j	Real total school resource package expenditure per student to school *j*. The finance figures represent allocations directly related to student learning (AUD$, thousand)
	$grant\_perstu_j$	Real general support grant expenditure per student to school *j* (AUD$, thousand)
	$percapita_j$	Real educational allocation on literacy and numeracy program (based on full-time equivalent) expenditure per student to school *j* (AUD$, thousand)
	$rural\_perstu_j$	Real rural allocation expenditure per student to school *j* (AUD$, thousand). The figures are the total allocations to schools based on Rurality Index that takes into account the school's isolation, size of centre/township and distance from the nearest town
	st_ratio_j	Student-teacher ratio of the j^{th} school

a. Test Score Variables

For the estimation, the dependent variables are represented by test scores. Tests in reading (*read*) and writing (*write*) are taken as a measure of literacy performance while numeracy performance is measured by the numeracy test scores (*numer*). The scale of the test scores, as used by the DoE, Tas., is based on a Rasch scale. The scale of measurement is from 0 to 600 and is centred on a value of 300. In order to interpret the result, note that a difference of 10-15 score points is the average difference for each year of schooling. An individual student score that is 15 points above (or below) the average score, for example, suggests that the student performance, on average, is about one year ahead (or behind) of the student's cohort (DoE, Tas, 2007, pp. 4-7).

Table 5.2: Summary Statistics of the Dependent Variables

Test	Year	Mean	Std. dev.	Min	Max
Reading	Year 3 in 2003	364	93.94	0	489
	Year 5 in 2005	392	93.31	0	485
	Year 7 in 2007	417	33.52	0	503
Writing	Year 3 in 2003	360	96.93	0	499
	Year 5 in 2005	393	104.22	0	509
	Year 7 in 2007	412	37.64	0	543
Numeracy	Year 3 in 2003	372	93.0	0	527
	Year 5 in 2005	396	92.27	0	504
	Year 7 in 2007	416	30.75	0	510

The Rasch scale allows a comparison of relative test difficulty to be made when using common questions. For example, sets of questions in Years 3, 5 and 7 numeracy are repeated in different tests—some questions in the Year 3 test also appear in the Year 5 test. Students' performances on either test are then compared by using the results from these common questions. Another example of comparison of the test difficulty is to examine the numeracy tests in Years 3 and 5, where a sample of students in Years 3 and

5 attempt both tests. The relative difficulties of both tests can then be compared.[5] The advantage of the procedure is that it takes into account the relative difficulty of tests in Years 3, 5, and 7. Once test difficulty is measured, progress of students attempting the tests is comparable, regardless of their year levels.[6]

In Table 5.2, the summary statistics of the cohort's performance in reading, writing and numeracy for Years 3, 5 and 7 are shown. The raw mean score in the three tests for the cohort show a continuous improvement. The improvement may be explained by the value-added in the cohort's literacy and numeracy understanding over the years (refer to the value-added model of educational production function in Section 3.2.2).

b. Student/Family Background Variables

For each student in the cohort, the data on the number of days (per 100 schooling days) they were absent from school (*absent*), their gender (*d_male*), and their indigenous status (*d_indig*) are employed to capture the students' background characteristics. The summary statistics of the number of days absent from school and the student/family background variables are provided in Tables 5.3 and 5.4. As shown in Table 5.3, there is a rising trend in the number of days absent from school over the period. I expect that as the number of days absent from school increases, the students' literacy and numeracy performance decreases.

In Table 5.4, it is shown that the proportion of male students is 52.4% while 47.6% are female students. The cohort of students comprises 406 indigenous students or 9.5% of the entire sample. Dummy variables are used to represent the gender and the

[5] For details see DoE, Tas. (2007). *The Literacy and Numeracy Monitoring Program 2007 Analysis and Interpretation Guide*, Educational Performance Services. VER 29.11.2007: 1-17.
[6] See Low and Chia (2010, p. 2) for a detailed explanation on Rasch scale construction.

indigenous status of the student. The students are assigned 1 if they are male and a 1 if they are an Aborigine/Torres Strait Islander (indigenous). Since I observe the same cohort of students, the statistics on gender and indigenous status of the students (also the parents' occupational status and educational level) are constant across the observed periods. The within-variation of the variables for each student is zero. As a result, an estimation based on a FE model will exclude all of these variables.

Table 5.3: Summary Statistics of the Number of Days Absent per 100 Schooling Days

Year	Mean	Std. dev.	Min	Max
2003	5.3	5.41	0.5	86.5
2005	5.78	5.90	0.5	90
2007	7.99	8.31	0.5	86.6

Table 5.4: Summary Statistics of the Student/Family Background Variables

Student / Family Background Variables	2003		2005		2007	
	Total	%	Total	%	Total	%
Gender						
Male students	2447	52.39	2447	52.39	2447	52.39
Female students	2224	47.61	2224	47.61	2224	47.61
Indigenous status						
Indigenous students	406	9.52	406	9.52	406	9.52
Non-indigenous students	4265	90.48	4265	90.48	4265	90.48
Parental occupation						
Mothers in type 1 occupation	339	7.26	339	7.26	339	7.26
Mothers other than in type 1 occupation	4332	92.74	4332	92.74	4332	92.74
Fathers in type 1 occupation	353	7.56	353	7.56	353	7.56
Fathers other than in type 1 occupation	4318	92.44	4318	92.44	4318	92.44
Parental education						
Mothers with tertiary qualification	1856	39.73	1856	39.73	1856	39.73
Mothers with non-tertiary qualification	2815	60.27	2815	60.27	2815	60.27
Fathers with tertiary qualification	1908	40.85	1908	40.85	1908	40.85
Fathers with non-tertiary qualification	2763	59.15	2763	59.15	2763	59.15

In Table 5.4, parental occupation and education are employed to represent the family background characteristics. The variables are expected to have a positive effect on students' academic performance due to positive spillover benefits of highly educated and professional parents on their children's academic achievement.

For parental occupation, a dummy, 1 (*d_mumwork* =1; *d_dadwork* =1), is given for parents in senior management in large business organisation, government administration and defence and qualified professionals, and other business managers, arts, media, sportspersons and associate professionals. A dummy, 0, means the parent is employed in one of the following areas: machine operator, hospitality staff, assistants, labourers and related workers, tradesmen/women, clerks and skilled office, sales and service staff, not in paid work in last 12 months, or not stated or unknown. As shown in Table 5.4, the percentages of mothers and fathers of the cohort with type 1 occupation (*d_mumwork* and *d_dadwork*) are 7.26% for *d_mumwork* and 7.56% for *d_dadwork*.

The percentages of mothers and fathers with a tertiary qualification (*d_mumedu* and *d_dadedu*) are 39.73% for *d_mumedu* and 40.85% for *d_dadedu*. A dummy variable, 1, is given if the parents obtained beyond Year 12 or equivalent level of schooling, such as gaining post-secondary schooling certificate, diploma/advanced diploma, or a bachelor degree or above.

c. School Resource Variables

In Table 5.5, the descriptive statistics of the school resource variables are presented. All the figures in Table 5.5 are based on school-level data. For years 2003 and 2005, the presented figures refer to the primary schools (when the cohort was in Year 3 and 5). When the cohort was in Year 7, school-level data for year 2006 (the year when the cohort was in Year 6 of primary school) are employed. The reason for not employing secondary school resource data for 2007 is because the amount of financial allocations to secondary schools is almost doubled as compared to the allocations to primary schools (due to larger size of secondary schools). The consequence of employing secondary school resource data would be that the growth in the expenditure (a continuous variable) would contaminate the parameter estimates. Further, since the examination for secondary schools is conducted in May every year, the literacy and numeracy results for Year 7 in 2007 were more reflective of what the cohort had learned in 2006. Accordingly, it is considered better to use the 2006 school resource data for Year 7 performance in order to ensure that the effects of school resources under the same institutional setting (primary school) are maintained.

I am aware that using the previous year's school resource data for the 2007 test performance creates an inconsistency. I however, maintain the Year 7 performance in order to have longer time period for the cohort. With T = 3, the time series of the panel is large enough to allow for more 'within' variation for the cohort. Manifestly, some care needs to be exercised when interpreting the results of the estimation. But it is possible to go further than providing a warning of care of interpretation.

My defence of using contemporaneous data is twofold. First, it lies in the fact that data on school resources in the previous year is not available for year 2002. Second, it is possible to mount a defence of using contemporaneous data for the school resource data for Year 5 based on strong correlations between the data for 2004 and 2005. The correlation coefficients between 2004 and 2005 for *srp_perstu, grant_perstu, percapita, rural_perstu* and *st_ratio* are 0.955, 0.994, 0.995, 0.997 and 0.977. The strong positive correlations between the two years imply using either set (2004 or 2005) of the data may result in almost the same coefficient estimates for the variables.

Four of five of the school resource variables, as shown in Table 5.4, relate to school finances: (i) real total school resource package expenditure per student (*srp_perstu*); (ii) real general support grant expenditure per student (*grant_perstu*); (iii) real educational allocation on literacy and numeracy program allocation (based on full-time equivalent) expenditure per student (*percapita*) and (iv) real rural disadvantaged allocations per student (*rural_perstu*). The fourth variable measuring the rural disadvantaged (*ruralexp*) expenditure is derived by summing up the allocations provided to schools based on the index of rural status. The index is formulated based on three major criteria: (i) isolation, (ii) size of centre and (iii) distance.[7]

The financial variables on school resources are categorised into the specific expenditures in order to investigate their specific effects on students' academic achievement. The approach of categorising the financial variables into their specific expenditures was employed by Lopus (1990). The author found that an estimation based on a specific category of expenditure (the author used the term 'disaggregated') resulted in higher R-squared as compared to a model of educational production function that was estimated based on an aggregated expenditure (Lopus, 1990, p. 283). The work therefore suggests that an estimation based on a specific category of expenditure variable is better in the fitting of model of educational production function.

Table 5.5: Summary Statistics of the School Resource Variables

School Resource Variables	Year	Mean	Std. dev	Min	Max
Real total resource package per student or *srp_perstu* (AUD$, 2007 base year)	2003	874.10	262.76	571.83	6083.33
	2005	800.97	257.57	484.45	6633.81
	2006	1001.96	297.24	624.84	5559.74

[7] To account for rural disadvantage of a school, the DoE, Tas, has established a rural status index. The index takes into account the distance of the school from the nearest district office, isolation of the school such that it is set apart from neighbouring centres (i.e. island) and size of the centre (town) in which the school is located. The expenditures also take into account additional cost burdens, such as freight and travelling expenses. The allocation is unrelated to enrolment level (Cooper, 1992).

Real general support grant per student or *grant_perstu* (AUD$, 2007 base year)	2003 2005 2006	352.81 355.45 382.43	88.40 87.94 90.35	253.59 254.69 270.32	2148.17 2241.07 1761.55
Real student (based on full-time equivalent) expenditure per student or *percapita* (AUD$, 2007 base year)	2003 2005 2006	227.57 229.97 248.02	13.83 11.34 10.83	203.71 194.11 206.06	285.19 282.76 316.45
Real rural disadvantaged allocations per student or *rural_perstu* (AUD$, 2007 base year)	2003 2005 2006	36.94 37.03 37.52	74.92 76.83 78.40	0.44 0.45 0.46	1689.88 1915.82 1998.33
Student-teacher ratio or *st_ratio*	2003 2005 2006	17.88 17.91 17.89	1.36 1.36 1.38	8.6 5.9 7.7	19.1 19.0 19.1

The non-financial variable employed is the student-teacher ratio (*st_ratio*). The ratio is calculated as the number of full-time students figure divided by the number of teaching staff. For student-teacher ratio (*st_ratio*), the variable is expected to have negative effects on students' academic achievement. Higher student-teacher ratio may result in low students' academic achievement due to lack of student engagement and lack of teacher attention towards an individual student.

In addition to the school resource variables in Table 5.5, the rural/urban status of schools is also included. Schools are classed as rural (*d_rural*), where a dummy variable 1 is assigned for any school that is considered as isolated (such as in an island/located in a remote location) and/or located near/in a small township (with a population in the range of 200 to 999 persons) or located in a village/rural area (with a population fewer than 200 persons). The dummy variable is included under the school resource category in order to capture the effects of geographical location that may result in lack of teaching/learning facilities (such as a poorly stocked library or an insufficient number of students to conduct a group activity) in rural schools. A negative sign is expected for the coefficient of *d_rural*. The lack of teaching/learning facilities in rural schools may result in a disadvantaged learning environment for the students, manifested in low academic achievement. The number of schools categorised as rural or urban is shown in Table 5.6. The rural or urban status of the school for all the three years, as shown in Table 5.6, refers to primary and combined schools only. There were 73 rural and 66 urban primary schools in Tasmania. For all the 26 combined (primary and secondary) schools, they all fell under the category of rural status.

Table 5.6: Number of Rural/Urban Schools

Rurality status of schools	2003	2005	2006
No. of rural primary schools	73	73	73
No. of urban primary schools	66	66	66
No. of rural combined schools	26	26	26
No. of urban combined schools	0	0	0

As set out in Section 5.0, the primary aim of the present chapter is to measure the effect of educational expenditure on students' academic achievement. All of the employed financial variables, therefore, stand as key policy variables. The variables are expected to have positive effects on students' performance. More financial resources to schools imply better teaching and learning facilities that may improve students' academic achievement.

d. Peer Background Variables

Four variables are employed to capture the effect of peers on a student's academic achievement. Data for each school on the percentage of indigenous students (Aborigine and Torres Strait Islander–ATSI); the percentage of students who had English as a Second Language (ESL) program; the percentage of disabled students and the level of suspensions from each school are used to gauge the effect of peers. To represent the peer background variables, school-level data has been employed. The use of school-level is appropriate because the data represent group peer effects. All of these variables are expected to have a negative effect on students' academic achievement because of the associated disadvantages.

In Table 5.7, the data for Year 7 are based on the cohorts' school-level data in 2006 (when they were in Year 6). The reason for using the 2006 data to represent the peer background variables is as argued in Section 5.1.3-c (for using the 2006 school resource variables). As shown in the table, the number of students in each of the peer variables represents the minority group of overall students per school (on average, there are 360 students per school). The influence of peers, as captured by the variables, may be small or insignificant.

Table 5.7: Summary Statistics of the Peer Background Variables

Peer Background Variables	Year	Mean	Std. dev.	Min	Max
Indigenous students (%)	2003	0.55	0.39	0	1.61
	2005	0.56	0.40	0	2.12
	2006	0.56	0.42	0	2.35
Students in the English as a Second Language Program (%)	2003	0.55	1.48	0	7.89
	2005	0.67	1.28	0	5.64
	2007	0.54	1.25	0	8.75
Students with severe disability (%)	2003	0.62	0.61	0	3.53
	2005	0.64	0.57	0	2.31
	2007	0.62	0.53	0	2.44
Suspension rate (per 100 students)	2003	4.24	9.77	0	50.7
	2005	3.68	7.31	0	49.9
	2007	3.32	5.81	0	42.73

5.2 Estimation Results and Discussion

In this section, I present and discuss the results obtained from the various estimations of educational production function. The results are an outcome of undertaking the mathematical specifications and estimation strategies, as outlined in Section 3.2.4. The software package used to run the estimations was Stata 11.

I ran four regression models, namely, the Fixed Effects (FE), Random Effects, (RE), Between Effects (BE) and Pooled GLS models. For each of the models, the reading, writing and numeracy test scores were logged and used as the dependent variables. All the independent variables, with the exception of the dummy variables, were also logged. With the logged dependent and independent variables, the interpretation of the results is expressed in terms of elasticity—a one per cent change in an independent variable is associated with the estimated percentage change in the dependent variable, *ceteris paribus.* Estimations results for reading, writing and numeracy performance are provided in Table 5.10.

As discussed in Section 3.2.4-a, the choice between the FE and RE models can be determined by running a Hausman test. The full results from Stata for reading, writing and numeracy estimations on the test are provided in Appendix 5.1. As shown in Appendix 5.1, the null hypothesis that the individual-specific effects are uncorrelated with the regressors, $\operatorname{cov}\left(\alpha_i, \mathbf{X}_{ikt}\right) = 0$, is rejected at the 95% confidence interval—the null is rejected for reading, writing and numeracy estimations. The FE model is therefore the more appropriate model specification.

The loss of the variables with no within-variation makes the FE model incapable of rendering the effects of gender, indigenous status and parental occupation and education. I therefore provide the results based on the RE, BE and pooled GLS with the purpose of capturing the effects of these variables. Caution however is required when interpreting the results based on each of these three models since the estimations may be inconsistent due to the violation of the assumption that the individual-specific effects are uncorrelated with the regressors, $\operatorname{cov}(\alpha_i, \mathbf{X}_{kit}) = 0$, as I have elaborated in Sections 3.2.4-c and 3.2.4-d.[8] The results based on the pooled GLS model are the preferred estimates for the variables with no within-variation since the standard errors under the pooled GLS model are smaller as compared to the RE and BE model—suggesting a more efficient estimate. I still provided the results based on the RE and BE models for the purpose of reference.

5.2.1 School Resources Effects on Literacy and Numeracy Performance

The discussion of the effects of school resource on students' academic achievement starts with an account of the multicollinearity problem and the rationale to use the per student financial resources measure instead of total financial resources. The multicollinearity problem needs to be addressed because its presence results in inefficient estimates and unexpected changes in coefficient signs, leading to misleading conclusions. As shown in Appendix 5.2, strong correlations (more than 90% correlations) have been found among the school financial variables (*lnsrp_perstu*, *lngrant_perstu*, *lnrural_perstu*, and *lnpercapita*), indicating the problem of multicollinearity. The multicollinearity problem is solved by dropping three of the school resource variables, leaving the final model with *lnpercapita* and *lnst_ratio* to

[8] Since the BE and pooled GLS require the same assumption as the RE model, the Hausman test can be used to compare whether the assumption holds. Based on the Hausman test, evidence has been found that the null hypothesis that the individual-specific effects are uncorrelated with the regressors, $\operatorname{cov}(\boldsymbol{\alpha}_i, \mathbf{X}_{kit}) = 0$, is rejected at the 95% confidence interval. The FE model therefore remains the most efficient model as compared to the BE and pooled GLS models.

capture the effect of school resources on students' academic achievement.[9] To address the multicollinearity problem, each of the variables is included one by one and its value assessed. If by adding the variable contributes to the better fitting of the model, then it is retained. The other school financial variables in the model are then re-tested to see if they are still contributing significantly to the fitting of the model. From the described process above, only *lnpercapita* has been found to contribute significantly to the model in terms of high coefficient estimate and positive (meeting expectation) coefficient sign. Since *lnst_ratio* is the only variable available to capture the effect of class size, the variable is therefore retained.

The next important issue in relation to financial resources to school is to identify whether an educational dollar spent is a private or public good. If an educational dollar spent is a private good, then the dollar spent is exclusive to an individual student. Conversely, if an educational dollar spent is a public good, then the effect of the dollar spent is shared by many students. To investigate whether an educational dollar spent is a private or public good, the following model is employed:

$$\ln A_{ijt} = b_0 + b_1 \ln E_{ijt} + b_2 \ln S_{ijt} + b_3 \ln T_{ijt} + e_{ijt} \qquad (5.1)$$

where *A* represents test scores, *E* denotes total financial expenditure, *S* denotes the number of students, *T* denotes the number of teachers and *e* is the error term. The subscripts *i* denotes the i^{th} student ($i = 1, \ldots, N$), j denotes the j^{th} school ($j = 1, \ldots, J$) and *t* denotes the time period ($t = 1, \ldots, T$).

If $b_1 = -b_2$ (b_1 is positive since total financial expenditure is expected to have a positive effect on test scores while b_2 is negative since more students are expected to

[9] Another solution to the multicollinearity problem in the school financial variables is to sum them together. This solution however, assumes that a dollar in each different category of the school financial variables has the same effects on students' academic achievement. Alternatively, it is admitted that principal component analysis (PCA) is one possible solution to the multicollinearity problem.

have a negative effect on test scores), then the per capita measure is appropriate because equation (5.1) can now be re-written as:

$$\ln A_{ijt} = b_0 + b_1 \ln\left(\frac{E_{ijt}}{S_{ijt}}\right) + b_3 \ln T_{ijt} + e_{ijt} \tag{5.2}$$

A Wald *F*-test (to test restrictions on parameters) is undertaken to check the null hypothesis that $b_1 + b_2 = 0$. If the null hypothesis is rejected, then using the per student school financial expenditure (E_{ijt}/S_{ijt}) is not appropriate. The alternative hypothesis, $b_1 + b_2 > 0$ or $b_1 > -b_2$, shows that there is a public goods elements to spending. In other words, the alternative hypothesis implies that an educational dollar spent is not exclusive to an individual student, rather the effects is shared by many students (the educational dollar is a public good).

Table 5.8: Estimation Results for an Analysis of the Appropriateness of Using Per Capita Expenditure Instead of Total Expenditure

Variables	(1) *lnread*	(2) *lnwrite*	(3) *lnnumer*
Constant (b_0)	3.384*	5.914*	4.401**
	(1.872)	(2.081)	(1.824)
lnexpenditure (b_1)	0.434	-0.0110	0.208
	(0.296)	(0.329)	(0.288)
lnstudent (b_2)	-0.626**	-0.0996	-0.354
	(0.258)	(0.287)	(0.251)
lnteacher_lag (b_3)	0.338*	0.105	0.330*
	(0.127)	(0.141)	(0.123)
Observations	12,396	12,396	12,396
Number of group	4,256	4,256	4,256
R-squared	0.002	0.000	0.001

Note: *, ** and *** denote the level of significance at 1%,5% and 10%.
The figures in () are standard errors.

Table 5.9: Hypothesis Testing for the Appropriateness of Using Per Capita Expenditure Instead of Total Expenditure

Model	Null hypothesis	F-statistics	Prob>F	Decision
1	$b_1 + b_2 = 0$	2.43	0.1190	Do not reject the null
2	$b_1 + b_2 = 0$	0.65	0.4202	Do not reject the null
3	$b_1 + b_2 = 0$	1.48	0.2233	Do not reject the null

In Table 5.8, the estimation results of equation (5.1) are presented. The results are based on three FE models, using *lnread* (model1), *lnwrite* (model 2) and *lnnumer* (model3) as the dependent variables. Under models 1 and 3, the coefficient signs for all the variables are as expected—positive for *lnexpenditure* (natural log of real total student allocation expenditure); negative for *lnstudent* (natural log of the number of students) and positive *lnteacher_lag* (natural log of the number of teachers in the previous year[10]). As shown in Table 5.9, the null hypothesis that $b_1 + b_2 = 0$ is not rejected at 95% confidence level. The use of per capita school financial variable is therefore appropriate.

Since the use of per student school financial variable has been proven to be appropriate, the estimation results in Table 5.10 are based on *lnpercapita*. Under the Fixed Effects (FE) model, the variable educational *lnpercapita* has the expected positive effects on literacy and numeracy scores. A percentage increase in *percapita* is associated with a 0.38% increase in reading score, a 0.36% increase in writing scores and a 0.43% increase in numeracy scores, *ceteris paribus*. The findings therefore point to a positive statistically significant benefit of educational expenditure per student on literacy and numeracy achievement.

The variable *lnst_ratio* is another school resource variable employed to measure the effect of class size on students' academic achievement. As shown in Table 5.10, *lnst_ratio* has the expected negative sign and the effects of the variable on literacy and

[10] For 2007, the variable *teacher_lag* is based on the number of teachers in 2005; for 2005 it is based on the number of teachers in 2003 and for 2003, it is based on the number of teachers in 2000. The variable is employed to overcome the problem of endogeneity and multicollinearity when the current number of teachers is used as one of the regressors. The variable, *teacher_lag*, is already determined and therefore not endogenous. A problem with using data of the current number of teachers is that the number of teachers may be determined by the number of students and possibly expenditure, and therefore is endogenous, leading to biased results. In addition, a problem of high multicollinearity has been found between the number of current students and current teachers. The problem of multicollinearity results in inefficient estimates.

numeracy are statistically significant. In other words, significant evidence has been found to support the hypothesis of the negative relationship between the level of student-teacher ratio and the performance of Tasmanian students in literacy and numeracy.

Table 5.10: Regression Results for Reading, Writing and Numeracy Test Scores

Variables	*lnread*				*lnwrite*				*lnnumer*			
	FE	RE	BE	GLS	FE	RE	BE	GLS	FE	RE	BE	GLS
d_male	—	-0.1143*	-0.1088*	-0.1135*	—	-0.1652*	-0.1589*	-0.1643*	—	-0.0713*	-0.0656**	-0.0704*
		(0.0277)	(0.0277)	(0.0244)		(0.0298)	(0.0298)	(0.0265)		(0.0273)	(0.0272)	(0.0239)
d_indig	—	-0.5420	-0.0363	-0.0526	—	-0.0468	-0.0213	-0.0445	—	-0.0071	0.0105	-0.0053
		(0.0372)	(0.0377)	(0.0328)		(0.0401)	(0.0406)	(0.0356)		(0.0366)	(0.0371)	(0.0321)
Lnabsent	-0.111*	-0.1536*	-0.1994*	-0.1626*	-0.1525*	-0.2063*	-0.2610*	-0.2165*	-0.1024*	-0.1502*	-0.2027*	-0.1608*
	(0.0178)	(0.0127)	(0.0180)	(0.0123)	(0.0196)	(0.0138)	(0.0194)	(0.0133)	(0.0175)	(0.0125)	(0.0177)	(0.0120)
d_mumwork	—	0.0824	0.0655	0.0790	—	0.0574	0.0417	0.0544	—	0.0413	0.0261	0.0383
		(0.0572)	(0.0572)	(0.0503)		(0.0617)	(0.0616)	(0.0547)		(0.0563)	(0.0563)	(0.0493)
d_dadwork	—	0.1062**	0.0928***	0.1030**	—	0.0817	0.0675	0.0788	—	0.0609	0.0515	0.0586
		(0.0565)	(0.0565)	(0.0497)		(0.0609)	(0.0609)	(0.0540)		(0.0556)	(0.0557)	(0.0487)
d_mumedu	—	0.0456	0.0350	0.0439	—	0.0714**	0.0581**	0.0695**	—	0.0297	0.0204	0.0283
		(0.0323)	(0.0315)	(0.0376)		(0.0339)	(0.0339)	(0.0300)		(0.0309)	(0.0310)	(0.0271)
d_dadedu	—	0.0609***	0.0394	0.0581**	—	0.0757**	0.0487	0.0725**	—	0.1034*	0.0842*	0.1007*
		(0.0312)	(0.0313)	(0.0274)		(0.0336)	(0.0338)	(0.0298)		(0.0307)	(0.0309)	(0.0269)
lnatsi	0.0395	0.0205	-0.0178	0.0162	0.0485**	0.0257	-0.0237	0.0208	0.0474**	0.0269	-0.0146	0.0217
	(0.0218)	(0.0176)	(0.0304)	(0.0175)	(0.0239)	(0.0192)	(0.0327)	(0.0191)	(0.0213)	(0.0172)	(0.0299)	(0.0172)
lnesl	-0.0711*	-0.0296**	0.0494	-0.0180	-0.0381	-0.0010	0.0684**	0.0108	-0.0370***	0.0064	0.0975*	0.0196
	(0.0213)	(0.0180)	(0.0336)	(0.0181)	(0.0233)	(0.0196)	(0.0362)	(0.0197)	(0.0208)	(0.0176)	(0.0331)	(0.0178)
lndisable	0.0011	-0.0448	-0.1281*	-0.0564**	-0.0279	-0.1055*	-0.2252*	-0.1227*	-0.0032	-0.0325	-0.0981**	-0.0409
	(0.0358)	(0.0282)	(0.0470)	(0.0280)	(0.0392)	(0.0307)	(0.0507)	(0.0304)	(0.0350)	(0.0276)	(0.0463)	(0.0274)
lnsusprate	-0.0392	-0.0585*	-0.0831*	-0.0635*	-0.0332***	-0.0393*	-0.0486**	-0.0416*	-0.0143	-0.0379*	-0.0721*	-0.0444*
	(0.0672)	(0.0220)	(0.0196)	(0.0129)	(0.0183)	(0.0142)	(0.0237)	(0.0141)	(0.0163)	(0.0128)	(0.0217)	(0.0127)
lnst_ratio	-0.7246*	-1.1323	-2.0830*	-1.2183*	-0.7557*	-1.0343*	-2.0316*	-1.0947*	-0.6556*	1.0240*	-1.8664*	1.1071*
	(0.1563)	(0.1206)	(0.2578)	(0.1203)	(0.1711)	(0.1313)	(0.2778)	(0.1308)	(0.1528)	(0.1182)	(0.2538)	(0.1179)
lnpercapita	0.3801*	0.2786*	-0.1539	0.2499*	0.3588*	0.3362*	0.1064	0.3222*	0.4324*	0.3297*	0.0593	0.2999*
	(0.273)	(0.655)	(0.1379)	(0.0652)	(0.0923)	(0.0713)	(0.1486)	(0.0709)	(0.0825)	(0.226)	(0.1258)	(0.0639)
d_rural	0.5478*	0.03784*	0.4177*	0.3707*	0.5863*	0.4223*	0.4647*	0.4141*	0.4911*	0.3733*	0.4210*	0.3704*
	(0.0518)	(0.0287)	(0.0400)	(0.0270)	(0.0568)	(0.0311)	(0.0430)	(0.0294)	(0.0507)	(0.0282)	(0.0393)	(0.0265)
Constant	0.3186	0.3117	0.0784	0.2558	0.2482	0.2002	-0.2445	0.1408	0.3984	0.2571	-0.1219	0.2004
	(2.474)	(0.1147)	(0.1572)	(0.1076)	(0.1265)	(0.1242)	(0.1694)	(0.1170)	(0.1129)	(0.1126)	(0.1547)	(0.1055)
Total obs	11,887	11,887	11,887	11,887	11,887	11,887	11,887	11,887	11,887	11,887	11,887	11,887
No of group	4,072	4,072	4,072	4,072	4,072	4,072	4,072	4,072	4,072	4,072	4,072	4,072
R-squared	0.4136	0.4115	0.5744	-	0.3650	0.3630	0.5369	-	0.4274	0.4258	0.5822	-

Note: *, ** and *** denote the level of significance at 1%, 5% and 10%. The figures in () are standard errors. Equation (5.5) for the FE model has no constant. Since the constant for the FE model is not significant, it is equal to zero.

I also extend the analysis of the effects of the school resource variables (*lnpercapita* and *lnstratio*) on literacy and numeracy performance by adding the squared-variables, $lnpercapita^2$ and $lnst\_ratio^2$, as regressors. The squared-variables are included in order to investigate any non-linear effect of the variables. The inclusion of the variable $lnpercapita^2$ is to examine whether the effects of financial resources to schools continue if more monies are allocated to schools. By having the variable $lnst\_ratio^2$, on the other hand, the purpose is to investigate whether the effects of class size continue if further reduction in class size is pursued.

Results based on the FE polynomial regression are presented in Appendix 5.3. Evidence of significant diminishing effects of more monies to school has been found for numeracy performance only (the coefficient sign for *lnpercapita* is significantly positive and $lnpercapita^2$ is significantly negative). Based on the FE polynomial estimations (Appendix 5.3), at the 2006 average *percapita* of $248.02, a 1% increase (which is equivalent to $2.48 real dollar increase per student) in *percapita* affects numeracy scores by 0.88%, *ceteris paribus*. If the 2006 average *percapita* is doubled; at $496.04, a 1% increase (which is equivalent to $4.96 real dollar increase per student) in *percapita* affects numeracy scores by 0.86%, *ceteris paribus.* The analysis shows that between the average 2006 *percapita* level and at the twice of that amount, a diminishing effect of more *percapita* has set in but at a very small rate (0.02 percentage points). The findings from the analysis imply that although money matters in an effort to improve Tasmanian students' numeracy performance, the effects of more monies to schools diminish. For the effects of whether a continuous reduction in student-teacher ratio persists if further reduction in the ratio is pursued, no significant evidence has been found. Although the coefficient sign for *lnst_ratio* is negative and *lnst_ratio*^{2} is positive when *lnnumer* is employed as the dependent variable, both variables are statistically insignificant.

From the results of FE model in Table 5.10, at 95% confidence level, there is statistical support that schools in rural areas perform better on average than schools in urban areas in literacy and numeracy achievements. The high performance of rural schools may be due to more attention is given by the DoE. Tas to rural schools in terms of teaching and learning supports for rural communities.

5.2.2 Student/Family Background Effects on Literacy & Numeracy Performance

In Table 5.10, due to no within variations, the effects of gender (*d_male*), indigenous status of a student (*d_indig*), and parental occupation (*d_mumwork*, *d_dadwork)* and education (*d_mumedu*, *d_dadedu*) are absent in the FE model. To capture the effects of these variables, estimations based on the pooled GLS model are analysed.

Gender of a student has been found to be statistically significant in affecting the literacy and numeracy performance, where the female students on average perform better than the male students in both literacy (reading and writing) and numeracy. The estimations based on the pooled GLS on reading, writing and numeracy show that holding other factors constant, a male student's scores on the subjects, on average are 0.11%, 0.16% and 0.07% lower than a female student's scores. Evidence of better performance of female students in literacy based on the case of public primary schools in Tasmania was found earlier by Boardman (2006).[11] In addition, I have also found the evidence of lower performance of male students in numeracy. All the findings here point

[11] Boardman's study was based on a qualitative analysis (survey) involving students aged 5.00-5.03 years in reading and in the Performance Indicators of Primary Schools (PIPS) evaluations.

to the need for a formulation of policy to improve the literacy and numeracy performance of the male students.

From the results in Table 5.10, concern is also raised about the performance of indigenous students. Evidence of poor performance of indigenous students has been found to be very significant. The results from the pooled GLS estimation show that, holding other factors constant, an indigenous student's reading, writing and numeracy scores, on average are 0.05%, 0.04% and 0.005% lower than a non-indigenous student's scores. The lower socio-economic conditions of indigenous people may be one contributing factor to the lower performance of indigenous students' academic achievement.

Absenteeism from school also has a significant negative effect on the students' literacy and numeracy performance. An interpretation of the results of the FE model implies that a 1% rise in the number of days absent from school leads to a decline in reading scores by 0.16%; writing scores by 0.22%; and numeracy scores by 0.16%, other things being constant. A policy that targets a reduction in the absenteeism rates needs to be formulated in an effort to improve Tasmanian students' academic achievement.

Still on Table 5.10, I have found no statistical evidence to support the hypothesis that a student whose parents worked in a high-status occupation performs better than a student whose parents worked in a low-status occupation. From Table 5.11, the variables that represent parents in type 1 occupation (*d_mumwork* and *d_dadwork*) have the expected positive signs but are statistically insignificant in explaining students' academic achievement. I have found, however, the expected positive and significant effects of parental education (*d_mumedu* and *d_dadedu*) on students' academic achievement. Based on the poled GLS results, the effects of mother with tertiary qualification on a student's reading, writing and numeracy scores are on average 0.04%, 0.07% and 0.02% higher than a student whose mother had less than tertiary qualification, *ceteris paribus.*[12] The results in Table 5.10 also point to the positive significant effects of father's educational level on a student's academic achievement. Based on the pooled GLS model, holding other factors constant, the performance in reading, writing and numeracy of a student whose father held a tertiary qualification is on average 0.06%, 0.07% and 0.10% higher than a student whose father held a qualification less than tertiary education. Parental education, therefore, is an important factor that explains the performance of Tasmanian students in literacy and numeracy.

5.2.3 Peer Background Effects on Literacy & Numeracy Performance

Four variables used to capture the effects of peers are *atsi*, *esl*, *disable* and *susprate*. The results for *esl* (the number of students who had English as a Second Language) under the FE model are statistically significant with negative effects on reading and numeracy performance. Test scores in reading and numeracy of a student decline by 0.07% and 0.04% for every 1% increase in *esl, ceteris paribus*. The reason for the negative effects may be due to the disruption (such as teachers have to pay more attention to the struggling student) in the learning process of the other students as a result of the presence of an *esl*-student in a classroom.

In Table 5.10, the result from the FE model for *susprate* is statistically significant with the expected negative effects only on writing performance. Test scores in writing decline by 0.03% for every 1% increase in the level of suspension rate, *ceteris paribus*.

[12] The finding of the effects of mother's educational level here is parallel with the results of many previous studies such as by Rivkin et al. (2005), Schiller et al. (2002), Goldhaber & Brewer (1996), Ferguson & Ladd (1996), Ehrenberg and Brewer (1994)S and Mumane et al. (1981).

Students with serious disciplinary level (that lead to suspension from school), therefore, have a negative effect on the test score performance of other students. The negative relationship may be explained by the anti-social behaviour of this group of students (such as bullying), resulting in interruptions to their peers' learning process.

With the estimations of Tasmanian educational production functions, as given in Table 5.10, clearer understanding of the relationships between educational inputs and educational outputs has now been established. The policy implications that can be derived from the analysis and the limitations of the study are discussed in Chapter 7.

5.3 Conclusions

In this chapter, I have investigated the determinants of Tasmanian students' academic achievement by estimating an educational production function. The primary objective of the analysis is to evaluate the effects of school resources, in particular, education expenditure on students' academic achievement. In order to have a proper measure of school financial resources, I have demonstrated that educational expenditure per student is the appropriate variable to be employed in estimating the effects of school financial resources on students' academic achievement. The variable *percapita,* therefore, has been employed to investigate the effects of educational spending per student on literacy and numeracy performance of Tasmanian students. Evidence of the positive and significant effects of the variable on reading, writing and numeracy performance has been recorded. The results from the FE model show that a one percentage increase in *percapita* is associated with a 0.38% increase in reading score, a 0.36% increase in writing scores and a 0.43% increase in numeracy scores, *ceteris paribus*. Another school resource variable employed to capture the effects of class size on students' academic achievement is *st_ratio* (student-teacher ratio). The effect of the variable is also found to be statistically significant. A reduction in the class size by 1% results in improvements in reading, writing and numeracy performance by 0.72%, 0.76% and 0.66%, *ceteris paribus.*

From the study, I also have found that gender of a student is statistically significant in affecting the literacy and numeracy performance, where male students on average perform less well than female students in literacy and numeracy. Evidence of a low performance of an indigenous student (as compared to a non-indigenous student) in reading and numeracy has also been found. Performance in literacy and numeracy is also significantly influenced by the number of days a student absent from school.

I also have found the expected positive effects of parental education on students' academic achievement, where a student whose parents held tertiary qualification on average perform better than a student whose parents had less than tertiary qualification, *ceteris paribus.* The effects of parental occupation on students' academic achievement, however, are statistically insignificant.

In terms of peer effects, based on the FE results, there has been a negative effect of more students who had English as a Second Language in a school (*esl*) on a student's reading and numeracy achievements. Evidence of a negative relationship between the level of suspension rates (*susprate*) and students' academic achievement has been found only on the writing performance. The negative relationships of the two variables (*esl* and *susprate*) on students' academic achievement may be due to disruptions to the learning and teaching processes caused by these two groups of peers.

The results from the estimations of Tasmanian educational production function in this study stand as a crucial source of insight to a more informed debate over education policy in Tasmania. With the identification of the variables that significantly affect a student's academic achievement, a policy that targets those variables can be formulated and may be implemented depending on feasibility issues and the trade-off between various policy measures.

Appendix 5.1: Hausman Test

The following results are the Hausman test estimations from Stata for reading scores [dependent variable =*ln(read)*]

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       FE           RE         Difference          S.E.
-------------+----------------------------------------------------------------
    lnabsent |   -.1109547    -.1535572        .0426026        .0125921
      lnatsi |    .0395333     .0205095        .0190237        .0128957
       lnesl |   -.0710888    -.0296323       -.0414566        .0114646
  lndisable |    .0010742     -.044814        .0458881        .0220521
  lnsusprate |   -.0392375    -.0584619        .0192244        .0104428
 lnst_ratio |   -.7246091    -1.132344       -.4077351         .099316
 lnpercapita|    .3801281      .278563         .101565        .0530955
     d_rural |    .5478862     .3784242         .169462        .0431497
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       89.98
                Prob>chi2 =      0.0000
```

The following results are the Hausman test estimations from Stata for writing scores [dependent variable = *ln(write)*]

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       FE           RE         Difference          S.E.
-------------+----------------------------------------------------------------
    lnabsent |   -.1524977    -.2062686        .0537709        .0139022
      lnatsi |    .0485447     .0256844        .0228603        .0142731
       lnesl |   -.0380613      .000966       -.0390274        .0127036
  lndisable |   -.0279396    -.1055023        .0775627          .02439
  lnsusprate |   -.0331534    -.0393464         .006193         .011547
 lnst_ratio |    -.755737    -1.034258        .2785209        .1097017
lnpercapita |     .3587546     .3361742        .0225803        .0586728
     d_rural |    .5862769     .4223426        .1639342        .0474653
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       83.18
                Prob>chi2 =      0.0000
```

The following results are the Hausman test estimations from Stata for numeracy scores [dependent variable = *ln(numer)*]

```
                     ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       FE           RE         Difference          S.E.
-------------+----------------------------------------------------------------
    lnabsent |   -.1024357    -.1501833        .0477477        .0122736
      lnatsi |    .0473967     .0269291        .0204676        .0125613
       lnesl |   -.0370201     .0064054       -.0434255        .0111652
   lndisable |   -.0031966     -.032454        .0292574        .0214845
  lnsusprate |   -.0143056     -.037943        .0236374        .0101747
 lnst_ratio |   -.6556276    -1.024005        .3683776        .0968073
 lnpercapita|    .4324261     .3296983        .1027278        .0517458
     d_rural |    .4911206     .3733878        .1177328        .0421136
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       78.24
                Prob>chi2 =      0.0000
```

Appendix 5.2: A Correlation Matrix of the School Resource Variables

	lnsrp_perstu	*lngrant_perstu*	*lnpercapita*	*lnrural_perstu*	*lnst_ratio*
lnsrp_perstu	1				
lngrant_perstu	0.9696	1			
lnpercapita	0.9099	0.9549	1		
lnrural_perstu	0.9929	0.9893	0.9495	1	
lnst_ratio	0.1597	0.2277	0.4654	0.2272	1

Appendix 5.3: Fixed Effects Estimations based on a Polynomial Specification

Variables	*lnread*	*lnwrite*	*lnnumer*
lnabsent	-0.177*	-0.226*	-0.171*
	(0.0188)	(0.0209)	(0.0183)
lnatsi	0.03543	0.0320	0.0320
	(0.0441)	(0.0491)	(0.0429)
lnesl	-0.00915	-0.0176	-0.00229
	(0.0334)	(0.0372)	(0.0325)
lndisable	0.0289	0.00748	0.00249
	(0.0342)	(0.0380)	(0.0333)
lnsusprate	-0.0299	-0.0125	-0.0182
	(0.0205)	(0.0228)	(0.0199)
lnst_ratio	-0.457	0.200	-0.00435
	(0.633)	(0.704)	(0.616)
lnstratio^2	-0.0137	0.0115	0.0152
	(0.0158)	(0.0176)	(0.0154)
lnpercapita	1.197*	0.904***	1.049***
	(0.276)	(0.307)	(0.268)
lnpercapita^2	-0.00132	0.0103	-0.0150**
	(0.00715)	(0.00795)	(0.00696)
d_rural	0.260***	0.0643	-0.00217
	(0.139)	(0.155)	(0.135)
Constant	0.601	0.511	0.258
	(2.552)	(2.838)	(2.484)
Observations	11,887	11,887	11,887
Number of gorup	4,072	4,072	4,072
R-squared	0.013	0.015	0.013

Note: *, ** and *** denote the level of significance at 1%,5% and 10%.
The figures in () are standard errors.

6 An Evaluation of the Technical Efficiency of Tasmanian Public Primary Schools

6.0 Introduction

In this chapter, I evaluate the level of technical efficiency and the determinants of technical efficiency of Tasmanian public primary schools. To ensure robustness of the estimation, the analysis of technical efficiency in this chapter involves two frontier estimation methods, namely Stochastic Production Frontier (SPF) and Data Envelopment Analysis (DEA). Both DEA and SPF provide a measure of technical efficiency. A non-parametric approach such as DEA is common in the school efficiency literature because the technique can provide efficiency scores from a straightforward use of inputs and outputs (see Appendix 4.1). The technique cannot distinguish however, between statistical noise and inefficiency. As a result, all of the deviations (firms below the frontier) from the constructed DEA frontier (the identified best-practice firms) are attributed to inefficiency. To avoid the shortcoming, the Stochastic Production Frontier (SPF) is offered and applied here as an appealing alternative to DEA (see Appendix 4.1 for a theoretical framework of SPF). Since each of the techniques has its own advantages and shortcomings, both techniques are employed in the analysis of technical efficiency of public primary schools in Tasmania.

The assessment of the productivity and efficiency of schools is a crucial ingredient in any effort to maintain and improve the quality of public education. As mentioned in Section 2.5, there has been no study undertaken to evaluate the level of school efficiency in Tasmania. Many questions remain unexplained. Are most Tasmanian schools grossly inefficient with just a few high achievers? Are the schools for the most part close to the frontier? What are the characteristics of the efficient schools? What would the inefficient schools need to do to emulate the performance of the efficient schools? Manifestly, these are many pressing questions. The dearth of research raises serious questions about how the Tasmanian Government could even begin to mount a well-targeted educational policy. Further, the analysis in Chapter 5 on the estimation of educational production functions does not provide any direct answers to the efficiency issue. Thus, there is a need for a study that assesses the level of technical efficiency of public primary schools in Tasmania. In addition, an investigation into the possibility of technical change over the study period is also explored. An important aspect of the analysis is to analyse whether schools in Tasmania have experience technical efficiency progress from 2003 to 2007, which is possible with the availability of panel data at hand.

School-level panel data are employed for the estimations of SPF and DEA. In Chapter 5, however, student-cohort level panel data have been employed for the investigation of factors that influence students' academic achievement. The use of school-level data in this chapter is because of the different objective of the chapter, where in order to measure the level of technical efficiency of schools in Tasmania, the use of school-level data is appropriate (refer to Section 4.2 for details on how previous works to measure schools' technical efficiency were undertaken).

An outline of the chapter is as follows. The discussion based on the SPF is provided in Section 6.1. Model specifications employed under the SPF are discussed in Section 6.1.1. Descriptions of the data used for the SPF estimation follow in Section 6.1.2 and the SPF results are discussed in Section 6.1.3. I provide some concluding remarks on the SPF analysis in Section 6.1.4. The discussion based on the DEA is provided in Section 6.2. Model specifications employed under the DEA are detailed in Section 6.2.1. Descriptions of the data used for the DEA estimations follow in Section 6.2.2 and the DEA results are discussed in Section 6.2.3. In Section 6.2.4, some concluding remarks on the DEA estimations are provided. I provide a comparison of the results obtained under both methods in Section 6.3. Section 6.4 offers some concluding remarks.

6.1 Stochastic Production Frontier (SPF)

6.1.1 SPF Specification

Mathematical specifications of SPF based on panel data for the case of Tasmanian public primary schools are provided in this section. The theoretical derivation of the SPF equation is offered in Chapter 4 (Appendix 4.1). In this section, the mathematical specifications are aimed at facilitating an estimating equation that accounts for the non-discretionary inputs/socio-economic environment (**Z**) that surrounds schools. The environmental factors are assumed to affect the degree of technical inefficiency but not the production technology. The justification for the assumption is that in formal education, schools are expected to achieve certain educational goals (such as to achieve the standard national literacy and numeracy goals) given the discretionary educational inputs and the available technology. In such a case, the shape of the production technology is exogenous of the non-discretionary/environmental factors. Any short fall in achieving the educational goals can be associated with the influence of the non-discretionary inputs/environmental factors surrounding schools. Socioeconomic factors of students such as parental education and occupational status, ethnic background and whether the school is in rural or urban area are the variables commonly employed to capture the environmental effect (Chakraborty, et al., 2001; Jeon & Shields, 2005).[1]

A specific approach proposed by Battese and Coelli (1995) is adopted for the estimation of Tasmanian frontier production function. The approach allows for an estimation of technical inefficiency effects in a stochastic production frontier for panel data. One advantage of the approach is that environmental factors are allowed to influence the stochastic component of the production frontier. The general form of the model is expressed as:

$$A_{jt} = f\left(\mathbf{X}_{jt}, \boldsymbol{\beta}\right) + \left(V_{jt} - U_{jt}\right), \tag{6.1}$$

where A_{jt} represents the production of the j^{th} school (j = 1, 2 .... , J) at time t (t = 1, 2 . . . . . T); $\mathbf{X}_{jt}$ is a (1 x k) vector of inputs of production associated with the j^{th} school; and $\boldsymbol{\beta}$ is a (k x 1) vector of the unknown parameters to be estimated. The term $\left(V_{jt} - U_{jt}\right)$ is a scalar of the composite stochastic term, where V_{jt} represents statistical noise and U_{jt} represents inefficiency. The stochastic components V_{jt} and U_{jt} are assumed to be independently distributed. The term V_{jt} is assumed to be an independent and identically distributed (iid) random variable with zero mean and σ_v^2 variance, $N\left(0, \sigma_v^2\right)$. The term

[1] Extant literature of school efficiency usually distinguishes between fixed and environmental effects. Student's fixed effects are usually represented by socioeconomic variables like family income, parent marital status, parental education/occupational status and ethnic background. The environmental effects are represented by the geographical factors like urban or rural school (Chakraborty, et al., 2001). The Battese and Coelli (1995) approach treats technical inefficiency as a function of the environmental factors.

U_{jt} is a non-negative random variable, assumed to be independently distributed, such that U_{jt} is obtained by truncation of the normal distribution (at zero) with $\mathbf{Z}_{jt}\boldsymbol{\delta}$ mean and σ^2 variance, or $N\left(\mathbf{Z}_{jt}\boldsymbol{\delta},\sigma^2\right)$—see below.

The inefficiency term, U_{jt}, in equation (6.1) is specified as:

$$U_{jt} = \mathbf{Z}_{jt}\boldsymbol{\delta} + W_{jt} \tag{6.2}$$

where $\mathbf{Z}_{jt}$ represents a (1 x m) vector of school-specific environmental variables associated with technical inefficiency over time; $\boldsymbol{\delta}$ is a (m x 1) vector of unknown coefficients to be estimated, and W_{jt} is a random variable with $N\left(0,\sigma^2\right)$ truncated at $-\mathbf{Z}_{jt}\boldsymbol{\delta}$ i.e., $W_{jt} \geq -\mathbf{Z}_{jt}\boldsymbol{\delta}$. The parameters of equations (6.1) and (6.2) are estimated by Maximum Likelihood procedure.[2]

Based on equation (6.1), the translog SPF model for Tasmanian public primary schools is expressed as:

$$\begin{aligned}\ln(avg\_test_{jt}) = {} & \beta_0 + \ln(srprxp_{jt})\beta_1 + \ln(grantexp_{jt})\beta_2 + \ln(edperstu_{jt})\beta_3 + \\ & \ln(ruralexp_{jt})\beta_4 + \ln(st\_ratio_{jt})\beta_5 + [\ln(srprxp_{jt})]^2\beta_6 + \\ & [\ln(grantexp_{jt})]^2\beta_7 + [\ln(edperstu_{jt})]^2\beta_8 + [\ln(ruralexp_{jt})]^2\beta_9 + \\ & [\ln(st\_ratio_{jt})]^2\beta_{10} + \ln(srprxp_{jt})\ln(st\_ratio_{jt})\beta_{11} + \\ & \ln(grantexp_{jt})\ln(st\_ratio_{jt})\beta_{12} + \ln(edperstu_{jt})\ln(st\_ratio_{jt})\beta_{13} + \\ & \ln(ruralexp_{jt})\ln(st\_ratio_{jt})\beta_{14} + (V_{jt} - U_{jt})\end{aligned} \tag{6.3}$$

where *avg_test* is the average test score of school; *srprxp* is the average real total school resource package expenditure; *grantexp* is the average real general support grant expenditure; *edperstu* is the average real educational expenditure per student; *ruralexp* is the average real rural allocation expenditure; and *st_ratio* is student-teacher ratio. The

[2] See Coelli (1996) for a specification and estimation of a stochastic frontier analysis based on the Maximum Likelihood procedure.

independent variables are the discretionary variables ($\mathbf{X}_{jt}$)—refer to Table 6.1 for a detailed definition of the variables. The term $\left(V_{jt} - U_{jt}\right)$ is the composite error term as defined in equation (6.1).

In relation to the discussion in Chapter 4, equation (6.3) describes the stochastic production frontier (recall Figure 4.1). In equation (6.3), the discretionary variables are considered as an important component of the production technology. The translog form of the function allows for a more flexible production function.

Based on equation (6.2), the technical inefficiency (U_{jt}) model of school j in Tasmania in year t is expressed as:

$$\begin{aligned} U_{jt} = {} & \delta_0 + atsi_{jt}\delta_1 + esl_{jt}\delta_2 + disable_{jt}\delta_3 + male_{jt}\delta_4 + mumwork_{jt}\delta_5 + \\ & mumedu_{jt}\delta_6 + dadwork_{jt}\delta_7 + dadedu_{jt}\delta_8 + susprate_{jt}\delta_9 + \\ & absent_{jt}\delta_{10} + d\_rural_{jt}\delta_{11} + W_{jt} \end{aligned} \tag{6.4}$$

where technical inefficiency is a function of the observable environmental variables $\left(\mathbf{Z}_{jt}\right)$. The terms *atsi* is the number of Aboriginal and Torres Strait Islander students; *esl* is the number of students who involve in the English as a Second Language Program; *disable* is the number of students on the Severe Disabilities Register/the High Needs Register; *male* is the percentage of male students; *mumwork* is the number of mothers of Years 3 and 5 students who work in type 1 occupations; *mumedu* is the number of mothers of Years 3 and 5 students with a tertiary qualification; *dadwork* is the number of fathers of Years 3 and 5 students who work in type 1 occupations: *dadedu* is the number of fathers of Years 3 and 5 students with a tertiary qualification;, *susprate* is student suspension rate; *absent* is the average days absent from school per year of students in

Years 3 and 5: and *d_rural* is a dummy of rural status of school *j* (1 if school *j* is a rural school)—refer to Table 6.1 for more details.

A translog production function is assumed to be present for the Tasmanian schools' stochastic production frontier for the years 2003, 2005 and 2007. Four SPF and technical inefficiency equations are estimated (explained below). Estimates based on the four outputs are undertaken so that a comparison of technical efficiency scores and the determinants of inefficiency across the different outputs can be analysed.[3] The comparison allows for an investigation into the issue whether schools are only technically efficient in one specific area (such as only efficient in producing high scores in literacy of Year 3) or are they technically efficient across various areas (such as in producing higher literacy and numeracy scores for different Years 3 and/or 5).[4] Each of the four models (called model I, II, III and IV) is different in terms of the dependent variable and the corresponding independent variables employed, where:

- for model I the dependent variable is the average *literacy* score of students in Year 3 at school *j* (*avg_lit3*) and the independent variables are based on the average data that corresponds to the Year 3 students at the j^{th} school.
- for model II, the dependent variable is the average *literacy* score of Year 5 at school *j* (*avg_lit5*) and the independent variables are based on the average data that corresponds to Year 5 students at school *j*.

[3] I am aware of the distance function technique in the parametric approach that allows for a multi-output and multi-input stochastic production model as Perelman and Gonzales (2011) had applied.
[4] To evaluate the level of technical efficiency of primary schools in Tasmania, the estimation is based on dataset of Years 3 and 5. These Years are chosen because the standard assessment of literacy and numeracy performance in Australia for primary schools is based on Years 3 and 5 performances.

- for model III, the dependent variable is the average *numeracy* score of Year 3 at school *j* (*avg_num3*) and the independent variables are based on the average data that corresponds to Year 3 students at school *j*.
- for model IV, the dependent variable is the average *numeracy* score of students in Year 5 at school *j* (*avg_num5*) and the independent variables are based on the average data that corresponds to the Year 5 students at the j^{th} school.

The procedure I use to measure the technical efficiency of each school and how I conduct the hypothesis test is discussed in the next sub-sections.

a. Measure of Technical Efficiency

Technical efficiency (TE) is the ratio of the observed output to the estimated frontier that represents the output of a technically efficient firm using the same input vector [see equation (A4.2)]. Technical efficiency (TE) is given by:

$$\mathrm{TE}_{jt} = \left(\frac{A_{jt}}{f\left(\mathbf{X}_{jt},\boldsymbol{\beta}\right)\cdot\exp\left(V_{jt}\right)_{jt}} \right) = \left(\frac{f\left(\mathbf{X}_{jt},\boldsymbol{\beta}\right)\cdot\exp\left(V_{jt}\right)\cdot\exp\left(-U_{jt}\right)_{t}}{f\left(\mathbf{X}_{jt},\boldsymbol{\beta}\right)\cdot\exp\left(V_{jt}\right)} \right) = \exp\left(-U_{jt}\right) \quad (6.5)$$

Consistent with equation (6.2), technical efficiency of production for the j^{th} school at the t^{th} period, therefore, is defined by:

$$\mathrm{TE}_{jt} = \exp\left(-U_{jt}\right) = \exp\left(-\mathbf{Z}_{jt}\boldsymbol{\delta} - W_{jt}\right) \quad (6.6)$$

where the technical efficiency score for each school *j* at time *t* is a negative exponential function of the environmental variables of school *j* at time t ($\mathbf{Z}_{jt}$).

b. Hypothesis Testing

The procedures used to conduct the hypothesis tests are discussed in this section. A series of hypothesis tests (described below) are undertaken to detect the presence of inefficiency (U_{jt}) and whether U_{jt} is a stochastic variable. The tests are important because the validity of the SPF and inefficiency models depends on the distributional assumptions made about the composite error term, as explained in the account of equations (6.1) and (6.2). The tests are based on the generalised likelihood-ratio statistic, estimated by imposing restrictions on the model. A null hypothesis is evaluated based on the significance of the imposed restrictions. The generalised likelihood ratio (LR) statistic is defined by:

$$LR = -2[L(H_R)-L(H_U)] \sim \chi^2(J) \tag{6.9}$$

where $L(H_R)$ and $L(H_U)$ are the values of the log-likelihood function for the restricted and unrestricted models and J is the number of restrictions.[5] A chi-square distribution is used to conduct the hypothesis, as described below.

Three null hypotheses are tested. First, I test the null hypothesis that the inefficiency effects are absent, H_0: $\gamma = \delta_0 = \delta_1 = \ldots = \delta_{11} = 0$, where δ_i ($i = 0, \ldots, 11$) is the parameter of the inefficiency model, as given in equation (6.4) and γ is the proportional variation in output from the estimated frontier, defined by $\gamma = \sigma_u^2 / \left(\sigma_v^2 + \sigma_u^2\right)$. The log-likelihood function for the unrestricted model is obtained by estimating equations (6.3) and (6.4) and the value of the log-likelihood estimation for the restricted model is obtained by estimating equation (6.3) based on Battese and Coelli's

[5] Coelli (1995, p. 250) shows that if the technical inefficiency effects are absent (such that $\sigma_u^2 = 0$) in the model, H_o: $\gamma = 0$, then, γ has a mixed chi-square distribution with the number of degrees of freedom given by the number of restrictions imposed (since $\gamma = 0$ is a value on the boundary of the parameter space for γ).

(1992) specification.[6] The log-likelihood statistic is then computed using equation (6.9) and the obtained value is compared to the critical value of the chi-square distribution. If the test statistic exceeds the critical value, the null is rejected.

The second null hypothesis, H_o: $\gamma = 0$, specifies that the inefficiency effects are not stochastic. The restricted model is estimated using standard OLS (under OLS, there is no inefficiency term U_{jt}, therefore, $\gamma = 0$).

The third null hypothesis that I test, H_0: $\delta_1 = \ldots = \delta_{11} = 0$, specifies that the inefficiency effects are not a linear function of the explanatory variables of the inefficiency model. In other words, the third hypothesis examines whether the inefficiency effects are not dependent on the environmental variables. The log-likelihood function for the restricted model is obtained by estimating Battese and Coelli's (1995)[7] model with Z_{jt} (the explanatory variables of the inefficiency model) is set as a vector containing 1.

6.1.2 Data and Sample Description for the SPF Estimation

School-level panel data are employed for the estimation of SPF. The cross-section of the panel data consists of 163 (J = 163) public primary schools in Tasmania.[8] The time-series of the panel data involves the three school calendar years, 2003, 2005 and 2007 (T = 3). The constructed panel is a balanced one. A description of the variables employed in the study is given in Table 6.1. An analysis of the descriptive statistics of the output and input variables is provided below.

[6] See Coelli (1996, p. 24)
[7] The model is as expressed in equations (6.1) and (6.2).
[8] Combined schools (schools that provide primary and secondary education) are included in the sample.Two primary schools are excluded because the data on test scores are not available. The two schools are Sandy Bay Infant School and Cape Barren Island School.

Table 6.1: Variable Descriptions Used for the Efficiency Estimations

Variable		Description
Test Score Variables (**A**)	avg_lit3_{jt}	Average score in reading and writing of students in Year 3 in school *j* at time *t*
	avg_lit5_{jt}	Average score in reading and writing of students in Year 5 in school *j* at time *t*
	avg_num3_{jt}	Average score in numeracy of students in Year 3 in school *j* at time *t*
	avg_num5_{jt}	Average score in numeracy of students in Year 5 in school *j* at time *t*
Discretionary Variables (**X**)	$srpexp_{jt}$	Average real total school resource package expenditure per student to school *j* at time *t* (AUD$, thousand). The figures represent allocations directly related to student learning
	$grantexp_{jt}$	Average real general support grant expenditure per student to school *j* at time *t* (AUD$, thousand)
	$edperstu_{jt}$	Average real educational expenditure on literacy and numeracy program per student to school *j* at time *t* (AUD$, thousand). The allocation is made based on full-time enrolment)
	$ruralexp_{jt}$	Average real rural allocation expenditure per student to school *j* at time *t* (AUD$, thousand). The figures are the total of allocations to schools based on Rurality Index that takes into account schools' isolation, size of centre/township and distance
	st_ratio_{jt}	Student-teacher ratio of school *j* at time *t*
Non-Discretionary/Environmental Variables (**Z**)	$atsi_{jt}$	Percentage of Aboriginal and Torres Strait Islander (ATSI) students in school *j* at time *t*
	esl_{jt}	Percentage of students who involved in the English as a Second Language (ESL) Program in school *j* at time *t*
	$disable_{jt}$	Percentage of students on the Severe Disabilities Register/the High Needs Register in school *j* at time *t*
	$male_{jt}$	Percentage of male students in school *j* at time *t*
	$mumwork_{j}$	Percentage of mothers of Years 3 and 5 students who work in senior management in large business organisation, government administration and defense and qualified professionals (type 1 occupation) in school *j*
	$mumedu_{j}$	Percentage of mothers of Years 3 and 5 students in school *j* with a tertiary qualification
	$dadwork_{j}$	Percentage of fathers of Years 3 and 5 students who work in senior management in large business organisation, government administration and defense and qualified professionals (type 1 occupation) in school *j*

	$dadedu_j$	Percentage of fathers of Years 3 and 5 students in school *j* with a tertiary qualification
	$susprate_{jt}$	Student suspension rate in school *j* at time *t*
	$absent_{jt}$	Average days absent from school per year of students in Years 3 and 5 in school *j* at time *t*
	d_rural_j	Dummy of rurality status of school *j* (1 if school *j* is a rural school)

a. Output Variable **(A)**

In order to construct the school-level data, the student-cohort level data of school *j* are averaged to obtain the educational outputs (average literacy of Year 3, average literacy of Year 5, average numeracy of Year 3 and average numeracy of Year 5). In Appendix 6.1, I explain how the average output data was constructed using mathematical notation.

Table 6.2: Average Test Scores of Students in Years 3 and 5

Test	Statistics	Year 3			Year 5		
		2003	2005	2007	2003	2005	2007
Literacy	Mean	366.7	363.6	362.6	382.6	393.2	391.2
	Std error	1.1	1.0	1.1	1.0	1.0	1.0
	Min	306.5	319.0	325.5	316.3	358.0	359.5
	Max	395.4	392.9	396.0	412.9	426.4	427.5
Numeracy	Mean	376.1	369.4	365.1	389.9	397.3	394.3
	Std error	1.3	1.2	1.2	1.0	1.1	1.0
	Min	336.1	335.0	321.8	354.5	363.3	348.0
	Max	426.3	407.0	408.7	430.0	438.6	439.6

In Table 6.2, the summary statistics of the average literacy and numeracy of Years 3 and 5 for 2003, 2005 and 2007 are shown. Based on the average scores, the performance of students in Year 3 in literacy and numeracy was declining over the years (the mean difference for the literacy and numeracy scores are significantly different at 95% confidence level). For Year 5, the average literacy and numeracy scores had shown an improvement from 2003 to 2005 (at 5% level of significance) but both scores declined from 2005 to 2007. With the test scores as the dependent variables, lower level of technical efficiency is expected for Year 3 between 2003 and 2005 as compared to Year 5 for the same period.

***b. Discretionary Inputs* (X)**

All of the discretionary input data were in the form of school-level per capita figures. Five educational inputs are considered as discretionary inputs of education because they are under the direct control of the DoE, Tas. The variables consist of four categories of financial figures, namely *srpexp*, *grantexp*, *edperstu* and *ruralexp*; and one non-financial figure, *st_ratio*. The estimation of the SPF model is based on these five variables—refer to equation (6.3).

One set of data on the discretionary variables is employed when estimating models I, II, III and IV. The one dataset is employed because the original data provided is a school-level data. As such, the data do not vary by grade. The consequence of the procedure (employing the same data on the discretionary variables) is that the estimated technical efficiency is sensitive to the variation in the dependent variables. Since the SPF technique takes into account the relative amount of educational inputs received by each school in the construction of the production frontier, schools with relatively lower literacy and numeracy scores (educational outputs) are expected to have low technical efficiency.

In Table 6.3, I provide the descriptive statistics of the discretionary variables for the 163 public primary schools in Tasmania for 2003, 2005 and 2007. Based on per capita allocations, schools in Tasmania received the largest allocation under the educational allocation on literacy and numeracy program expenditure per student (*edperstu*), followed by school resource package expenditure (*srpexp*), general support grant expenditure (*grantexp*), and rural allocation expenditure (*ruralexp*). A stable student-teacher ratio (*st_ratio*) had also been recorded over the period, averaging at 17.0.

Table 6.3: Summary Statistics of the Discretionary Variables (X) Used for the SPF Estimations

Variable	Statistics	Tasmanian Public Primary Schools		
		2003	2005	2007
srpexp (AUD$, '000)	Mean	214.201	204.042	301.838
	Std dev	119.231	113.336	166.923
	Min	44.703	42.925	68.860
	Max	641.411	672.476	937.039
grantexp (AUD$, '000)	Mean	86.904	89.957	93.450
	Std dev	48.798	49.556	51.705
	Min	19.214	16.860	22.575
	Max	286.350	283.930	294.629
edperstu (AUD$, '000)	Mean	55.384	57.365	60.210
	Std dev	34.199	35.552	37.659
	Min	2.551	1.466	3.156
	Max	195.312	191.481	193.621
ruralexp (AUD$, '000)	Mean	10.069	10.414	11.241
	Std dev	12.836	12.351	13.071
	Min	0	0	0
	Max	112.667	94.359	98.328
st_ratio	Mean	17.1	17.0	17.0
	Std dev	2.0	2.2	2.3
	Min	8.6	5.9	5.0
	Max	19.1	19.0	19.0

c. Non-Discretionary/Environmental Variables (Z)

In the case of the inefficiency model, eleven environmental variables are considered as the independent variables, as expressed in equation (6.4). The 11 variables represent the socio-economic background attributed to school *j*. Any disadvantage condition in the socio-economic background (such as school *j* is located in rural area) is expected to lead to a higher level of technical inefficiency of school *j*.[9] In Table 6.4, I provide the summary statistics of the environmental variables, which describe the degree of socio-economic heterogeneity between schools.

[9] Recall that in the construction of the SPF model [as given in equations (6.1) and (6.2)], the environmental variables are allowed to affect the stochastic term of the production frontier.

In Table 6.4, notice that the data employed for *mumwork, mumedu, dadwork* and *dadedu* are identical for both Years 3 and 5 over the entire period. The presence of identical figures is because the data on parental education and occupation according to grade-specific were not available. The consequence of employing the same data for parental education and occupation is that the difference in the value of the estimators for the variables is sensitive to the variation in technical inefficiency scores obtained under the four different outputs of education. Schools with a higher percentage of parents with tertiary qualification and who worked in type 1 occupation are expected to be more efficient as compared to schools with low percentage of parents in those categories. Positive spillover benefits of highly educated and professional parents on their children's academic achievement may require less educational inputs from schools. As a result, the variables *mumwork, mumedu, dadwork* and *dadedu* are expected to have a negative sign in the inefficiency model.

The variables *atsi, esl* and *disable* are employed to capture the effects of socio-economic disadvantaged surrounding schools. Schools with larger number of students in those categories are expected to be less efficient (positive coefficient signs are expected in the inefficiency model) because more school resources are needed to support disadvantaged students. The data for *atsi*, *esl* and *disable*, as shown in Table 6.4, vary from 2003 to 2007, but the data employed to represent Year 3 students are also used for Year 5 students. The reason for using the same data for Years 3 and 5 is because the available data did not vary by grade.

Table 6.4: Summary Statistics of the Environmental Variables (Z) Used for the SPF Estimations

Variables	Statistics	Year 3			Year 5		
		2003	2005	2007	2003	2005	2007
atsi (% of students)	Mean	5.33	5.60	5.23	5.33	5.60	5.23
	Std dev	4.49	4.65	4.37	4.49	4.65	4.37
	Min	0	0	0	0	0	0
	Max	19.44	26.94	25.83	19.44	26.94	25.83
esl (% of students)	Mean	1.13	1.32	1.35	1.13	1.32	1.35
	Std dev	0.41	0.81	0.92	0.41	0.81	0.92
	Min	0	0	0	0	0	0
	Max	2.50	4.17	6.67	2.50	4.17	6.67
disable (% of students)	Mean	0.56	0.56	0.56	0.56	0.56	0.56
	Std dev	0.13	0.10	0.18	0.13	0.10	0.18
	Min	0	0	0	0	0	0
	Max	3.51	2.5	2.78	3.51	2.5	2.78
male (proportion of male students)	Mean	0.51	0.52	0.52	0.51	0.52	0.52
	Std dev	0.12	0.12	0.13	0.10	0.14	0.12
	Min	0	0	0	0	0	0
	Max	1	1	1	1	1	1
mumwork (% of mothers)	Mean	12.39	12.39	12.39	12.39	12.39	12.39
	Std dev	11.12	11.12	11.12	11.12	11.12	11.12
	Min	0.28	0.28	0.28	0.28	0.28	0.28
	Max	69.44	69.44	69.44	69.44	69.44	69.44
mumedu (% of mothers)	Mean	28.51	28.51	28.51	28.51	28.51	28.51
	Std dev	22.06	22.06	22.06	22.06	22.06	22.06
	Min	1.39	1.39	1.39	1.39	1.39	1.39
	Max	79.75	79.75	79.75	79.75	79.75	79.75
dadwork (% of fathers)	Mean	16.55	16.55	16.55	16.55	16.55	16.55
	Std dev	10.69	10.69	10.69	10.69	10.69	10.69
	Min	0.28	0.28	0.28	0.28	0.28	0.28
	Max	71.85	71.85	71.85	71.85	71.85	71.85
dadedu (% of fathers)	Mean	31.08	31.08	31.08	31.08	31.08	31.08
	Std dev	23.37	23.37	23.37	23.37	23.37	23.37
	Min	1.94	1.94	1.94	1.94	1.94	1.94
	Max	82.82	82.82	82.82	82.82	82.82	82.82
susprate (no. of suspensions per 100 students)	Mean	4.43	3.90	4.74	4.43	3.90	4.74
	Std dev	12.02	7.32	7.98	12.02	7.32	7.98
	Min	0	0	0	0	0	0
	Max	130.1	49.9	52.97806	130.1	49.9	52.97806
absent (no. of days per 100 schooling days)	Mean	10.51	11.02	11.33	11.29	11.73	11.80
	Std dev	3.17	3.30	3.26	3.32	3.73	3.45
	Min	3.75	1.33	4.00	4.33	2.00	3.00
	Max	27.55	24.25	31.25	31.00	25.00	22.06

d_rural (dummy variable)	Mean	0.60	0.60	0.60	0.60	0.60	0.60
	Std dev	0.49	0.49	0.49	0.49	0.49	0.49
	Min	0	0	0	0	0	0
	Max	1	1	1	1	1	1

Only the data on *male* and *absent* vary according to grade-specific (Years 3 and 5) and from year to year. The mean for *male* for 2003, 2005 and 2007 however, was identical for Years 3 and 5, but variation was evident in the standard deviation, minima and maxima figures. On absenteeism, the average number of days absent (*absent*) for both Years 3 and 5 had increased from 2003 to 2007. The average number of days students in Year 5 were absent however, was larger compared to students in Year 3. I therefore expect the impact of absenteeism for Year 5 to be more significant in explaining technical inefficiency of schools than Year 3.

To represent rural/urban schools, I assign a dummy variable 1 for rural schools and 0 for urban schools.[10] From the 163 schools in the sample, there are 98 rural schools and 65 urban schools. Rural schools are expected to be technically less efficient (a positive coefficient sign is expected for *d_rural* in the inefficiency model) as compared to urban schools because of socio-economic disadvantages due to geographical location. Remote location may result in lack of teaching/learning facilities (such as a poorly stocked library or an insufficient number of students to conduct a group activity) in rural schools. The lack of teaching/learning facilities in rural schools may result in a disadvantaged learning environment for the students, manifested in low academic

[10] Rural or urban status is determined based on the isolation status of a school (such as located in an island) and the size of centre (town) in which the school is located. A dummy variable, 1, is assigned for any school that is considered as isolated and located near/in small township area. Otherwise, the schools are considered as urban schools.

achievement. Results of the estimations of SPF are provided and discussed in Section 6.1.3.

6.1.3 Results of SPF Estimations

The SPF results are obtained by estimating the models specified in Section 6.1.1. Models I, II, III and IV are estimated based on a translog functional form, as given by equation (6.3). The translog form is used because of its flexibility. The software package used to run the estimation is FRONTIER 4.1.[11] In Table 6.5, the estimation results of models I, II, III and IV are shown. For the various models, the dependent variables are *avg_lit3*, *avg_lit5*, *avg_num3* and *avg_num5*.

Before the results are discussed, I test the null hypothesis that the inefficiency effects are absent from the model as described in Section 6.1.1-b. The validity of the SPF model depends on the rejection of the null hypothesis. As shown in Table 6.6, the null hypothesis is rejected for all the models. The rejection of the null hypotheses under models I, II, III and IV suggests that the translog SPF model is appropriate.

Recall that the second hypothesis test deals with the existence of the stochastic component in the error term. The null hypothesis, H_o: $\gamma = 0$, tests whether the inefficiency effects are not stochastic. As shown in Table 6.7, the LR statistics for models I, II, III and IV exceed the critical value of the chi-square distribution at 5% level of significance. The null hypothesis is therefore rejected, suggesting the inefficiency effects are stochastic.

[11] The software is downloadable free from the website of The Centre of Efficiency and Productivity Analysis at http://www.uq.edu.au/economics/cepa/frontier.htm

Table 6.5: Translog Stochastic Production Frontier and Inefficiency Models for Years 3 and 5 for Public Primary Schools in Tasmania

Variables	Models / Dependent var.	Model I ln(avg_lit3)	Model II ln(avg_lit5)	Model III ln(avg_num3)	Model IV ln(avg_num5)
Production Frontier					
C	β_0	-0.4636	-1.0192	-2.5088***	3.2812***
		(1.1068)	(1.2869)	(1.3050)	(1.8205)
ln(srpexp)	β_1	0.5238*	0.1490	0.1662	-0.0466
		(0.1520)	(0.1422)	(0.2189)	(0.1631)
ln(grantexp)	β_2	0.3721	1.0331*	1.4042*	0.2209
		(0.3271)	(0.3649)	(0.4832)	(0.4340)
ln(edperstu)	β_3	-0.4089**	-0.6363*	-0.6821*	-0.1148
		(0.1617)	(0.1958)	(0.2124)	(0.2543)
ln(ruralexp)	β_4	0.2540*	0.1576*	0.2495*	0.2151*
		(0.0514)	(0.0558)	(0.0770)	(0.0661)
ln(st_ratio)	β_5	1.6263*	2.2859*	1.5596***	1.0570***
		(0.6049)	(0.7025)	(0.8854)	(0.9460)
$\ln(\text{srpexp})^2$	β_6	-0.0159*	-0.0037	-0.0042	0.0109***
		(0.0053)	(0.0053)	(0.0078)	(0.0062)
$\ln(\text{grantexp})^2$	β_7	-0.0395*	-0.0407*	-0.0773*	-0.0215
		(0.0111)	(0.0115)	(0.0193)	(0.0146)
$\ln(\text{edperstu})^2$	β_8	0.0529*	0.0346*	0.0755*	0.0056
		(0.0104)	(0.0108)	(0.0183)	(0.0140)
$\ln(\text{ruralexp})^2$	β_9	0.0006**	0.0001	0.0003	0.0007
		(0.0003)	(0.0003)	(0.0004)	(0.0004)
$\ln(\text{st\_ratio})^2$	β_{10}	0.1177	-0.1070	0.3540	-0.0574
		(0.1761)	(0.1755)	(0.2892)	(0.2102)
ln(srpexp)ln(st_ratio)	β_{11}	0.0504	0.0228	0.0335	0.0815
		(0.0476)	(0.0473)	(0.0686)	(0.0498)
ln(grantexp)ln(st_ratio)	β_{12}	0.1389	-0.0782	0.0957	0.0655
		(0.0914)	(0.1042)	(0.1313)	(0.1176)
ln(edperstu)ln(st_ratio)	β_{13}	-0.2253*	-0.0085	-0.3147**	0.0207
		(0.0871)	(0.0966)	(0.1460)	(0.1156)
ln(ruralexp)ln(st_ratio)	β_{14}	-0.0881*	-0.0541*	-0.0859*	-0.0754*
		(0.0176)	(0.0189)	(0.0261)	(0.0222)
Inefficiency Equation					
C	δ_0	0.0056	0.0281**	0.0536**	0.0271***
		(0.0177)	(0.0120)	(0.0223)	(0.0139)
Atsi	δ_1	-0.0078	-0.0014	-0.0156	0.0013
		(0.0066)	(0.0052)	(0.0103)	(0.0039)
Esl	δ_2	-0.0034	0.0007	0.0010	0.0007
		(0.0035)	(0.0015)	(0.0014)	(0.0008)
Disable	δ_3	-0.0068	-0.0038	-0.0129**	-0.0002
		(0.0043)	(0.0033)	(0.0061)	(0.0025)
Male	δ_4	0.0768*	0.0523*	0.0108	0.0171***
		(0.0154)	(0.0131)	(0.0203)	(0.0101)
Mumwork	δ_5	-0.1196*	-0.0422*	-0.1548*	-0.0118
		(0.0302)	(0.0141)	(0.0380)	(0.0098)
Mumedu	δ_6	-0.0419	-0.0778	-0.0479	-0.0159
		(0.0277)	(0.0277)	(0.0381)	(0.0180)
Dadwork	δ_7	0.0720*	0.0194	0.0901*	0.0050
		(0.0251)	(0.0167)	(0.0303)	(0.0114)
Dadedu	δ_8	-0.0148	-0.0065	-0.0196	0.0125
		(0.0269)	(0.0146)	(0.03638)	(0.0183)
Susprate	δ_9	0.0008*	0.0005**	0.0005***	0.0005*
		(0.0002)	(0.0002)	(0.0003)	(0.0002)
Absent	δ_{10}	0.0007**	0.0013**	0.0015***	0.0013*
		(0.0007)	(0.0006)	(0.0009)	(0.0004)
d_rural	δ_{11}	0.0176***	0.0010	0.0097	0.0102
		(0.0096)	(0.0061)	(0.0130)	(0.0080)
Variance Parameters					
Sigma-squared	$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.0013*	0.0007*	0.0017*	0.0007*
		(0.0001)	(0.0001)	(0.00002)	(0.0000)
Gamma	$\gamma = \sigma_u^2 / \sigma^2$	0.8573*	0.7542*	0.6487*	0.0301*
		(0.0317)	(0.0508)	(0.0662)	(0.0066)
Log-likelihood function		1124.98	1169.26	978.33	1085.49
LR test of the one-sided error		165.86	212.71	87.36	52.87

Note: *, ** and *** denote level of significance at 1%, 5 % and 10%. Figures in () are standard errors.

Table 6.6: Likelihood Ratio Test of the Hypotheses for OLS Specifications involving the Parameters of the Inefficiency Models for Models I, II, III and IV

Model	Hypothesis test	Log-likelihood of restricted model	$\chi^2_{\alpha=0.05}$	Test statistic	Decision rule
I	H_0: $\gamma = \delta_0 = \ldots = \delta_{11} = 0$	1063.4	21.02	123.16	Reject the null
II	H_0: $\gamma = \delta_0 = \ldots = \delta_{11} = 0$	1074.1	21.02	188.32	Reject the null
III	H_0: $\gamma = \delta_0 = \ldots = \delta_{11} = 0$	952.9	21.02	50.86	Reject the null
IV	H_0: $\gamma = \delta_0 = \ldots = \delta_{11} = 0$	1069.3	21.02	32.38	Reject the null

Table 6.7: Likelihood Ratio Test of the Existence of a Stochastic Component in the Error Term

Model	Hypothesis test	Log-likelihood of restricted model	$\chi^2_{\alpha=0.05}$	Test statistic	Decision rule
I	H_o: $\gamma = 0$	1042.06	3.84	165.84	Reject the null
II	H_o: $\gamma = 0$	1062.91	3.84	210.7	Reject the null
III	H_o: $\gamma = 0$	934.65	3.84	87.36	Reject the null
IV	H_o: $\gamma = 0$	1059.06	3.84	52.86	Reject the null

Table 6.8: Likelihood Ratio Test of the Hypotheses of Linear Restrictions for the Parameters of the Inefficiency Models

Model	Hypothesis test	Log-likelihood of restricted model	$\chi^2_{\alpha=0.05}$	Test statistic	Decision rule
I	H_0: $\delta_1 = \ldots = \delta_{11} = 0$	1050.59	19.67	148.78	Reject the null
II	H_0: $\delta_1 = \ldots = \delta_{11} = 0$	1073.13	19.67	190.26	Reject the null
III	H_0: $\delta_1 = \ldots = \delta_{11} = 0$	936.55	19.67	83.56	Reject the null
IV	H_0: $\delta_1 = \ldots = \delta_{11} = 0$	1059.06	19.67	52.86	Reject the null

For the third hypothesis test, I examine the null that the inefficiency effects are not dependent on the environmental variables, or H_0: $\delta_1 = \ldots = \delta_{11} = 0$. At 5% level of significance, I reject the hypothesis for all the models, as shown in Table 6.8. The rejection of the null suggests that the joint effects of these eleven explanatory variables on the inefficiency of production is significant even the individual effects of one or more of the variables may not be statistically significant.

The translog frontier models I, II, III and IV in Table 6.5 provide a satisfactory fit based on the log-likelihood function. One important point to note is that the interpretation of the parameters of the SPF models, the β's, is not central to the objective of the analysis.[1] Rather, the SPF models are used to estimate the frontier and from there, a measure of schools' technical inefficiency is obtained and then, the parameters of the factors that influence schools' technical inefficiency are estimated. The parameters of the inefficiency model, δ's, and the score of schools' technical efficiency are of crucial interest of the discussion here. I provide the interpretation of the SPF estimation based on the results of model I below.

a. Translog SPF Model

For model I, given the total average of *srpexp* of \$240.027 thousand and the total average of *st_ratio* of 17.0 from 2003 to 2007, a 1% increase in *srpexp* results in an increase in average literacy of Year 3 by 0.84%, *ceteris paribus*. Holding other factors constant, for a 1% increase of *grantexp*, at the total average *grantexp* of \$90.104 thousand and the total average *st_ratio* of 17.0, the average literacy score of Year 3 increases by 0.41%. Given the total average of *ruralexp* of \$10.575 thousand and the

[1] The estimates of β's give the parameters of factors that affect test scores—refer to Chapter 5.

total average of *st_ratio* of 17.0, a 1% increase in *ruralexp* leads to an increase in average literacy of Year 3 by 0.007%, *ceteris paribus*. From the estimations, the expected positive effect of the financial resources on students' academic achievement has been found to be small based on the SPF. These results are not directly comparable to the results found in Chapter 5 because the coefficients there provide direct estimates of the elasticities, while here due to the interaction terms of the translog form the elasticity cannot be attained directly. The point of this section was not to calculate elasticities but instead to measure of schools' technical efficiency.

Inefficiency Model

The coefficients of the inefficiency model, the δ's as presented in Tables 6.5, are of particular interest to the study. The variables *atsi*, *esl*, *disable* and *male* are four environmental variables employed to capture the effects of the students' characteristics in terms of their ethnicity (*atis* and *esl*), disability (*disable*) and gender (*male*) on schools' technical inefficiency. As shown in Table 6.5, no significant evidence of the effects of *atsi* and *esl* on technical inefficiency has been found across any of the models. The insignificant effects of *atsi* and *esl* imply that the variables are not important in explaining schools' technical inefficiency in Tasmania. The effects of *disable* are also insignificant in models I, II and IV. The variable, however, is significant under model III, where the negative magnitude of *disable* on technical inefficiency under the model is not as expected. Based on the results of model III, an increase in *disable* by 1% is associated with a 0.0129 point decrease in technical inefficiency, *ceteris paribus*. Since the percentage of students with severe disability in a school is on average 1.6%, the effects are small. From the findings, in general, the variables *atsi*, *esl* and *disable* that are employed to capture the effects of a disadvantaged socio-economic environment have not been found to be important in explaining schools' technical inefficiency.

In regard to gender, the effects of *male* are only significant under models I, II and IV. A 1% increase in *male* in school *j* leads to an increase in school *j*'s technical inefficiency by 0.0768 points under model I, 0.0523 points under model II, and 0.0171 under model IV, *ceteris paribus.* When numeracy scores of Year 3 (model III) is used as the output, the effects of *male* on technical inefficiency however, are statistically insignificant. The findings based on the gender of students suggest that gender matters in resource utilisation for the teaching of literacy and numeracy.

I employ the variables *mumwork, mumedu, dadwork* and *dadedu* to represent the effects of parents' occupational and educational status on technical inefficiency. The results for *mumwork* in Table 6.5 show that schools characterised with a higher percentage of mothers who work in professional and management jobs are more efficient than schools with a lower percentage of mothers who work in professional and management jobs. The negative coefficient sign for the variable suggests a negative relationship between *mumwork* and technical inefficiency. For example, technical inefficiency of school *j* decreases by 0.1196, 0.0422 and 0.1548 under models I, II and III for an increase in the percentage of mother who worked in professional and management jobs, holding other factors constant. One explanation why the variable affects technical inefficiency in an opposite direction to the expected sign is the possibility of positive influence (such as good time management and hardworking) of such group of mothers on their children. The positive influence, in turn, may result in well-behaved children. The good behaviour of students (high disciplinary level) may be associated with less school resources needed to monitor the students.

The effects of *dadwork* on technical inefficiency however run counter to expectation. The positive coefficient sign of *dadwork* (the variable is significant under models I and III) is not congruent with the result of *mumwork*. The interpretation of the result suggests that technical inefficiency of school *j* increases by 0.072 (under model I) and 0.0901 (under model III) for a one per cent increase in *dadwork*, holding other factors constant. One possible explanation for the positive relationship is because this group of fathers may spend too much time at work, resulting in less attention given to children. The lack of attention, in turn, results in low students' academic achievement and as a consequence leads to high technical inefficiency of schools.

Although the expected negative relationship is found between parental education (*mumedu* and *dadedu*) and schools' technical inefficiency, the effects of the variables are insignificant. The findings imply that parental education is not an important variable in an explanation of schools' technical inefficiency in Tasmania.

I also investigate the effects of students' disciplinary level on schools' technical inefficiency by including the variables *susprate* and *absent.* Higher disciplinary problems (given by higher *susprate* and *absen*t*)* are expected to result in higher technical inefficiency (I expect a positive relationship). The disruption to the learning process caused by problematic students (such as vandalism) may divert school resources away from productive use, resulting in higher technical inefficiency. As shown in Table 6.5, small but significant positive effects of *susprate* on technical inefficiency have been found across all the models. The coefficient estimates between suspension rate and technical inefficiency are 0.0008, 0.0005, 0.0005 and 0.0005 points across all the respective models, *ceteris paribus*. Given the robust[2] effects of *susprate* on technical inefficiency, preventive measures to reduce the number of serious disciplinary problems (that can result in a suspension of a student from school) of students may need to be put in place as one way for Tasmanian public primary schools to improve their level of technical efficiency depending on the cost-benefit analysis of the policy.

Based on the results in Table 6.5, evidence of a significant positive effect of *absent* on technical inefficiency has also been found across all the models. The estimated parameters under models I, II, III and IV are 0.0007, 0.0013, 0.0015 and 0.0013, respectively. The significant effects of *absent* suggest that absenteeism is an important factor in affecting technical inefficiency. As such, a policy that aims at reducing the level of absenteeism rate should be examined in an effort to improve the level of Tasmanian schools' technical efficiency.

For the dummy variable, *d_rural* (if rural school = 1), I expect a positive relationship between the variable and technical inefficiency. The expectation is based on the socio-economic disadvantages associated with rural schools that may require more resources. Only under model I, are the effects of *d_rural* on technical inefficiency significant, where on average, rural schools are 0.0176 points more inefficient than urban schools, *ceteris paribus.* Even though the coefficient signs for *d_rural* are positive (as expected) under models II, III and IV, the estimated parameters are not statistically significant. The significant effects of the variable under model I (the dependent variable is *avg_lit3*) impy that the disadvantaged position of rural schools are more pressing on their resources for the teaching of literacy of Year 3 students.

[2] Robust here means that the effects of the regressors remain unchanged even when the situation or condition varies. The variables are usually found to be statistically significant and the coefficient signs meet the expectations even when tested under different models.

b. Technical Efficiency Scores

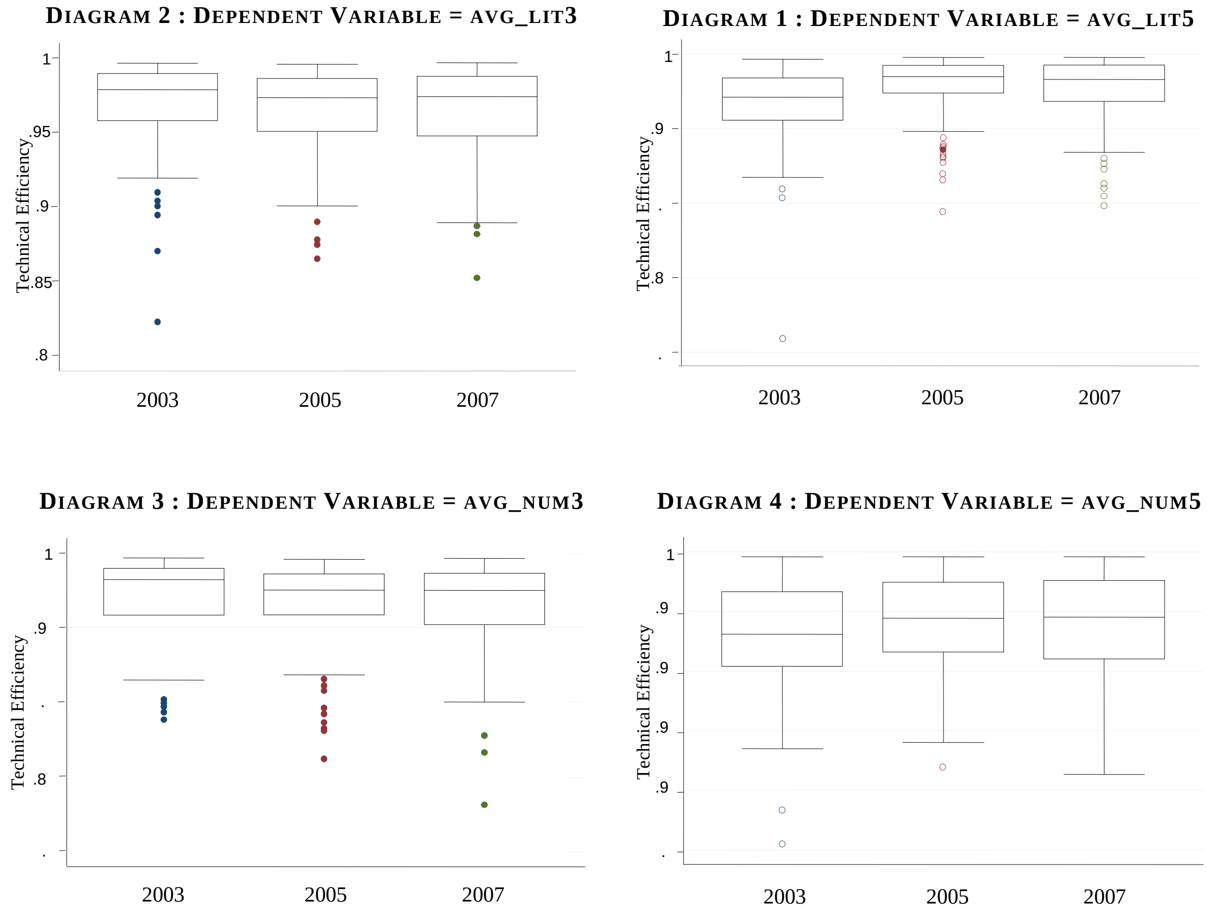
Now I turn the discussion to the evaluation of technical efficiency scores of Tasmanian public primary schools. Summary statistics of the technical efficiency results are provided in Table 6.9. As shown in Table 6.9, the overall level of technical efficiency of public primary schools in Tasmania is high, averaging at 96%. In other words, on average, only 4% of the school resources are wasted as a result of being technically inefficient.

Table 6.9: Summary Statistics for SPF Efficiency Scores

Model	Statistics	2003	2005	2007	Total Average
I	Mean	0.9692	0.9658	0.9652	0.9668
	Std dev	0.0277	0.0275	0.0286	0.0279
	Min	0.8223	0.8642	0.8520	0.8223
	Max	0.9968	0.9962	0.9972	0.9972
II	Mean	0.9466	0.9717	0.9695	0.9626
	Std dev	0.0246	0.0233	0.0246	0.0266
	Min	0.8018	0.8877	0.8916	0.8018
	Max	0.9891	0.9978	0.9979	0.9979
III	Mean	0.9679	0.9629	0.9611	0.9640
	Std dev	0.0263	0.0283	0.0294	0.0281
	Min	0.8903	0.8625	0.8352	0.8352
	Max	0.9969	0.9960	0.9967	0.9969
IV	Mean	0.9531	0.9533	0.9526	0.9530
	Std dev	0.0162	0.0164	0.0167	0.0164
	Min	0.8837	0.9136	0.9197	0.8837
	Max	0.9991	0.9988	0.9985	0.9991

Public primary schools in Tasmania are also found to be technically efficient across various areas. The correlation coefficient of the SPF efficiency scores based on *avg_lit3* and *avg_num3* is 0.85. Based on *avg_lit5* and *avg_num5,* the correlation coefficient of the SPF technical efficiency scores is 0.83. The high correlations across the different areas suggest schools that are technically efficient in producing higher literacy scores are also in general, technically efficient in producing higher numeracy scores.

Figure 6.1: Box Plot of the SPF Technical Efficiency Scores



An illustration of the shape of the technical efficiency scores from the various models is presented using box plot diagrams in Figure 6.1. The high technical efficiency scores is evident from the box plot diagrams, where the middle half of the technical efficiency scores (known as the inter-quartile range or the range between the 25th and 76th percentile of the scores), in general, falls above 0.95. The high technical efficiency is also shown by the right-skew of the scores, as illustrated by the position of the median of technical efficiency—median is illustrated by the line within the box. The dots (points beyond the whiskers[3]) show the extreme out values of the technical efficiency scores, considered as outliers. Schools with technical efficiency scores as given by the lower dots (outliers) may require closer examination in order to understand the reason for their relatively low technical efficiency scores. I provide more specific analyses of the results in Section 6.3 when I compare the SPF technical efficiency against the DEA technical efficiency scores based on *avg_lit3* in 2007 as the output.

As shown in Table 6.9, for each respective model, the average technical efficiency scores are found to be stable throughout the study period, suggesting no technical efficiency change in the industry. Lack of investment in new technologies can be one reason for the stagnation in technical efficiency. If spending on Information and Communication Technology (ICT) is used as a measure to investigate the level of adoption of new technologies by Tasmanian public primary schools, the real ICT total expenditures for 2003, 2005 and 2007 had declined from AUD$2,650,627, AUD$2,487,771 to AUD$2,339,536 (MCEETYA, 2007).[4] The decline in spending may cause a slow adoption of new technologies by schools. Schools therefore are forced to rely on the previous/existing teaching technology. Another possibility is that spending on technology may not affect schools' technical efficiency. The effects of ICT spending on schools' technical efficiency however, are not part of this study. The topic can be one area for future research to explore. Further, the small standard deviations and ranges of technical efficiency between the minima and maxima scores (as shown in Table 6.9) implies that technical efficiency scores for all the 163 public primary schools in Tasmania are closely clustered around the average. One conclusion of the result is that

[3] The whiskers (upper or lower) extend to the maximum or minimum of 1.5 times the inter-quartile range of the data.

[4] The given data are a trend data, not a school-level data that can be employed in the estimation.

after controlling for the environmental effects, the small variation in the technical efficiency scores can be attributed to the small variation in the level of outputs (average test scores) employed—refer to Table 6.2.

6.1.4 Concluding Remarks on the SPF Analysis

Four translog stochastic frontier production functions have been estimated to measure the level of technical efficiency of Tasmanian public primary schools using panel data. The dependent variables under each of the four models are *avg_lit3* (model I), *avg_lit5* (model II), *avg_num3* (model III) and *avg_num5* (model IV). The purpose of employing the four dependent variables is to allow for a comparison of technical efficiency scores and the determinants of technical inefficiency across the different outputs. I have incorporated the socio-economic conditions surrounding schools, by employing 11 environmental variables (that represent the socio-economic conditions) in the technical efficiency measure. By controlling for the effects of the environmental variables, the measure of technical efficiency obtained is net of any socio-economic advantages/disadvantages surrounding schools. From the estimation, I have found high and constant level of technical efficiency at 96% from 2003 to 2007. The invariant technical efficiency scores across time suggest that no technical efficiency change has been experienced by public primary schools in Tasmania over the period.

I also estimated the effects of socio-economic conditions of schools using the inefficiency model as given by equation (6.4). From the 11 environmental variables employed, positive effects of *susprate* (significant for all the models), *absent* (significant for all the models), *male* (only significant under models I, II and IV), *d_rural* (only significant under model I) and *dadwork* (significant under models I and III but results are not as expected) have been found on technical inefficiency. The significant variables with negative effect on technical inefficiency are *mumwork* (significant models I, II and IV) and *disable* (only significant under model III and the negative sign is not as expected). The remaining variables, namely, *mumedu, dadedu, atsi* and *esl* have been found to be insignificant in explaining schools' technical inefficiency in Tasmania. In the next section, I provide an evaluation of technical efficiency and determinants of technical efficiency based on DEA technique.

6.2 Data Envelopment Analysis (DEA)

6.2.1 DEA Specifications

In this section, I provide the estimates of technical efficiency of Tasmanian public primary schools based on DEA panel data. The theoretical framework of DEA has been described in Section 4.2.2. One educational output and five educational inputs are employed for the DEA analysis. Details of the input-output selection; the DEA orientation; the approach to deal with the environmental variables; and the panel data analysis of DEA are provided in the first part of this section. The discussion sets out the analytical foundation of the estimates presented in Section 6.2.3.

a. Input-Output Selection

For the estimation of technical efficiency, the specified DEA model consists of one output and five educational inputs. The outputs are *avg_lit3*, *avg_lit5*, *avg_num3* and *avg_num5* (see Table 6.1 for the definition of each variable). The five input variables employed for each of the models are *srpexp, grantexp, edperstu*, *ruralexp* and *st_ratio* (see Table 6.1 for the definition of each variable).[5] Although DEA permits an estimation based on multiple-outputs and multiple-inputs, a single-output and multiple-

[5] Note that the same inputs and output used to estimate the SPF model, as given by equation (6.3), are employed for the DEA model.

inputs approach is undertaken here. A separate solution of DEA linear programming is undertaken for each output (single-output and multiple-inputs approach) in order to allow for a comparison of the estimation results across the different outputs employed. The approach allows for an investigation into whether schools are only technically efficient in one specific area (such as only in producing high literacy results of Year 3) or they are technically efficient across various areas (such as in producing high scores in both literacy and numeracy of Year 3). In addition, in order to avoid confounding the effects of environmental factors, only the discretionary inputs of education are considered (refer to Section 6.2.1-c for an explanation of the approach taken in order to deal with the environmental variables). The estimates obtained from the approach would provide the Department of Education, Tasmania, with information on the variables within their direct control that require attention in order to improve schools' technical efficiency.

b. DEA Orientation

An output-oriented linear programming problem of DEA is solved for both constant returns to scale (CRS) and variable returns to scale (VRS) models. By solving the linear programming problem under both the CRS and VRS assumptions using the same data, any change in the measured efficiency can be attributed to scale inefficiency (for details on scale inefficiency, refer to Section 4.2.2-d).

An output-oriented DEA is estimated because improving students' academic achievement is one major objective of schools. Smith and Andrew (2006) suggest that a proper strategy for schools to utilise resources/inputs is to expand their output given the level of inputs available (output-oriented) rather than a strategy of conserving input in order to achieve the given level of output (input-oriented). The input-oriented approach is improper, in particular in the context of public schools, because they are not a profit-oriented organisation.[6]

The linear programming problem based on an output-oriented DEA sets schools with the highest students' academic achievement (relative to the peers or other schools) to form the frontier. The level of efficiency of other schools is evaluated based on their position relative to the frontier. Under the approach, the underlying theoretical framework is to maximise test scores given the amount of discretionary inputs available to school. Manifestly, there are other objectives of education, such as in producing a well-rounded and law-abiding citizen. The use of only test scores as the output of education means that the DEA analysis here would lose a great deal of of its significance due to the problem of limited data on other educational outputs. Schools that are excellent in sports but not in academic achievement, for example, would be technically inefficient in this case. If sports achievement is taken into account, then the technical efficiency score might change. In the absence of additional data I proceed, mindful of the inherent limitation.

The linear programming problem used to measure output-oriented technical efficiency is given by equations (4.8) and (4.11) for each respective CRS and VRS assumptions (refer to Section 4.3.1-c). Once both CRS and VRS DEA models have been estimated, the calculation of scale efficiency (SE) for each school is obtained by

[6] An input-oriented technical efficiency is not an appropriate approach to measure schools' technical efficiency because such an approach focuses on input minimisation given the level of output (such as test scores). Under the approach, regardless of students' academic achievement, schools that employ the least level of inputs relative to their peers are considered to be technically efficient and form the frontier. The approach runs counter to one of the main objectives of public education, which is to maximise students' academic achievement subject to a resource constraint. Since schools are expected to fully utilise the resources (inputs) allocated in order to achieve the objective, employing the input-oriented approach may result in to a misleading conclusion.

dividing the CRS-technical efficiency by the VRS-technical efficiency, or, SE = TE_{CRS}/TE_{VRS} (refer to Section 4.3.1-d for the derivation of the equation).

c. Adjusting for the Environmental Factors

Factors beyond the control of the Department of Education (**Z**) are excluded from equations (4.8) and (4.9) in order to avoid confounding their effects on the technical efficiency estimates. Differences in the environmental factors create a cross-sectional heterogeneity across schools. The factors that constitute the socio-economic heterogeneity in the production environment, however, need to be considered when comparing the efficiency scores because some schools may perform better than the other schools due to their socio-economic advantage. Two methods, called methods A and B, are employed to account for the heterogeneity in the production environment. The purpose of undertaking the two methods is to investigate the difference, if any, on the DEA technical efficiency scores after adjusting for the environmental factors.

Method A

In the first method, a two-stage procedure is undertaken where a DEA linear programming problem is solved in the first stage using the discretionary inputs—the first-stage involves solving equations (4.8) and (4.11). In the second stage, a Tobit regression is estimated, where the efficiency scores obtained from the first stage are regressed upon the environmental variables.[7] The technical efficiency score of each school is then adjusted to the estimated Tobit coefficients multiplied by each school's environmental variables in order to account for the environmental effects (refer to Section 6.3 for the application). A Tobit model is employed (instead of the OLS)

[7] [7] In research to evaluate schools' technical efficiency, a two-stage procedure was employed by Noulas & Ketkar (1998), Stupnytskyy (2004) and Borge & Lim (2005), just to name but a few.

because the model accommodates the use of a latent variable with known theoretical lower and upper limits. The efficiency scores are used as the dependent latent variable that has a minimum limit score of 0 and a maximum limit score of 1. The specification of the Tobit model is expressed as:

$$y_{jt} = \tau_0 + atsi_{jt}\tau_1 + esl_{jt}\tau_2 + disable_{jt}\tau_3 + male_{jt}\tau_4 + mumwork_{jt}\tau_5 + mumedu_{jt}\tau_6 + dadwork_{jt}\tau_7 + dadedu_{jt}\tau_8 + susprate_{jt}\tau_9 + d\_rural_{jt}\tau_{10} + e_{jt} \qquad (6.10)$$

where y_{jt} is the DEA technical efficiency score of the j^{th} school (j = 1, …, J) at time t (t = 1, …, T); τ is the unknown parameters to be estimated; e_{jt} is the error term assumed to be normally distributed with zero mean $E\left(e_{jt}\right)=0$, and the explanatory variables are as defined in Table 6.1.

Caution however needs to be exercised when interpreting the results of the Tobit regression. Since the first-stage variables (the various categories of educational expenditure) employed in the first-stage (DEA) are to a certain degree, correlated with the second-stage variables (socio-economic variables), the estimation results may be biased. The correlation is a consequence of the way the educational expenditures (used in the first-stage) were allocated to schools in Tasmania. Factors associated with socio-economic disadvantaged had been considered in how schools received the funding. An alternative estimation of DEA based on method B therefore is considered.

Method B

In the case of the second method, separate estimations for rural and urban schools are undertaken.[8] The cross-sectional dimension of the panel for rural schools involves 98 schools (J = 98) while the cross-sectional dimension for urban schools

[8] Refer to Maragos & Despotis (2003) for an example of this method in research to evaluate schools' technical efficiency.

involves 65 schools (J = 65). The basis for the rural and urban division is based on a significant difference found between the rural and urban schools in terms of the socio-economic variables (in particular the average percentage of parents with tertiary qualification and high occupational status (see Section 6.2.2 when I discuss Table 6.12). The division provides some socio-economic homogeneity in the production environment of schools in each division. As such, schools are relatively more comparable in terms of their socio-economic conditions within their respective division. Given the four educational outputs, and rural and urban divisions of the schools, eight separate DEA models are estimated.

d. Measuring change in technical efficiency

The availability of panel data also permits the estimation of technical efficiency change. The estimation of technical efficiency change is possible with a panel dataset due to repeated observations on the same individual schools in the sample at different points in time. For the estimation, the time dimension of the panel data involves three calendar years; namely, 2003, 2005 and 2007, or, T = 3.

Technical efficiency change is obtained by estimating the DEA frontier using data from a different time period. For instance, estimation of a frontier is made using data for period t, then another estimation is undertaken using data t + 1 and so on until the final period T. The technique allows the production technology to exhibit technical efficiency change. The industry is said to experience technical efficiency progress when there is a significant increase in the average technical efficiency scores from year t to year t + 1. Technical efficiency regress occurs when there is a significant decline in the average technical efficiency scores from year t to year t + 1.

6.2.2 Data and Sample Description Used for the DEA Estimations

A school-level panel dataset is employed for the DEA estimations. The cross-sectional dimension of the data employed for method A (the two-stage procedure) involves 163 public primary schools in Tasmania. I have detailed the analysis of the descriptive statistics for the data employed under method A in Section 6.2.2. Note that the same outputs and inputs data employed under method A are used for the SPF estimations. The discussion in this section will focus on the analysis of data used for method B.

For method B, two sets of school-level panel data are constructed, where schools are divided into 98 rural and 65 urban schools in the construction of the cross-section dimension of the panel.[9] The time series of the panel datasets involve three school calendar years, 2003, 2005 and 2007. The constructed panel datasets are balanced ones.

The summary statistics of the average literacy and numeracy of Years 3 and 5 for rural and urban schools for 2003, 2005 and 2007 are shown in Table 6.10. Based on the average scores, the performance of urban schools in both literacy and numeracy is better, in general, than the rural schools. As found in Chapter 5 (an analysis based on an educational production function), a favourable socio-economic environment such as better parental education contributes positively to students' literacy and numeracy performance. This factor can be one reason for the better performance of urban schools since urban schools have higher percentage of parents with tertiary qualification than rural schools, as shown in Table 6.12. In addition, as shown in Table 6.10, a comparison according to year level shows that the average literacy and numeracy of students in Year

[9] Combined schools (schools that provide primary and secondary education) are also included. Two schools are excluded because of major missing data. The schools are Sandy Bay Infant School and Cape Barren Island School.

5 was higher than students in Year 3. The higher performance of Year 5 may be attributed to their seniority, where they have more value-added to their innate abilities than Year 3 students.[10]

Table 6.10: Summary Statistics of Test Scores of Years 3 and 5 Students according to Rural and Urban Schools

Tests	Statistics	Year 3			Year 5		
		2003	2005	2007	2003	2005	2007
Literacy	**Rural schools**						
	Mean	365.84	361.88	361.82	382.90	391.06	388.40
	Std dev	14.18	13.22	13.14	11.84	12.22	11.97
	Min	306.50	319.00	325.50	316.33	358.00	359.50
	Max	395.36	392.41	389.75	401.58	426.38	418.00
	Urban schools						
	Mean	368.08	366.07	363.80	382.21	396.29	395.30
	Std dev	12.58	12.46	14.18	13.41	12.91	13.37
	Min	339.00	335.56	331.77	352.36	362.02	367.66
	Max	389.11	392.87	396.04	412.92	422.19	427.50
Numeracy	**Rural schools**						
	Mean	375.61	368.23	363.86	390.47	395.49	392.54
	Std dev	15.88	15.65	15.04	11.48	14.56	11.43
	Min	336.10	335.00	321.75	354.45	363.31	348.00
	Max	417.00	407.00	398.91	417.48	438.57	419.44
	Urban schools						
	Mean	376.76	371.11	366.95	389.08	399.99	397.02
	Std dev	16.98	13.58	15.51	15.89	14.21	14.95
	Min	338.60	342.05	330.73	357.12	368.36	359.26
	Max	426.30	405.85	408.73	430.02	429.86	439.56

Five discretionary educational inputs (**X**), namely *srpexp*, *grantexp*, *edperstu*, *ruralexp* and *st_ratio*[11] are employed for the estimation of DEA under method B. The data are school-level data provided by the Department of Education, Tasmania. Given how the data were provided (the data is a school-level data and not traceable to grade), separation of the data according to grade (in particular Years 3 and 5) is impossible. As such, the DEA approach here employs the same input data for the four different outputs of education. One limitation of employing the same input data for the different outputs is that the variation of the computed technical efficiency is due to the variation of the

[10] Refer to the value-added model of educational production function in Chapter Three for further discussion. Since the measure of test scores was based on Rasch scale, the reported scores had taken into account test difficulties. The higher performance of Year 5 therefore could not be attributed to easier test.
[11] See Table 6.1 for the definition of each variable.

outputs. Since the variation in the outputs employed are small (as shown in Table 6.10), I expect the variation in the technical efficiency also to be small.

Table 6.11 Summary Statistics of the Discretionary Variables of Rural and Urban Schools in Tasmania (AUD$ '000 per student)

Variable	Statistics	Rural schools			Urban schools		
		2003	2005	2007	2003	2005	2007
srpexp (AUD$ '000)	Mean	203.565	199.702	289.240	232.696	212.957	324.107
	Std dev	132.114	130.789	187.817	93.982	79.426	126.671
	Min	44.702	42.925	68.860	65.472	69.464	126.571
	Max	641.411	672.476	937.039	486.193	449.974	706.612
grantexp (AUD$ '000)	Mean	86.935	88.741	92.179	87.897	92.914	96.400
	Std dev	55.229	55.553	58.850	36.999	38.505	38.441
	Min	20.993	22.669	22.575	26.808	28.832	33.585
	Max	286.350	283.930	294.629	205.974	218.808	222.623
edperstu (AUD$ '000)	Mean	50.678	51.650	53.936	63.293	66.840	70.547
	Std dev	36.913	37.890	40.444	27.795	29.211	30.220
	Min	5.102	5.637	4.926	21.257	20.971	23.888
	Max	195.312	191.481	193.621	152.687	163.686	172.266
ruralexp (AUD$ '000)	Mean	16.312	16.876	18.155	0.578	0.609	0.660
	Std dev	13.292	12.222	12.748	0.521	0.528	0.579
	Min	3.421	3.622	3.860	0	0	0
	Max	112.667	94.359	98.328	2.765	2.756	2.653
st_ratio	Mean	16.38	16.21	16.11	18.41	18.35	18.41
	Std dev	1.98	2.14	2.28	0.55	0.65	0.57
	Min	11.4	10.9	9.9	16.5	16.0	16.6
	Max	18.9	18.9	18.9	19.1	19.0	19.0

In Table 6.11, summary statistics of the input variables are shown. Urban schools received more financial allocations than rural schools for the spending categories *srpexp*, and *grantexp* for 2003, 2005 and 2007. The reason for the larger financial allocation to urban schools was due to the larger number of students in urban schools than rural schools. For the expenditure category *ruralexp*, on the other hand, the allocation to rural schools exceeded the allocation to urban schools since this spending was made based on the distance a school is located from the nearest township area.

The degree of heterogeneity in socio-economic environment of public primary schools in Tasmania is shown in Table 6.12. The statistics of rural and urban schools, as shown in Table 6.12, for the ten environmental variables that represent socio-economic characteristics of schools show a significant degree of heterogeneity. In particular, the number of mothers in type 1 occupation (*mumwork*) for urban schools is significantly larger than rural schools by an average of 50%. The number of fathers in type 1 occupation (*dadwork*) for urban schools, on the other hand, is on average, 45% significantly larger than rural schools. A comparison of parent's educational level shows that on average, the number of mother with tertiary qualification (*mumedu*) for urban schools is 63% higher than rural schools. On the other hand, on average, 50% more fathers with tertiary qualification (*dadedu*) are found for urban schools as compared to rural schools. Note that the data employed for *mumwork, mumedu, dadwork* and *dadedu* as shown in the table are the same for both Years 3 and 5 for 2003, 2005 and 2007 in each respective rural and urban division (the reason for the same data employed has been explained in Section 6.2.2-c).

The socio-economic heterogeneity between rural and urban schools in Tasmania is also evident in the summary statistics of *atsi*, *esl* and *disable,* as shown in Table 6.12. The average number of indigenous students (*atsi*) between rural and urban schools was approximately the same for 2003, 2005 and 2007, but the standard deviation and range between minimum and maximum were larger for rural schools.

Table 6.12: Summary Statistics of the Environmental Variables of Years 3 and 5 Students

Variables	Schools	Statistics	Year 3			Year 5		
			2003	2005	2007	2003	2005	2007
atsi (no. of students)	Rural schools	Mean	18.76	20.18	18.85	18.76	20.18	18.85
		Std dev	17.69	18.84	17.80	17.69	18.84	17.80
		Min	0.00	0.00	0.00	0.00	0.00	0.00
		Max	70.00	97.00	93.00	70.00	97.00	93.00
	Urban schools	Mean	19.86	20.17	18.80	18.76	20.18	18.85
		Std dev	13.57	13.12	12.08	17.69	18.84	17.80
		Min	1.00	0.00	0.00	0.00	0.00	0.00
		Max	61.00	57.00	54.00	70.00	97.00	93.00
esl (no of students)	Rural schools	Mean	0.02	0.12	0.09	0.02	0.12	0.09
		Std dev	0.14	0.39	0.29	0.14	0.39	0.29
		Min	0.00	0.00	0.00	0.00	0.00	0.00
		Max	1.00	2.00	1.00	1.00	2.00	1.00
	Urban schools	Mean	1.11	2.72	3.00	1.11	2.72	3.00
		Std dev	2.19	4.17	4.75	2.19	4.17	4.75
		Min	0.00	0.00	0.00	0.00	0.00	0.00
		Max	9.00	15.00	24.00	9.00	15.00	24.00
disable (no of students)	Rural schools	Mean	1.26	1.33	1.65	1.26	1.33	1.65
		Std dev	1.51	1.64	1.91	1.51	1.64	1.91
		Min	0	0	0	0	0	0
		Max	7	8	7	7	8	7
	Urban schools	Mean	2.34	2.38	2.72	2.34	2.38	2.72
		Std dev	2.48	2.29	2.32	2.48	2.29	2.32
		Min	0	0	0	0	0	0
		Max	13	9	10	13	9	10
male (proportional)	Rural schools	Mean	0.51	0.53	0.52	0.51	0.52	0.53
		Std dev	0.14	0.14	0.15	0.13	0.16	0.14
		Min	0	0	0	0	0	0
		Max	1	0.909091	1	1	1	1
	Urban schools	Mean	0.52	0.52	0.52	0.52	0.51	0.51
		Std dev	0.08	0.09	0.09	0.06	0.10	0.09
		Min	0.33	0.33	0.30	0.35	0.23	0.32
		Max	0.67	0.86	0.73	0.64	0.72	0.76
mumwork (no of mothers)	Rural schools	Mean	33.06	33.06	33.06	33.06	33.06	33.06
		Std dev	31.46	31.46	31.46	31.46	31.46	31.46
		Min	1	1	1	1	1	1
		Max	154	154	154	154	154	154
	Urban schools	Mean	61.97	61.97	61.97	61.97	61.97	61.97
		Std dev	58.09	58.09	58.09	58.09	58.09	58.09
		Min	2	2	2	2	2	2
		Max	250	250	250	250	250	250
mumedu (no of mothers	Rural schools	Mean	82.13	82.13	82.13	82.13	82.13	82.13
		Std dev	68.04	68.04	68.04	68.04	68.04	68.04
		Min	5	5	5	5	5	5
		Max	318	318	318	318	318	318
	Urban schools	Mean	133.55	133.55	133.55	133.55	133.55	133.55
		Std dev	85.66	85.66	85.66	85.66	85.66	85.66
		Min	8	8	8	8	8	8
		Max	359	359	359	359	359	359
dadwork (no of fathers)	Rural schools	Mean	44.92	44.92	44.92	44.92	44.92	44.92
		Std dev	40.16	40.16	40.16	40.16	40.16	40.16
		Min	2	2	2	2	2	2
		Max	181	181	181	181	181	181
	Urban schools	Mean	81.77	81.77	81.77	81.77	81.77	81.77
		Std dev	71.78	71.78	71.78	71.78	71.78	71.78
		Min	1	1	1	1	1	1
		Max	291	291	291	291	291	291
dadedu (no of fathers)	Rural schools	Mean	93.45	93.45	93.45	93.45	93.45	93.45
		Std dev	77.11	77.11	77.11	77.11	77.11	77.11
		Min	7	7	7	7	7	7
		Max	337	337	337	337	337	337
	Urban schools	Mean	139.71	139.71	139.71	139.71	139.71	139.71
		Std dev	87.12	87.12	87.12	87.12	87.12	87.12
		Min	11	11	11	11	11	11
		Max	398	398	398	398	398	398
susprate (suspension per 100 students)	Rural schools	Mean	3.69	4.26	5.05	3.69	4.26	5.05
		Std dev	5.78	6.73	7.34	5.78	6.73	7.34
		Min	0	0	0	0	0	0
		Max	26.4	30.6	38.18182	26.4	30.6	38.18182
	Urban schools	Mean	5.54	3.35	4.27	5.54	3.35	4.27
		Std dev	17.69	8.15	8.89	17.69	8.15	8.89
		Min	0	0	0	0	0	0
		Max	130.1	49.9	52.97806	130.1	49.9	52.97806
absent (no of days)	Rural schools	Mean	10.65	11.32	11.82	11.38	11.93	12.26
		Std dev	3.49	3.72	3.78	3.62	4.10	3.72
		Min	3.75	1.33	4.00	4.33	2.00	3.00
		Max	27.55	24.25	31.25	31.00	25.00	22.06
	Urban schools	Mean	10.29	10.57	10.59	11.15	11.42	11.11
		Std dev	2.63	2.52	2.08	2.83	3.09	2.88
		Min	5.20	5.22	5.36	5.33	4.24	5.82
		Max	19.00	18.00	16.35	20.57	23.67	21.71

As shown in Table 6.12, urban schools had more students who had English as a Second Language Program (*esl*) and disabled students (*disable*) as compared to rural schools. The difference in the mean figures for the proportion of male students (*male*), suspension rate (*susprate*) and average days absent (*absent*) between rural and urban schools, on the other hand, were not significant. Since all the variables capture some degree of socio-economic disadvantage that may affect school performance in a negative way, fair performance evaluation of the schools can only be achieved when the effects of the variables are accounted for. In other words, without accounting for the socio-economic environment, the technical efficiency of DEA may be confounded by the disadvantage borne by a group of schools.

The heterogeneity in the cross-section of the panel is accounted for by dividing all the 163 schools into 98 rural and 65 urban schools. The division captures a significant difference in the socio-economic characteristics of schools, where schools with homogenous socio-economic characteristics are grouped together. The measure of technical efficiency of schools in the same group is therefore more comparable since the calculation is made based on schools with similar socio-economic characteristics. I now discuss the results of DEA in the next section.

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6.2.3 Results of DEA

The efficiency scores based on output-oriented DEA are obtained using a software package called DEAP 2.1.[12] The discussion starts with the results of DEA obtained under method A, followed by method B.

a. Method A (The Two-Stage Procedure)

First-Stage Procedure

The first-stage of the procedure involves the estimation of CRS-DEA based on equation (4.8) and VRS-DEA based on equation (4.11). Summary statistics of the DEA results for the 163 public primary schools in Tasmania are presented in Table 6.13. The first column of the table shows the various outputs employed for the estimations. Information on the mean, standard deviation, minimum and maximum of the DEA technical efficiency scores under constant returns to scale (CRS) and variable returns to scale (VRS) assumptions for 2003, 2005 and 2007 are shown in the table.

On examination of Table 6.13, all the average CRS- and VRS-technical efficiency scores show a declining trend from 2003 to 2007, except for the average VRS-technical efficiency where the output is based on *avg_num3*. The variations (as reflected by standard deviation) in technical efficiency scores, in general, had increased from 2003 to 2007. The results imply that public primary schools in Tasmania had become less efficient with the variation in the level of technical efficiency among schools widening over the period. The decline can be associated to deteriorating environmental factors—such as an increase in the absenteeism rates as can be observed in Table 6.12. In order to evaluate further by how much the environmental factors have

[12] The software package is downloadable for free from The Centre of Efficiency and Productivity Analysis (CEPA) at http://www.uq.edu.au/economics/cepa/deap.htm

an effect on technical efficiency, coefficient estimates based on a Tobit regression are provided in the next sub-section.

Table 6.13: Summary Statistics of DEA Efficiency Scores

Output	Statistics	2003 CRS	2003 VRS	2003 Scale	2005 CRS	2005 VRS	2005 Scale	2007 CRS	2007 VRS	2007 Scale
avg_lit3	Mean	0.8516	0.9490	0.8964	0.8182	0.9445	0.8655	0.8061	0.9323	0.8637
	Std dev	0.1024	0.0310	0.0946	0.1027	0.0314	0.0980	0.1175	0.0346	0.1146
	Minimum	0.6260	0.8350	0.6770	0.5900	0.8670	0.6520	0.5920	0.8560	0.6400
	Maximum	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
avg_lit5	Mean	0.8416	0.9494	0.8862	0.8140	0.9384	0.8663	0.8091	0.9355	0.8636
	Std dev	0.1044	0.0264	0.1050	0.1007	0.0325	0.0922	0.1171	0.0324	0.1111
	Minimum	0.6150	0.8940	0.6610	0.6050	0.8590	0.6580	0.5900	0.8700	0.6450
	Maximum	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
avg_num3	Mean	0.8491	0.9152	0.9271	0.8179	0.9299	0.8777	0.8020	0.9231	0.8676
	Std dev	0.0820	0.0411	0.0702	0.1208	0.0408	0.1105	0.1176	0.0415	0.1127
	Min	0.6510	0.8060	0.7460	0.5520	0.8370	0.6420	0.5810	0.8260	0.6510
	Max	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
avg_num5	Mean	0.8419	0.9384	0.8966	0.8266	0.9353	0.8824	0.7985	0.9263	0.8609
	Std dev	0.0962	0.0325	0.0930	0.1009	0.0391	0.0880	0.1134	0.0376	0.1075
	Min	0.6200	0.8540	0.6900	0.6060	0.8290	0.6830	0.5870	0.8440	0.6570
	Max	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

In Table 6.13, descriptive statistics of scale efficiency are also shown. Scale efficiency is given by the ratio of CRS-technical efficiency to VRS-technical efficiency. The correct way to interpret these results is that higher scale efficiency figure implies that fewer inputs are wasted due to non-optimal school size. As evident from Table 6.13, a small decline in the average scale efficiency over the period across all the models has been found. When *avg_num3* was employed as the output, for example, the average scale efficiency declined significantly from 92.7 per cent in 2003 to 87.77 per cent in 2005 and then, to 86.76 per cent in 2007. The observed declining trend in the average scale efficiency scores suggests a prevalent problem of non-optimal school size among public primary schools in Tasmania. This problem is caused by low population density, in particular, among rural schools in Tasmania.

<u>Second-Stage Procedure</u>

Based on the CRS- and VRS-technical efficiency scores obtained from the first-stage procedure, the second-stage procedure is based on the Tobit regression, as specified in equation (6.12). In Tables 6.14, I provide the list of the dependent variables employed in eight Tobit estimations for a convenient reference. In Table 6.15, I present the regression results of four Tobit models that employ the various CRS-technical efficiency scores as the dependent variables (models A, B, C and D). In Table 6.16, the regression results of another four Tobit models that employ the various VRS-technical efficiency scores as the dependent variables (models E, F, G and H) are presented.

Table 6.14: List of the Dependent Variables for the Tobit Regression Models

Model	Dependent Variable
A	CRS-technical efficiency based on *avg_lit3* as the output in the first-stage procedure
B	CRS-technical efficiency based on *avg_lit5* as the output in the first-stage procedure
C	CRS-technical efficiency based on *avg_num3* as the output in the first-stage procedure
D	CRS-technical efficiency based on *avg_num5* as the output in the first-stage procedure
E	VRS-technical efficiency based on *avg_lit3* as the output in the first-stage procedure
F	VRS-technical efficiency based on *avg_lit5* as the output in the first-stage procedure
G	VRS-technical efficiency based on *avg_num3* as the output in the first-stage procedure
H	VRS-technical efficiency based on *avg_num5* as the output in the first-stage procedure

Table 6.15: Tobit Coefficient Estimates of the Efficiency Model (Dependent Variable = Efficiency Estimates from the First-Stage DEA CRS Model)

Model	*A*	*B*	*C*	*D*
Variables				
atsi	-0.0064	-0.0810	-0.0071	-0.0106
	(0.0095)	(0.0093)	(0.0102)	(0.0097)
esl	-0.0001	-0.0055	-0.0006	-0.0011
	(0.0019)	(0.0018)	(0.0021)	(0.0019)
disable	-0.0025	-0.0033	-0.0025	-0.0003
	(0.0050)	(0.0047)	(0.0056)	(0.0050)
male	-0.0002*	-0.0174	-0.0701*	-0.0175
	(0.0001)	(0.0171)	(0.0202)	(0.0184)
mumwork	0.0190	0.0171	0.0288	0.0198
	(0.0313)	(0.0321)	(0.0317)	(0.0329)
mumedu	-0.0659	-0.0615	-0.0575	-0.0513
	(0.0602)	(0.0617)	(0.0609)	(0.0633)
dadwork	0.0717***	0.0844**	0.0690***	0.0878**
	(0.0395)	(0.0405)	(0.0401)	(0.0415)
dadedu	-0.1012***	-0.1246**	-0.1250**	-0.1455**
	(0.0555)	(0.0570)	(0.0563)	(0.0584)
susprate	-0.0001	0.0001	-0.0004	0.00002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
absent	-0.0013***	-0.0007	-0.0025*	-0.0005
	(0.0008)	(0.0007)	(0.0009)	(0.0007)
d_rural	-0.1750*	-0.1714*	-0.1674*	-0.1566*
	(0.0110)	(0.0112)	(0.0112)	(0.0115)
_cons	1.00239	1.0014	1.0486	0.9952
	(0.0147)	(0.0170)	(0.0190)	(0.0178)
Log Likelihood	681.69	689.75	620.65	672.53

Note: *, ** and *** denote level of significance at 1%, 5 % and 10% respectively. Figures in () are standard errors.

Table 6.16: Tobit Coefficient Estimates of the Efficiency Model (Dependent Variable = Efficiency Estimates from the First-Stage DEA VRS Model)

Model	***E***	***F***	***G***	***H***
Variables				
atsi	-0.0084***	-0.0076***	-0.0084	-0.0121**
	(0.0044)	(0.0041)	(0.0055)	(0.0048)
esl	-0.0013	-0.0016***	-0.0016	-0.0020***
	(0.0010)	(0.0009)	(0.0012)	(0.0011)
disable	-0.0035	-0.0033	-0.0053***	-0.0019
	(0.0027)	(0.0024)	(0.0032)	(0.0029)
male	0.0001***	-0.0131	-0.0136	-0.0098
	(0.00005)	(0.0099)	(0.0124)	(0.0117)
mumwork	0.0216***	0.0212***	0.0298***	0.0216
	(0.0123)	(0.0116)	(0.0158)	(0.0136)
mumedu	0.0138	0.0127	0.0093	0.0123
	(0.0237)	(0.0221)	(0.0303)	(0.0262)
dadwork	0.0155	0.0213	0.0246	0.0354**
	(0.0158)	(0.0148)	(0.0201)	(0.0174)
dadedu	-0.0538**	-0.0630*	-0.0876*	-0.0945*
	(0.0220)	(0.0206)	(0.0280)	(0.0243)
susprate	-0.0002	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
absent	-0.0007	-0.0009**	-0.0003	-0.0010**
	(0.0005)	(0.0004)	(0.0005)	(0.0004)
d_rural	-0.0178*	-0.0178*	-0.0245*	-0.0155*
	(0.0044)	(0.0041)	(0.0056)	(0.0049)
_cons	0.9717	0.9831	0.9744	0.9866
	(0.0068)	(0.0080)	(0.0107)	(0.0094)
Log Likelihood	890.11	955.42	821.72	870.20

Note: *, ** and *** denote level of significance at 1%, 5 % and 10% respectively. Figures in () are standard errors.

On the basis of an examination of both tables, a comparison of the log-likelihood of the fitted models shows relatively higher log-likelihood estimates for the Tobit models that employ the various VRS-technical efficiency scores as the dependent variables. As such, the estimated models in Table 6.16 are the preferred results for the discussion. Further, the use of the VRS-technical efficiency scores is more comparable with the results based on the SPF models in Section 6.1.3 since the distribution of the technical efficiency scores obtained under both models are closer (in terms of the average, standard deviation and range between minimum and maximum technical efficiency scores as shown in Tables 6.9 and 6.13).

Note that in Table 6.16, an inverse relationship is found between technical efficiency and *atsi*, *esl* and *disable.* These variables are considered to represent students with disadvantaged conditions towards learning. Under model E, F and H, for example, technical efficiency score declines by 0.084, 0.076 and 0.0121 points (small decline) for a 1% increase in *atsi*, *ceteris paribus*. There is also a small decline in technical efficiency by 0.0016 (model E) and 0.002 (model H) points for an increase in the percentage of students in the English as the Second Language Program (*esl*), holding other factors constant. As shown in Table 6.16, holding other things constant, as the percentage of severely disable students rises by one, the level of technical efficiency decreases by 0.0053 points in model G. For models E, F and H, the effect of *disable* on technical efficiency are not significant. Evidence of the significant negative effects of the three variables on technical efficiency implies that schools with the disadvantaged groups of students tend to be technically less efficient.

No conclusive evidence for the effect of *male* on technical efficiency is obtained from the results in Table 6.16. The effect of *male* is only significant under model E with a positive coefficient sign. For the other three models (F, G and H), the effect is statistically insignificant and the coefficient signs are negative.

In Table 6.16, the variables *mumwork* and *dadwork* are employed to capture the effects of family's income on technical efficiency. Robust effects of *mumwork* are found from the estimations in models E, F and G, where an increase in the percentage of mothers in type 1 occupation is associated with an increase in technical efficiency by 0.0216, 0.0212 and 0.0298, *ceteris paribus*. A positive effect of *dadwork* is only statistically significant under model H but not significant under models E, F and G (although the coefficient signs are positive). The positive effects can be explained perhaps by the advantaged position of wealthy families, who can afford better learning technology to support their children's learning (at home and/or at schools), and hence, less school resources are needed to assist the children.

Although the coefficient signs for *mumedu* in all the models in Table 6.16 are positive, the estimates are not statistically significant. Robust negative effects of fathers with tertiary qualification on technical efficiency, however, have been found with the coefficient parameters range from 0.05 to 0.09. The reason for the negative effects of *dadedu* on technical efficiency could be due to less time is spent by this group of fathers to engage with their children's learning.

I also include the variables *susprate* and *absent* in order to investigate the effects of poor disciplinary level of students on technical efficiency. Schools with high suspension (*susprate*) and absenteeism (*absent*) rates are expected to be less efficient because more resources are required to monitor and maintain the disciplinary level of the students. As shown in Table 6.16, the coefficient signs for both variables are negative, suggesting inverse relationships between the two variables with technical efficiency. The effects of *susprate* however, are statistically insignificant for all the models. For *absent*, only under models F and H, significant effects of the variable are found. An interpretation of the result in model F suggests that technical efficiency declines by 0.0009 point (a small decline) for every additional increase in average days absent from schools, *ceteris paribus.*

Still on Table 6.16, the variable *d_rural* is a dummy variable, where 1 is if the school is a rural school and 0 if the school is an urban school. A robust inverse relationship is found between *d_rural* and technical efficiency. From the results, on average, rural schools are technically less efficient than urban schools by 0.0178, 0.0178, 0.0245 and 0.0155 under each respective model, *ceteris paribus*. The effects of *d_rural* on technical efficiency are relatively the larger than the other observed variables. Low technical efficiency of rural schools as compared to urban schools is associated with the disadvantaged socio-economic environment, as shown in Table 6.12. Given the large effects of *d_rural* on technical efficiency, an estimation of DEA based on method B is essential because that method groups schools according to their rural or urban status. The division provides some degree of homogeneity in the production environment within the groups. Results based on method B are discussed in the next section.

b. Method B (Rural-Urban Division)

Method B is based on a division of schools into rural and urban categories as discussed in Section 6.2.1-d. In Table 6.17, I provide summary statistics of the efficiency scores obtained when the literacy performance of Years 3 and 5 students in rural and urban schools are employed as the output. In Table 6.18, on the other hand, I present summary statistics of the efficiency scores obtained when the numeracy scores of Years 3 and 5 students in rural and urban schools are employed as the outputs. Graphical representations of the average technical efficiency scores in Tables 6.17 and 6.18 are illustrated in Figures 6.2 and 6.3 in order to offer a more convenient comparison of the results.

The technical efficiency of rural and urban public primary schools in Tasmania is high throughout the study period, as shown in Table 6.17 and 6.18. The average VRS-efficiency scores based on Year 5 literacy performance as the output, for example, are 0.97, 0.95 and 0.95 for rural schools while for urban schools the scores are 0.96, 0.95 and 0.95 for the years 2003, 2005 and 2007 (as shown in Table 6.17). In Table 6.18, the average VRS-efficiency scores based on Year 5 numeracy performance as the output are 0.96, 0.94 and 0.96 for rural schools while for urban schools the scores are 0.95, 0.95 and 0.93 for the years 2003, 2005 and 2007.

As shown in Figures 6.2 and 6.3, average CRS-efficiency is lower than average VRS-efficiency for rural and urban schools. Lower CRS-efficiency scores are expected because under the CRS assumption, a comparison set of the best-practice schools is identified by constructing a line from the origin to the most outlying data plot of the entire data (refer to Figure 4.3). Accordingly, only a few schools lie on the frontier. Fewer schools, therefore, get the maximum efficiency score (equal to one). The best-practice schools under the VRS assumption, on the other hand, are identified by joining the extremal data plots given the entire data (refer to Figure 4.3 for a theoretical framework of DEA based on a diagram). Accordingly, more schools can fall on the frontier and get the maximum efficiency score (equal to one) as compared to the CRS procedure. Manifestly, the returns to scale assumption (CRS or VRS) made, therefore, is critical in the way DEA discriminates between the DMUs (schools).

A comparison between the average VRS- and CRS-technical efficiencies in Figures 6.2 and 6.3 shows a large difference between the two scores for rural schools but a smaller difference for urban schools. Based on the numeracy performance of Year 5 students in 2007 as the output measure (Table 6.18), for example, the difference between the average VRS- and CRS-technical efficiencies for rural schools is 0.168 (0.9552 – 0.7872 = 0.168) but it is only 0.0363 (0.9312 – 0.8949 = 0.0863) for urban schools. The difference between the two scores (CRS- and VRS-efficiency) is reflected in the scale efficiency score. Recall that the measure of scale efficiency is given by the ratio of the CRS-efficiency to the VRS-efficiency scores (see Section 4.2.2-d). As shown in Figures 6.4 and 6.5, the average scale efficiency of urban schools is higher than rural schools (urban schools are more scale efficient than rural schools). The higher scale efficiency of urban schools implies that fewer inputs of urban schools are wasted due to non-optimal school size.

An analysis of the scale efficiency scores provides a vital insight into the issue of school size on efficiency. Since school size is usually defined by the number of students or student-teacher ratio, lower scale efficiency of rural schools as compared to urban schools implies that the problem of non-optimal school size is more prevalent among rural schools in Tasmania (due to remote location and low population density).[13] In the next part of the discussion, a school-level analysis of rural schools' DEA results is analysed.

[13] Scale efficiency is found to be one main factor that results in the difference in urban-rural schools' technical efficiency in Tasmania. Until my work here, there was no hard evidence that the topic of scale efficiency was worthy of more investigation. Doing so here would require one to undertake another dissertation.

Table 6.17: Summary Statistics for the DEA Efficiency Scores based on Literacy Performance

Statistics	Year 3									Year 5								
	2003			2005			2007			2003			2005			2007		
	CRS	VRS	Scale	CRS	VRS	Scale	CRS	VRS	Scale	CRS	VRS	Scale	CRS	VRS	Scale	CRS	VRS	Scale
Rural Schools																		
Mean	0.8237	0.9499	0.8658	0.8012	0.9541	0.8381	0.7698	0.9419	0.8160	0.8156	0.9690	0.8413	0.8138	0.9482	0.8563	0.7883	0.9504	0.8278
Std dev	0.0943	0.0341	0.0805	0.1039	0.0351	0.0893	0.1082	0.0351	0.0998	0.0954	0.0223	0.0920	0.1074	0.0355	0.0913	0.1130	0.0321	0.1020
Min	0.6290	0.8350	0.6800	0.5960	0.8670	0.6590	0.5960	0.8560	0.6410	0.6180	0.9110	0.6470	0.6130	0.8590	0.6660	0.6120	0.8730	0.6500
Max	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Urban schools																		
Mean	0.9628	0.9684	0.9942	0.9119	0.9527	0.9573	0.9230	0.9452	0.9764	0.9502	0.9567	0.9933	0.9030	0.9545	0.9462	0.9175	0.9485	0.9670
Std dev	0.0208	0.0216	0.0068	0.0289	0.0268	0.0182	0.0361	0.0315	0.0148	0.0252	0.0254	0.0077	0.0309	0.0284	0.0236	0.0387	0.0298	0.0218
Min	0.9240	0.9290	0.9610	0.8580	0.9000	0.9300	0.8690	0.8850	0.9690	0.9090	0.9190	0.9520	0.8590	0.8890	0.9100	0.8390	0.8850	0.9170
Max	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Table 6.18: Summary Statistics for the DEA Efficiency Scores based on Numeracy Performance

Statistics	Year 3									Year 5								
	2003			2005			2007			2003			2005			2007		
	CRS	VRS	Scale	CRS	VRS	Scale	CRS	VRS	Scale	CRS	VRS	Scale	CRS	VRS	Scale	CRS	VRS	Scale
Rural schools																		
Mean	0.8460	0.9350	0.9034	0.7817	0.9355	0.8331	0.7713	0.9361	0.8222	0.8214	0.9565	0.8578	0.8095	0.9426	0.8568	0.7872	0.9552	0.8224
Std dev	0.0885	0.0448	0.0662	0.1130	0.0464	0.0921	0.1081	0.0393	0.0964	0.0924	0.0261	0.0841	0.1043	0.0468	0.0812	0.1143	0.0303	0.1032
Min	0.6540	0.8060	0.7360	0.5560	0.8420	0.6480	0.5810	0.8590	0.6510	0.6230	0.8990	0.6750	0.6120	0.8310	0.6900	0.6040	0.8510	0.6430
Max	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Urban schools																		
Mean	0.9166	0.9316	0.9841	0.9397	0.9503	0.9888	0.9138	0.9339	0.9785	0.9343	0.9453	0.9885	0.9171	0.9527	0.9627	0.8949	0.9312	0.9611
Std dev	0.0312	0.0346	0.0170	0.0301	0.0313	0.0127	0.0433	0.0391	0.0137	0.0301	0.0310	0.0119	0.0285	0.0277	0.0157	0.0459	0.0378	0.0253
Min	0.8350	0.8360	0.9040	0.8670	0.8900	0.9390	0.8430	0.8640	0.9350	0.8870	0.9020	0.9340	0.8700	0.9040	0.9220	0.8190	0.8480	0.9020
Max	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Figure 6.2: Average CRS- and VRS-Technical Efficiencies of Rural and Urban Schools for Years 3 and 5 (output = avg_lit3 & avg_lit5)

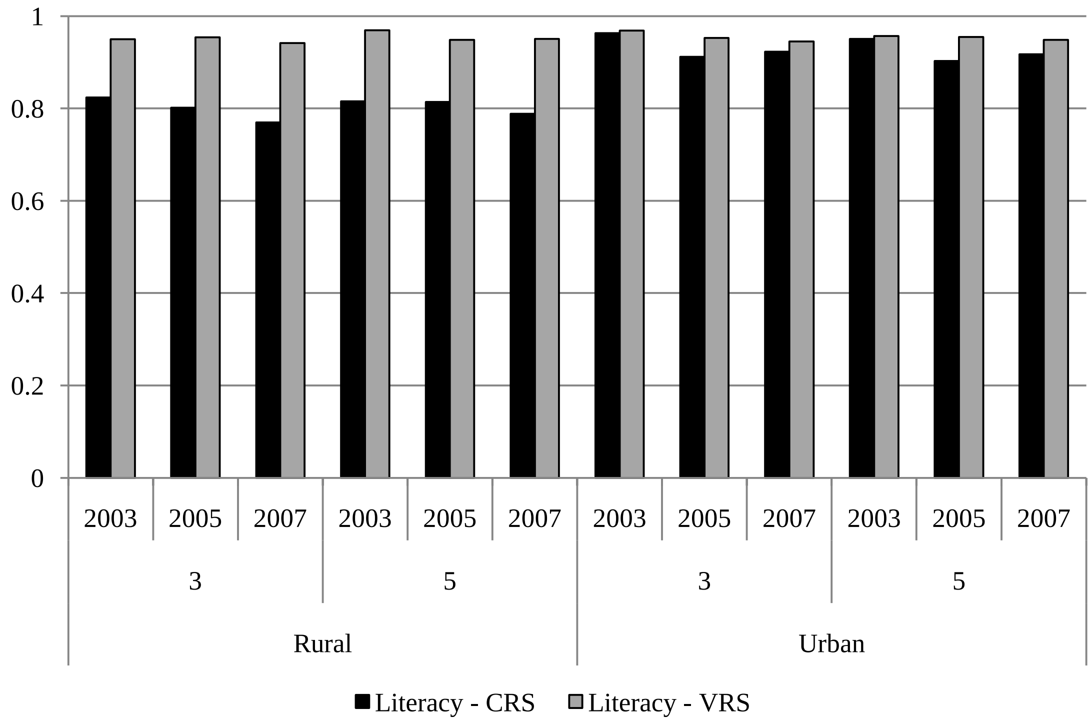


Figure 6.3: Average CRS- and VRS-Technical Efficiencies of Rural and Urban Schools for Years 3 and 5 (output = avg_num3 & avg_num5)

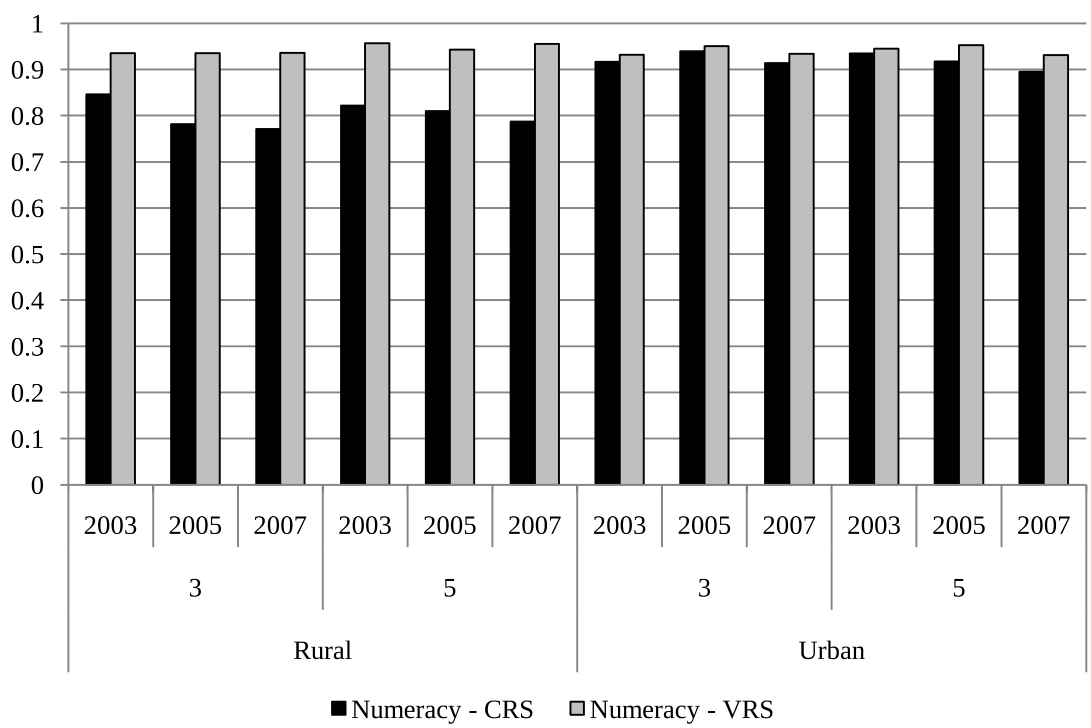


Figure 6.4: Average Scale Efficiency of Rural and Urban Schools for Years 3 and 5 (output = avg_lit3 & avg_lit5)

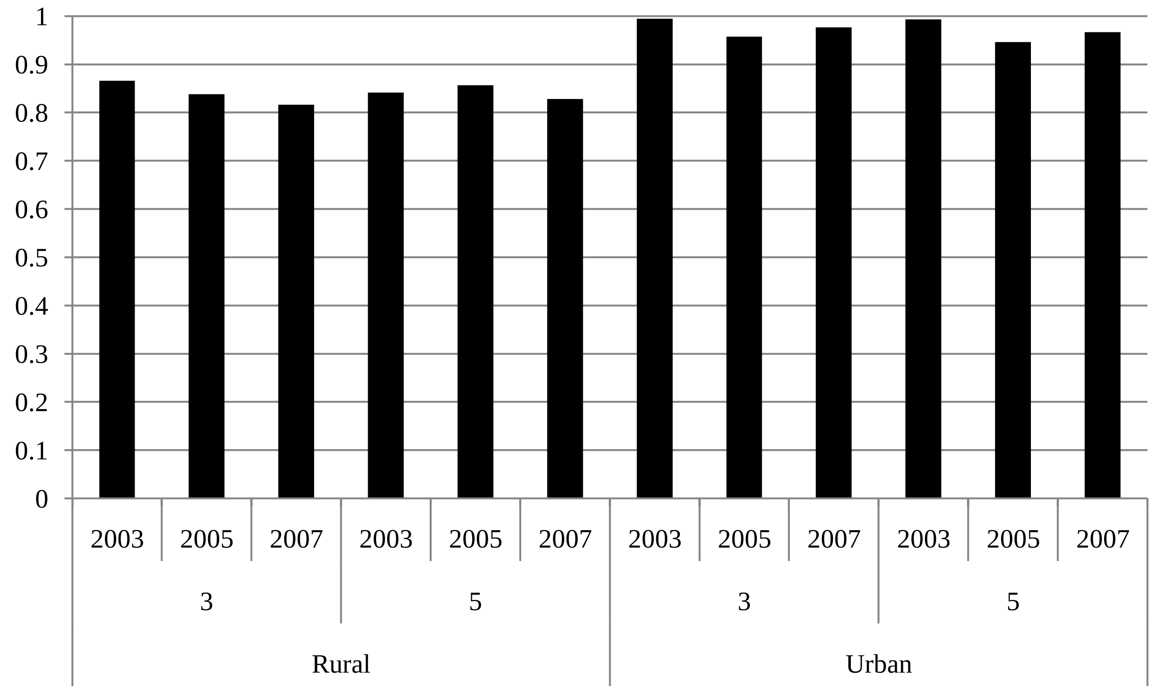
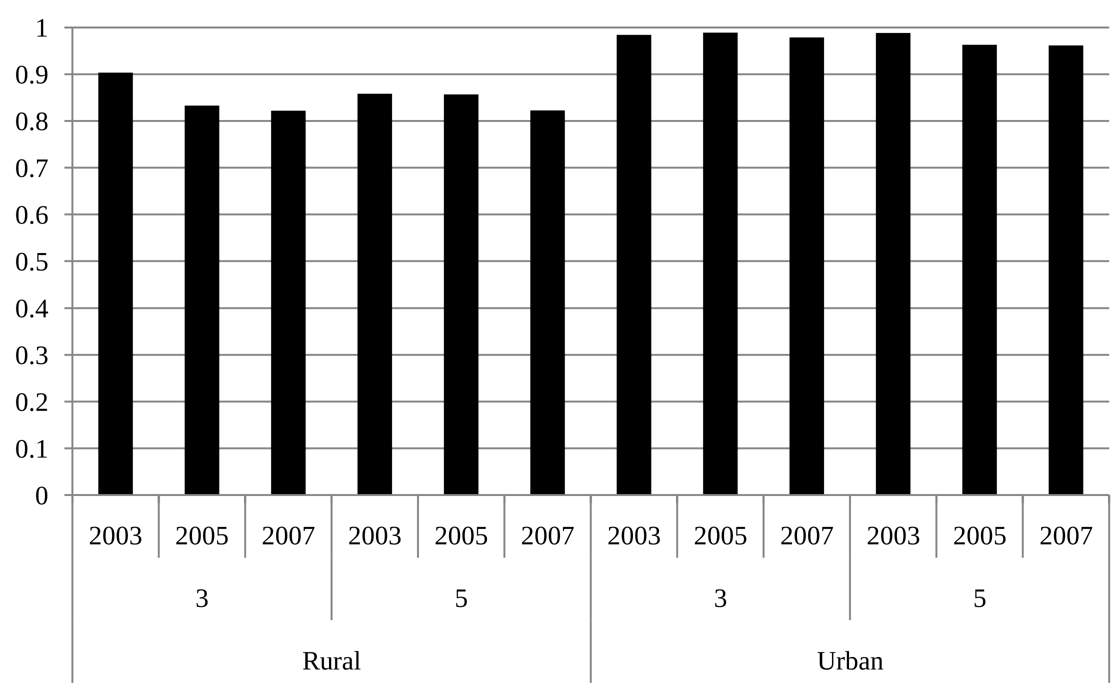


Figure 6.5: Average Scale Efficiency of Rural and Urban Schools for Years 3 and 5 put = avg_num3 & avg_num5)



c. *School-Level Analysis of the DEA Results*

The DEA results obtained under methods A and B point to the relatively lower technical efficiency of rural schools. The problem is present even after I controlled for the socio-economic disadvantages faced by rural schools (as controlled for under method B). The analysis in this section is based on a case of rural schools, focusing on how the inefficient rural schools might improve their level of technical efficiency.

In Table 6.19, I provide a ranking of rural schools that is constructed based on the VRS-technical efficiency scores—the output is the numeracy performance of Year 3 students in 2007.[14] The estimation results are chosen instead of the other generated results for two reasons: (i) the analysis is based on rural schools because from the Tobit regression as shown in Table 6.16, rural schools, on average, are less efficient than urban schools, and (ii) the output is the numeracy performance of Year 3 students in 2007 since the estimation results based on the output yields the lowest average VRS-efficiency of all the average VRS-efficiency scores for rural schools (refer to Table 6.14). The two points suggest that the largest improvement needed for rural schools to improve the performance of their Year 3 students lies in the area of numeracy.

The first column of Table 6.19 shows a ranking of the 98 rural public primary schools in Tasmania. The successive columns show the school code, VRS-technical efficiency scores, the original *avg_num3* scores, the projected[15] numeracy scores, the percentage difference between the projected and the original outputs and the role-model

[14] A ranking of urban schools is presented in Table 6.20. The output employed to estimate the VRS-technical efficiency scores is the numeracy performance of Year 3 students in 2007. The way to understand the table is similar to the description provided for Table 6.19 when I discuss the performance of rural schools.

[15] Refer to equation (4.12) for the formula to calculate the projected output (or output target).

count.[16] Since the list contains only rural schools, they are relatively comparable to one another.

The ranking of rural schools in Table 6.19 is sorted based on the VRS-technical efficiency scores (column 3). Since 14 of the 98 rural schools have VRS-technical efficiency equal to one (or 100% technically efficient), the next level of the sorting for the ranking is according to *avg_num3* scores (column 4), from highest to lowest. Since the estimation of DEA identifies the best-practice schools, those 14 schools play an important role as an exemplar (a role-model) for the non-efficient schools to learn from in an effort to improve their efficiency. The 14 schools form the VRS-frontier and the performance of the other schools is evaluated based on that frontier. From the frontier, the projected-output for each school is identified and it becomes the output-target for each school to achieve to be technically efficient.

Among the 14 efficient rural schools, the number of times each of them acts as an exemplar school (column 7) is also identified.[17] The objective of the exercise is to discriminate between superior and inferior exemplars among the identified efficient schools. The school with code 321, for example, appears 76 times as a role-model for the other schools with relatively the same level of inputs. In other words, School 321 is identified as the role-model for the other schools that have relatively similar capacity (level of inputs) to imitate in order to improve their efficiency. Although schools with the code numbers 027, 189 and 142 have efficiency scores equal to one, the number of

[16] Role-model count refers to the number of times an efficient DMU (school) appears as an exemplar to the inefficient DMUs. In the standard DEA literature, the term is called peer count. The term, in my opinion, is misleading because any DMU (with a relatively similar input capacity) that is not on the frontier, but has a relatively higher technical efficiency score than a DMU *j* could also be considered as a peer to the DMU *j*.

[17] The identification of peers is calculated using equation (4.10).

role-model count (column 7) for these schools is zero. They form part of the frontier but do not stand as a peer to the other schools. The reason for the situation is because the positions of these schools are at the lower end (near to the origin—recall Figure 4.3) of the frontier (note that the level of original output for these schools is low, as shown in column 4 of Table 6.19) and no other schools are relatively comparable to these schools in terms of use of inputs. Although these schools form parts of the frontier, an exclusion of them from the sample will not affect the efficiency scores of the other schools.

Since an output-oriented DEA is undertaken, the objective of the linear programming problem is to assess how much a school should improve its output given the level of inputs available. In column 5, the projected level of output for each school is presented—the calculation is based on equation (4.12). The projected-output figures, as shown in the table, provide some information on how the non-efficient rural schools could improve their performance. The projected output is obtained from the piecewise linear frontier constructed by joining the identified efficient schools (refer to Figure 4.3). The percentage difference between the projected and the original outputs shows the percentage improvement in *avg_num3* (test score) each school needs to achieve in order to be technically efficient. In other words, the projected-output figures stand as the key performance indicator for each school to become technically efficient. Notice that the original and the projected outputs for the efficient schools are identical and therefore, the percentage difference is zero for the efficient schools. The 98th ranked school (school-164), for example, is only 85.9% efficient (or 14.1% technically inefficient). To improve its technical efficiency, School 164 needs to improve the average numeracy score of its Year 3 students from 321.75 to 374.63 points.

As an example of the procedure, I now show the calculation of the projected output for School 164. After solving an output-oriented linear programming of DEA, four schools have been identified as the role-models for School 164, namely, School 269, School 286, School 194 and School 173. The values of λ's (weights) for each of the identified role-model schools are 0.066, 0.107, 0.168 and 0.659, respectively. With the information of the values of λ's and the average test scores for each of the identified role-model schools at hand, the projected output for School 164 can be computed using equation (4.12) as follows: (0.066 x 384.6) + (0.107 x 375.75) + (0.168 x 390.8) + (0.659 x 369.33) = 374.63. Further, since the value of lamda for School 173 is the largest (0.659) as compared to the other identified role-model schools, School 164 should imitate School 173 more closely than the other schools as it strives towards greater efficiency.

Table 6.19: Ranking of Rural Schools based on the VRS-technical Efficiency Scores in 2007, output = *avg_num3*

Ranking	School code	VRS-technical efficiency	Original output	Projected output	% difference	Role-model count
1	321	1	398.91	398.91	0.00	76
2	198	1	390.80	390.80	0.00	8
3	278	1	388.00	388.00	0.00	2
4	272	1	384.60	384.60	0.00	16
5	021	1	381.00	381.00	0.00	22
6	333	1	380.00	380.00	0.00	11
7	090	1	377.09	377.09	0.00	27
8	299	1	375.75	375.75	0.00	3
9	398	1	371.67	371.67	0.00	3
10	175	1	369.33	369.33	0.00	5
11	123	1	360.84	360.84	0.00	2
12	027	1	342.48	342.48	0.00	0
13	189	1	336.33	336.33	0.00	0
14	142	1	335.30	335.30	0.00	0
15	276	0.996	393.55	395.25	0.43	0
16	186	0.991	393.10	396.69	0.91	0
17	029	0.986	380.21	385.53	1.38	0
18	165	0.982	383.73	390.67	1.78	0
19	033	0.978	379.60	388.09	2.19	0
20	043	0.976	389.14	398.67	2.39	0
21	412	0.975	381.50	391.39	2.53	0
22	191	0.973	382.00	392.69	2.72	0
23	094	0.973	379.71	390.36	2.73	0
24	131	0.966	385.19	398.91	3.44	0

cont.

25	334	0.966	379.18	392.66	3.43	0
26	112	0.966	364.67	377.67	3.44	0
27	247	0.964	369.43	383.42	3.65	0
28	394	0.959	367.66	383.45	4.12	0
29	314	0.958	380.86	397.55	4.20	0
30	173	0.958	371.90	388.22	4.20	0
31	286	0.957	374.00	390.67	4.27	0
32	172	0.955	362.79	379.95	4.52	0
33	336	0.951	378.60	398.17	4.92	0
34	114	0.949	378.40	398.53	5.05	0
35	109	0.949	361.84	381.17	5.07	0
36	248	0.948	371.40	391.69	5.18	0
37	411	0.948	368.25	388.52	5.22	0
38	028	0.945	377.11	398.91	5.46	0
39	124	0.942	368.54	391.39	5.84	0
40	018	0.941	375.30	398.91	5.92	0
41	317	0.939	374.38	398.91	6.15	0
42	091	0.939	365.14	388.79	6.08	0
43	416	0.937	371.79	396.76	6.29	0
44	410	0.936	348.75	372.73	6.43	0
45	113	0.932	371.75	398.91	6.81	0
46	073	0.931	357.67	384.22	6.91	0
47	239	0.93	371.13	398.91	6.96	0
48	179	0.928	357.00	384.53	7.16	0
49	096	0.927	369.60	398.91	7.35	0
50	225	0.927	349.25	376.77	7.30	0
51	057	0.926	369.34	398.91	7.41	0
52	111	0.925	361.40	390.65	7.49	0
53	005	0.925	350.80	379.07	7.46	0
54	407	0.925	346.00	374.02	7.49	0
55	115	0.924	368.76	398.91	7.56	0
56	419	0.924	361.33	390.88	7.56	0
57	140	0.923	368.12	398.91	7.72	0
58	408	0.923	362.40	392.84	7.75	0
59	794	0.921	356.02	386.35	7.85	0
60	069	0.92	367.00	398.91	8.00	0
61	240	0.92	351.71	382.20	7.98	0
62	377	0.919	363.00	394.97	8.09	0
63	016	0.918	365.78	398.65	8.25	0
64	275	0.917	365.67	398.91	8.33	0
65	075	0.916	365.43	398.77	8.36	0
66	053	0.916	355.50	387.92	8.36	0
67	074	0.915	365.13	398.91	8.47	0
68	302	0.915	365.10	398.91	8.47	0
69	236	0.915	362.34	396.04	8.51	0
70	136	0.911	331.20	363.73	8.94	0
71	149	0.91	362.95	398.91	9.01	0
72	020	0.91	362.94	398.91	9.02	0
73	269	0.91	355.60	390.70	8.98	0
74	316	0.907	359.67	396.46	9.28	0
75	322	0.906	361.59	398.91	9.35	0
76	310	0.906	361.28	398.91	9.43	0
77	403	0.905	360.84	398.91	9.54	0
78	193	0.905	357.43	394.96	9.50	0
79	277	0.898	357.77	398.40	10.20	0
80	409	0.898	351.75	391.52	10.16	0
81	046	0.897	353.00	393.54	10.30	0
82	227	0.894	341.43	381.71	10.55	0
83	330	0.893	353.31	395.69	10.71	0
84	023	0.893	348.86	390.72	10.71	0
85	313	0.892	355.78	398.91	10.81	0
86	379	0.891	350.00	392.82	10.90	0
87	318	0.891	346.79	389.38	10.94	0
88	194	0.89	354.27	398.24	11.04	0
89	014	0.89	352.00	395.72	11.05	0
90	203	0.89	351.56	394.97	10.99	0

cont.

91	056	0.888	350.11	394.25	11.20	0
92	044	0.885	345.00	389.96	11.53	0
93	126	0.881	351.61	398.91	11.86	0
94	024	0.871	330.50	379.56	12.93	0
95	176	0.87	346.88	398.91	13.04	0
96	132	0.868	341.33	393.18	13.19	0
97	327	0.867	344.40	397.12	13.27	0
98	164	0.859	321.75	374.63	14.11	0

Table 6.20: Ranking of Urban Schools based on the VRS-technical Efficiency Scores in 2007, output = *avg_num3*

Ranking	School code	VRS-technical efficiency	Original output	Projected output	% difference	Role-model count
1	397	1	408.73	408.73	0.00	56
2	170	1	387.26	387.26	0.00	10
3	135	1	382.11	382.11	0.00	7
4	319	1	380.05	380.05	0.00	1
5	071	1	373.04	373.04	0.00	15
6	141	1	367.93	367.93	0.00	49
7	003	1	364.88	364.88	0.00	0
8	134	1	356.38	356.38	0.00	0
9	054	1	341.35	341.35	0.00	0
10	253	0.987	399.90	405.18	1.32	0
11	195	0.983	390.79	397.39	1.69	0
12	045	0.978	374.39	382.72	2.22	0
13	199	0.969	379.33	391.44	3.19	0
14	323	0.968	376.92	389.22	3.26	0
15	406	0.966	375.33	388.69	3.56	0
16	087	0.965	392.73	406.96	3.62	0
17	052	0.962	354.06	367.93	3.92	0
18	255	0.96	390.49	406.96	4.22	0
19	374	0.957	391.10	408.73	4.51	0
20	160	0.955	386.78	405.18	4.76	0
21	229	0.953	389.44	408.73	4.95	0
22	192	0.948	385.98	407.19	5.50	0
23	196	0.945	365.94	387.15	5.80	0
24	279	0.945	362.80	383.90	5.82	0
25	200	0.942	380.18	403.41	6.11	0
26	395	0.942	368.00	390.61	6.14	0
27	791	0.942	361.75	383.90	6.12	0
28	017	0.94	363.13	386.49	6.43	0
29	147	0.935	380.43	406.96	6.97	0
30	177	0.935	372.40	398.36	6.97	0
31	315	0.935	366.16	391.70	6.98	0
32	133	0.933	357.22	382.85	7.17	0
33	022	0.93	365.17	392.77	7.56	0
34	190	0.929	360.03	387.45	7.62	0
35	144	0.927	370.50	399.86	7.92	0
36	284	0.923	355.85	385.67	8.38	0
37	174	0.92	374.35	406.96	8.71	0
38	035	0.919	373.82	406.96	8.86	0
39	086	0.919	352.81	383.90	8.81	0
40	178	0.916	372.67	406.96	9.20	0
41	030	0.915	365.11	399.16	9.32	0
42	858	0.914	363.74	398.09	9.44	0
43	168	0.913	371.57	406.96	9.52	0
44	019	0.911	369.22	405.18	9.74	0
45	399	0.911	341.57	374.82	9.73	0
46	159	0.91	355.53	390.82	9.93	0
47	231	0.905	360.90	398.77	10.50	0
48	002	0.904	343.84	380.35	10.62	0
49	289	0.903	364.93	404.28	10.78	0

cont.

50	281	0.901	366.76	406.96	10.96	0
51	201	0.901	358.53	398.09	11.03	0
52	335	0.899	365.79	406.96	11.25	0
53	233	0.896	364.83	406.96	11.55	0
54	378	0.893	365.02	408.73	11.98	0
55	282	0.893	342.92	383.90	11.95	0
56	400	0.89	344.75	387.45	12.38	0
57	197	0.89	344.16	386.66	12.35	0
58	404	0.889	363.51	408.73	12.44	0
59	001	0.886	352.55	398.09	12.92	0
60	287	0.884	346.06	391.44	13.11	0
61	129	0.883	360.81	408.73	13.28	0
62	328	0.875	351.28	401.64	14.33	0
63	050	0.874	354.24	405.18	14.38	0
64	025	0.874	330.73	378.54	14.46	0
65	417	0.864	351.47	406.96	15.79	0

6.2.4 Concluding Remarks on the DEA Analysis

Two methods of DEA estimations have been undertaken to evaluate the technical efficiency level of Tasmanian public primary schools. In the first method (called method A), I employed a two-stage DEA procedure where the first-stage involved a solution to the DEA linear programming problem as specified in equations (4.8) and (4.9). I have found that schools in Tasmania are on average 95% technically efficient under the VRS assumption. In the second-stage procedure, a Tobit regression has been undertaken with the purpose to estimate the effects of socio-economic environment on technical efficiency. Based on the VRS-technical efficiency scores obtained from the first-stage procedure as the dependent variable (models E, F, G and H), the effects of the following variables on technical efficiency have been found:

- positive effects of *mumwork* and *dadwork*;
- negative effects of *atsi*, *esl, disable, dadedu, absent* and *d_rural*, and
- no significant effects of *male, mumedu* and *susprate.*

The results from the second method (called method B) were obtained by dividing schools into rural and urban categories. The division is to ensure that schools under the same homogenous socio-economic environment are compared with one another. Under the method, I have found that urban schools are on average more CRS-efficient than rural schools, as shown in Figures 6.2 and 6.3. Urban schools also have been found to be more scale efficient than rural schools. The higher scale efficiency of urban schools indicates that fewer inputs of urban schools are wasted due to non-optimal school size. Lower scores of scale efficiency for rural schools as compared to urban schools imply that the problem of non-optimal school size is more prevalent among rural schools in Tasmania (due to remote location and low population density). In the next section, I provide a comparison of the SPF and the DEA results.

6.3 Comparison of SPF and DEA Results

I now turn to a comparison of technical efficiency scores from the estimated SPF and DEA. The purpose of the comparison is to evaluate any similarities or differences from the results generated by the two methods employed. The comparison is based on the summary statistics in Table 6.21 and the constructed rankings in Table 6.22. The summary statistics and the constructed ranking are based on the technical efficiency scores of SPF and DEA, where the output is *avg_lit3* in 2007. The output is chosen for the purpose of example only. A discussion based on the technical efficiency scores based on the output (*avg_lit3* in 2007) is emphasised because the scores are the lowest as compared to the other outputs (refer to Table 6.2) and in need of largest improvement.[18]

For comparative purposes, the technical efficiency scores from method A of DEA are used instead of those from method B. The reason for using the results of method A of DEA is because the cross-section of the sample (163 schools) is similar to

[18] In Appendix 6.2, I also provide rankings of schools based on the technical efficiency scores obtained using the other various outputs (*avg_lit5*, *avg_num3* and *avg_num5* in 2007).

the cross-section of schools in the SPF analysis. Under method B, however, the division into rural and urban schools means each respective group has 98 and 65 schools, which means that the number of schools under the DEA does not align with the number of schools under the SPF. In addition, for a more comparable analysis, the technical efficiency scores of DEA (method A) are also adjusted according to the estimated coefficient parameters obtained from the second-stage Tobit regression. The purpose of the adjustment is to incorporate the influence of the environmental factors into the DEA technical efficiency.[19] In order to derive the adjusted-VRS score (called VRS-adjusted) for each school *j*, the VRS-technical efficiency score of school *j* is added with the coefficient parameters multiplied by school *j*'s environmental variables that have a negative sign (*atsi, esl, disable, dadedu, susprate* and *absent*); and minus the coefficient parameters multiplied by school *j*'s environmental variables that have a positive sign (*male, mumwork, mumedu* and *dadwork*). Based on the estimated coefficients of model E in Table 6.16, the formula to derive the VRS-adjusted technical efficiency of school *j* is given by:

$$\begin{aligned}\text{VRS-adjusted}_j = {} & \text{VRS}_j + 0.0002\,atsi_j + 0.0014\,esl_j + 0.0019\,disable_j + \\ & 0.0003\,dadedu_j + 0.0002\,susprate_j + 0.0007\,absent_j + \\ & 0.0194\,d\_rural_j - 0.0001\,male_j - 0.0003\,mumwork_j - \\ & 0.0001\,mumedu_j - 0.0002\,dadwork_j \qquad (6.11)\end{aligned}$$

[19] Note that in the first-stage estimation of DEA, no influence of the environmental factors has been considered in the construction of the production technology. The level of technical efficiency of schools, however, may be influenced by the conditions of the socio-economic environment. The environmental factors, therefore, need to be considered by adjusting their effects on the DEA technical efficiency. The technical efficiency scores under the SPF, on the other hand, consider environmental factors in the inefficiency equation. As such, the SPF estimations produce technical efficiency scores that incorporate environmental factors.

To derive the adjusted-CRS scores (called CRS-adjusted), on the other hand, the CRS-technical efficiency score of school *j* is added with the coefficient parameters multiplied by school *j*'s environmental variables that have a negative sign (*atsi*, *esl*, *disable*, *male*, *mumedu*, *dadedu*, *susprate* and *absent*); and minus the coefficient parameters multiplied by school *j*'s environmental variables that have a positive sign (*mumwork* and *dadwork*. Based on the estimated coefficients of model A in Table 6.16, the formula to derive the VRS-adjusted technical efficiency of school *j* is given by:

$$\text{CRS-adjusted}_j = \text{CRS}_j + 0.0001atsi_j + 0.0024esl_j + 0.0036disable_j + 0.0002\,male_j + 0.0003mumedu_j + 0.0006dadedu_j + 0.0001susprate_j + 0.0013absent_j + 0.1815d\_rural_j - 0.0003mumwork_j - 0.0007dadwork_j \qquad (6.12)$$

Table 6.21: A Comparison of Technical Efficiency Scores based on Summary Statistics, Output = *avg_lit3* in 2007

Efficiency Scores	Obs	Mean	Std. Dev.	Min	Max
SPF	163	0.965	0.029	0.852	0.997
VRS-adjusted	163	0.962	0.035	0.871	1.028
CRS-adjusted	163	0.979	0.030	0.847	1.20
VRS (non-adjustment)	163	0.932	0.035	0.856	1.000
CRS (non-adjustment)	163	0.806	0.118	0.592	1.000

As shown in Table 6.21, after the adjustment is made to the VRS-technical efficiency scores, there is a significant but small difference of 0.03 between the average adjusted-VRS and the average non-adjusted VRS technical efficiency scores. The difference between the adjusted-CRS and non-adjusted CRS scores is 0.173. The higher adjusted-VRS and adjusted-CRS (as compared to the non-adjusted scores) imply the negative influences of the socio-economic disadvantage outweigh the positive influences of the socio-economic advantage surrounding schools. After controlling for the net effects of the socio-economic environment, there is an upward increase in the average technical efficiency scores of schools in Tasmania, as shown by the higher average adjusted-VRS score than the the average non-adjusted VRS score.

Another observation of the results in Table 6.21 is the smaller difference between the average technical efficiency scores obtained under the SPF and the adjusted-VRS DEA (a difference of 0.003) as compared to the difference between the SPF and the non-adjusted VRS DEA (a difference of 0.043). The smaller difference between the SPF and the adjusted-VRS DEA implies that only after adjusting for the socio-economic environment surrounding schools, are the results between the two approaches more comparable.

In Table 6.22, three rankings of schools, constructed based on the technical efficiency scores under the SPF, the adjusted-VRS and the adjusted-CRS are shown—columns 2, 3 and 4. The first column is the school code used by the Department of Education, Tasmania. The ranking position of each school is given in columns 5, 6 and 7. As shown in the table, School 170 is ranked first under the SPF model with a technical efficiency of 0.9972. Based on the adjusted-VRS technical efficiency score, the same school is ranked fifth with an adjusted VRS score of 1.0281. On the basis of the non-adjusted VRS score, School 170 is ranked eleventh with a VRS score of one (the information is not provided in Table 6.22 to preserve space). The last ranked school based on the SPF and the adjusted-VRS technical efficiencies is one of the same—School 164. The technical efficiency scores for School 164 under the SPF, the adjusted-VRS and the non-adjusted VRS are 0.8524,0.8782 and 0.856. Under the non-adjusted VRS score, School 164 is ranked 162nd (the information is not provided to preserve space). Note that the same school (School 164) was also ranked last, based on method B of DEA as shown in Table 6.19.

In order to investigate the degree of correlation as well as the direction of the correlation of the rankings, Pearson's correlation coefficient has been computed based on the rankings. The Pearson's correlation matrix is presented in Table 6.23. Also in Table 6.23 are the correlations of school rankings under the non-adjusted DEA technical efficiency (the scores are not presented in Table 6.22 to preserve space). As shown in Table 6.23, higher correlations of school rankings have been recorded after an adjustment is made to the DEA technical efficiency scores. The correlation between the SPF ranking, for example, is only 0.6296 with the non-adjusted VRS ranking but the correlation improves to 0.8221 after the adjustment (the change is large). The highest correlation is obtained between the SPF and adjusted-VRS rankings, suggesting comparability of results despite of the methodological differences inherent in the two methods.

An investigation based on the other outputs (*avg_lit5*, *avg_num3* and *abg*_num5) also found robust and high correlation coefficients between the SPF and adjusted-VRS DEA rankings. In Appendix 6.2, I present the school rankings based on the SPF and adjusted-VRS DEA technical efficiency scores based on the various outputs. The correlation coefficients of the rankings between the SPF and adjusted-VRS DEA are 0.75, 0.72 and 0.72 for each respective output. A significant improvement in the correlation coefficients is recorded after an adjustment was made to the VRS technical efficiency scores according to schools' socio-economic environment.

From the comparison of the school ranking, as shown in Tables 6.2, 6.3 and Appendix 6.2, the ranking position of schools varies, depending on the techniques employed to measure technical efficiency. The difference in the ranking position across the various estimation techniques remains significant even after adjusting for the socio-economic conditions surrounding schools.

One important point to note from the exercise is that an evaluation of school performance based on school ranking is sensitive to the technique used. Significant difference in the rankings can be attributed to: (i) the different ways how the SPF and DEA techniques discriminate between schools in the construction of the production frontiers (refer to Chapter 4 for the discussion on the theoretical frameworks of the two techniques), and (ii) the different approaches how the SPF and DEA control for the environmental factors.

Table 6.22: Ranking of Schools based on Technical Efficiency Scores, Output = *avg_lit3* in 2007

School Code	SPF	VRS_adj	CRS_adj	SPF Rank	VRS_adj Rank	CRS_adj Rank
170	0.9972	1.0282	1.0146	1	5	34
87	0.9967	1.0127	0.9930	2	29	44
253	0.9963	1.0117	0.9584	3	30	78
231	0.9960	1.0269	1.0090	4	7	40
200	0.9958	1.0061	0.9614	5	35	70
397	0.9955	1.0152	0.9496	6	26	89
174	0.9951	1.0048	0.9640	7	38	68
229	0.9950	1.0110	0.9924	8	32	45
160	0.9949	1.0197	0.9593	9	20	75
147	0.9944	1.0146	0.9553	10	27	83
173	0.9941	1.0288	1.0097	11	4	39
135	0.9941	1.0154	1.0235	12	24	27
165	0.9941	0.9961	0.9325	13	51	105
43	0.9940	1.0301	0.9174	14	3	119
186	0.9939	1.0204	0.9340	15	17	103
281	0.9938	1.0094	0.9561	16	33	82
22	0.9936	1.0052	1.0172	17	37	30
168	0.9935	1.0218	0.9551	18	13	84
195	0.9934	0.9950	0.9590	19	53	76
255	0.9931	0.9792	0.9682	20	82	63
378	0.9930	0.9846	0.9408	21	68	99
201	0.9928	0.9977	1.0250	22	47	26
316	0.9921	1.0353	1.0164	23	2	31
302	0.9920	0.9865	0.8549	24	64	160
335	0.9920	1.0223	0.9863	25	11	49
19	0.9919	0.9887	0.9221	26	61	112

cont.

794	0.9919	0.9926	1.0156	27	58	33
233	0.9918	0.9949	0.9608	28	55	73
57	0.9918	0.9971	0.9193	29	50	116
374	0.9917	0.9832	0.9197	30	71	115
133	0.9917	1.0054	1.0382	31	36	20
198	0.9916	1.0270	1.0835	32	6	9
310	0.9914	1.0038	0.9254	33	40	110
3	0.9906	1.0151	1.0144	34	25	35
199	0.9903	1.0181	0.9716	35	21	58
276	0.9901	1.0207	0.9330	36	14	104
327	0.9901	0.9732	0.8799	37	90	147
96	0.9896	0.9944	0.8731	38	56	150
284	0.9895	0.9762	0.9783	39	85	52
35	0.9892	0.9830	0.9613	40	73	71
178	0.9881	0.9798	0.9493	41	80	90
29	0.9876	1.0001	0.9788	42	43	51
109	0.9873	0.9804	1.0426	43	77	18
333	0.9873	1.0240	1.1995	44	10	1
126	0.9872	0.9803	0.8986	45	78	136
394	0.9871	0.9917	1.0193	46	59	29
314	0.9869	0.9949	0.9109	47	54	130
94	0.9868	1.0036	0.9656	48	41	67
144	0.9866	0.9688	0.9718	49	97	57
16	0.9865	0.9836	0.9268	50	70	109
196	0.9864	0.9813	0.9775	51	75	53
140	0.9860	0.9985	0.8572	52	46	159
73	0.9859	1.0177	1.0482	53	22	16
192	0.9857	0.9830	0.9674	54	72	64
177	0.9856	0.9798	0.9609	55	81	72
299	0.9854	1.0242	1.1994	56	9	2
416	0.9848	1.0176	0.9112	57	23	129
321	0.9841	1.0080	0.9769	58	34	54
17	0.9841	0.9771	0.9923	59	84	46
175	0.9837	1.0206	1.1911	60	15	4
272	0.9829	1.0204	1.0528	61	18	14
323	0.9828	0.9815	0.9920	62	74	47
149	0.9818	0.9976	0.8901	63	48	140
20	0.9813	0.9953	0.8967	64	52	137
319	0.9813	1.0111	1.0040	65	31	42
21	0.9808	1.0264	1.1018	66	8	8
129	0.9806	0.9661	0.9578	67	101	80
124	0.9802	1.0042	0.9696	68	39	60
322	0.9798	0.9996	0.9158	69	45	123
74	0.9791	0.9802	0.9152	70	79	125
18	0.9786	0.9941	0.8732	71	57	149
412	0.9783	0.9997	0.9311	72	44	108
50	0.9769	0.9588	0.9449	73	107	94
247	0.9766	0.9907	1.0134	74	60	37
317	0.9757	0.9852	0.9188	75	66	118
71	0.9756	1.0369	1.0431	76	1	17
398	0.9754	1.0218	1.1974	77	12	3
69	0.9754	0.9741	0.9044	78	88	133
236	0.9752	0.9644	0.8261	79	103	163
45	0.9745	0.9757	1.0105	80	86	38
248	0.9744	0.9866	0.9515	81	63	86
75	0.9744	0.9805	0.9209	82	76	114
330	0.9738	0.9537	0.8603	83	116	158
377	0.9737	0.9852	0.8840	84	67	145
30	0.9733	0.9660	0.9429	85	102	96
313	0.9730	0.9691	0.8451	86	95	161
44	0.9725	1.0003	0.9695	87	42	61
90	0.9719	0.9782	1.0372	88	83	21
131	0.9717	0.9865	0.9325	89	65	106
123	0.9712	0.9567	1.1201	90	114	5
114	0.9712	0.9844	0.8852	91	69	142
86	0.9708	0.9530	0.9629	92	117	69

cont.

141	0.9703	1.0144	1.0202	93	28	28
113	0.9698	0.9741	0.8757	94	89	148
404	0.9684	0.9521	0.9395	95	118	101
179	0.9682	0.9724	1.0049	96	92	41
328	0.9666	0.9254	0.9093	97	146	132
28	0.9658	0.9592	0.8649	98	106	154
395	0.9649	0.9581	0.9505	99	108	87
134	0.9648	1.0197	1.0355	100	19	22
289	0.9647	0.9595	0.9498	101	105	88
46	0.9647	0.9686	0.8875	102	98	141
172	0.9634	0.9696	1.0282	103	94	25
406	0.9615	0.9883	0.9472	104	62	91
190	0.9614	0.9395	0.9409	105	136	98
287	0.9582	0.9721	0.9423	106	93	97
417	0.9578	0.9454	0.9224	107	128	111
279	0.9569	0.9437	0.9471	108	130	92
858	0.9550	0.9422	0.9448	109	133	95
159	0.9549	0.9412	0.9590	110	135	77
336	0.9546	0.9677	0.8844	111	100	144
112	0.9541	0.9973	1.1125	112	49	6
115	0.9534	0.9459	0.8697	113	126	152
278	0.9533	0.9755	0.9972	114	87	43
203	0.9525	0.9574	0.8728	115	110	151
400	0.9521	0.9394	0.9466	116	138	93
403	0.9517	0.9569	0.8605	117	112	157
277	0.9508	0.9679	0.9130	118	99	128
56	0.9494	0.9725	0.9354	119	91	102
399	0.9486	0.9485	0.9756	120	121	55
334	0.9484	0.9689	0.8848	121	96	143
318	0.9483	0.9456	0.9562	122	127	81
1	0.9481	0.9159	0.9025	123	154	134
136	0.9479	0.9162	1.0727	124	153	12
111	0.9471	0.9568	0.9701	125	113	59
791	0.9461	0.9171	0.9314	126	152	107
227	0.9451	0.9391	1.0156	127	139	32
408	0.9439	0.9394	0.9151	128	137	126
25	0.9437	0.9574	0.9689	129	109	62
14	0.9414	0.9491	0.9160	130	120	122
315	0.9414	0.9462	0.9000	131	125	135
91	0.9404	0.9602	0.9916	132	104	48
2	0.9397	0.9204	0.9166	133	150	120
142	0.9395	0.9102	1.0622	134	156	13
52	0.9377	0.9570	0.9747	135	111	56
407	0.9373	0.9216	1.0298	136	148	24
379	0.9366	0.9439	0.8626	137	129	155
191	0.9364	0.9540	0.9403	138	115	100
176	0.9363	0.9474	0.8327	139	123	162
286	0.9361	0.9386	0.8928	140	140	139
409	0.9344	0.9496	0.9603	141	119	74
269	0.9326	0.9364	0.9530	142	141	85
239	0.9325	0.9478	0.8946	143	122	138
54	0.9325	1.0205	1.0383	144	16	19
275	0.9291	0.9429	0.8655	145	132	153
194	0.9281	0.9470	0.9105	146	124	131
27	0.9256	0.9052	1.0524	147	159	15
132	0.9245	0.9279	0.8611	148	144	156
282	0.9238	0.9082	0.9131	149	158	127
197	0.9230	0.9157	0.9219	150	155	113
411	0.9221	0.9273	0.9163	151	145	121
24	0.9203	0.9416	1.0298	152	134	23
225	0.9162	0.9434	1.0785	153	131	10
33	0.9106	0.9188	0.9157	154	151	124
419	0.9092	0.9245	0.9580	155	147	79
53	0.9026	0.9302	0.9669	156	143	65
189	0.9015	0.9332	1.1018	157	142	7
5	0.9010	0.9096	1.0137	158	157	36

cont.

410	0.8946	0.9211	1.0746	159	149	11
193	0.8893	0.8914	0.8839	160	162	146
23	0.8876	0.8990	0.9189	161	161	117
240	0.8819	0.9026	0.9660	162	160	66
164	0.8524	0.8782	0.9821	163	163	50

Table 6.23: Correlation Coefficient Matrix for the Rankings, Output = *avg_lit3* in 2007

	SPF	VRS_adj	VRS (non-adjusted)	CRS_adj	CRS (non-adjusted)
SPF	1				
VRS_adj	0.8221	1			
VRS (non-adjusted)	0.6296	0.8247	1		
CRS_adj	0.2424	0.2928	0.3352	1	
CRS (non-adjusted)	0.149	0.2543	0.4859	0.6975	1

6.4 Conclusion

On the basis of a comparison of the estimations of the SPF and DEA models, high technical efficiency scores for public primary schools in Tasmania have been found. The average technical efficiency score for the studied period has been constant at 0.96 (or 96%) under the SPF and 0.95 (or 95%) under the VRS-DEA estimations (applied for both methods A and B of DEA). The constant technical efficiency score under the SPF and DEA also implies no technical efficiency change in the educational sector over the study period. In other words, there has been no shift in the Tasmanian educational production frontier from 2003 to 2007.

Based on the analysis of the determinants of technical efficiency, negative effects of socio-economic disadvantaged on technical efficiency have been found. Schools characterised with higher percentage of Aboriginal and Torres Strait Islander students (*atsi*); higher percentage of students who had English as the Second Language (*esl*); higher percentage of students with severe disability (*disable*); schools with high suspension (*susprate*) and absenteeism (*absent*) rates; and rural schools (*d_rural*) are technically less efficient. The unfavourable socio-economic environment, as characterised by those variables may contribute to inefficiency by requiring more resources at the school to be devoted to management issues rather than learning.

The only factor that has a positive effect on technical efficiency from the eleven environmental variables considered in the SPF and Tobit regressions was *mumwork* (the number of mother who worked in professional and management jobs).

No conclusive evidence have been found for the effects of gender (*male*), mother's education (*mumedu*) and father's work (*dadwork*) on schools' technical efficiency. Those socio-economic factors found to be significant need to be taken into account when evaluating school performance. In Section 6.3, it was found that even after controlling for the socio-economic difference, the constructed school rankings based on the SPF, the adjusted-VRS and the adjusted-CRS of DEA remained significant (in terms of school ranking position). Two points may explain the significant difference in the school ranking position from the various techniques employed in Section 6.3. Firstly, the basis of how the SPF and DEA techniques discriminate between schools in the construction of the production frontiers (refer to Chapter 4 for the discussion on the theoretical frameworks of the two techniques) matters, and secondly, the methodologies employed under the SPF and DEA to control for the environmental factors along different lines. It is therefore not surprising that the SPF and DEA approaches do not provide consistent ranking.

From the exercise, I also found that the SPF is a more favourable approach to measure technical efficiency. The approach accounts for the environmental effects in the estimation of technical efficiency without requiring a second-stage procedure as it is in DEA.

Appendix 6.1: Formulae used to Construct the School-Level Data

The purpose of this appendix is to indicate the definitions of the dependent variables used in the construction of the school-level data from the student-cohort level data provided by the Department of Education, Tasmania.

Variables	Formula
Average literacy of Year 3 (*avg_lit3*$_{jt}$)	$\frac{\sum_{i=1}^{n}\left(read3_{ijt} + write3_{ijt}\right)}{n_{jt}}$
Average literacy of Year 5 (*avg_lit5*$_{jt}$)	$\frac{\sum_{i=1}^{n}\left(read5_{ijt} + write5_{ijt}\right)}{n_{jt}}$
Average numeracy of Year 3 (*avg_num3*$_{jt}$)	$\frac{\sum_{i=1}^{n}\left(numer3_{ijt}\right)}{n_{jt}}$
Average numeracy of Year 5 (*avg_num5*$_{jt}$)	$\frac{\sum_{i=1}^{n}\left(numer5_{ijt}\right)}{n_{jt}}$
Average number of days absent for Year 3	$\frac{\sum_{i=1}^{n}\left(absent3_{ijt}\right)}{n_{jt}}$
Average number of days absent for Year 5	$\frac{\sum_{i=1}^{n}\left(absent5_{ijt}\right)}{n_{jt}}$

Note:

- $read3_{ijt}$ and $write3_{ijt}$ are the reading and writing scores of the i^{th} Year 3 student in school j at time t
- $read5_{ijt}$ and $write5_{ijt}$ are the reading and writing scores of the i^{th} Year 5 student in school j at time t
- $numer3_{ijt}$ is the numeracy score of the i^{th} Year 3 student in school j at time t
- $numer5_{ijt}$ are the numeracy scores of the i^{th} Year 5 student in school j at time t
- $numer3_{ijt}$ is the numeracy score of the i^{th} Year 3 student in school j at time t
- n_{jt} is the number of students who take the examination in school j at time t (i = 1, …, n)
- School j (j = 1, …, 163)
- Year t (t = 2003, 2005, 2007)

Appendix 6.2: School Rankings based on the SPF and the Adjusted-VRS Technical Efficiency Scores

Output	*avg_lit3* in 2007		*avg_lit5* in 2007		*avg_num3* in 2007		*avg_num5* in 2007	
School Code	SPF Rank	VRS_adj Rank	SPF Rank	VRS_adj Rank	SPF Rank	VRS_adj Rank	SPF Rank	VRS_adj Rank
1	123	154	96	140	120	150	105	155
2	133	150	136	156	117	140	106	127
3	34	25	33	19	80	12	23	12
5	158	157	156	149	156	131	147	137
14	130	120	113	118	144	153	123	124
16	50	70	90	121	78	113	100	140
17	59	84	47	71	69	46	47	74
18	71	57	94	99	103	95	132	141
19	26	61	11	25	40	71	31	63
20	64	52	60	50	102	107	69	59
21	66	8	112	54	72	26	104	83
22	17	37	34	86	25	68	33	105
23	161	161	139	139	158	151	125	94
24	152	134	162	161	162	160	163	163
25	129	109	91	105	160	158	154	142
27	147	159	102	133	134	156	114	131
28	98	106	123	145	73	87	79	126
29	42	43	75	61	21	19	51	66
30	85	102	83	88	115	96	75	50
33	154	151	53	39	128	53	134	111
35	40	73	25	47	29	56	22	48
43	14	3	26	23	18	16	32	68
44	87	42	131	98	150	145	124	88
45	80	86	37	56	34	27	24	20
46	102	98	107	93	130	137	130	143
50	73	107	62	101	87	127	50	22
52	135	111	81	76	101	82	141	154
53	156	143	147	141	147	126	131	116
54	144	16	111	8	155	8	133	132
56	119	91	108	80	116	98	74	55
57	29	50	59	70	37	90	49	44
69	78	88	80	90	59	88	65	97
71	76	1	58	3	51	1	41	41
73	53	22	152	131	124	102	156	115
74	70	79	63	95	114	128	56	54
75	82	76	41	34	50	70	44	40
86	92	117	73	106	63	86	83	121
87	2	29	4	64	1	6	2	3
90	88	83	109	103	86	89	95	100
91	132	104	127	129	133	97	112	110
94	48	41	117	128	74	81	81	113
96	38	56	43	49	14	39	17	16
109	43	77	138	148	83	136	139	146
111	125	113	155	151	146	120	159	130
112	112	49	84	7	118	57	82	5
113	94	89	120	142	98	105	97	125
114	91	69	76	83	85	78	77	93
115	113	126	29	44	91	116	68	80
123	90	114	146	150	49	115	151	145
124	68	39	125	79	67	66	144	112
126	45	78	118	127	60	111	118	120
129	67	101	21	55	75	117	35	95
131	89	65	122	138	79	52	120	135
132	148	144	158	155	153	157	162	162
133	31	36	51	97	70	60	80	148
134	100	19	133	17	93	22	129	129

cont.

135	12	24	38	20	43	13	26	10
136	124	153	134	154	142	161	137	159
140	52	46	49	45	42	47	45	56
141	93	28	70	32	68	17	61	52
142	134	156	149	159	127	163	150	156
144	49	97	30	78	44	83	54	114
147	10	27	3	2	5	4	6	24
149	63	48	56	36	27	63	62	33
159	110	135	129	158	92	110	111	161
160	9	20	13	10	17	20	13	15
164	163	163	153	73	163	162	128	70
165	13	51	77	108	24	25	58	38
168	18	13	36	42	41	45	43	103
170	1	5	2	5	4	2	3	2
172	103	94	82	69	106	123	101	90
173	11	4	31	12	8	18	11	6
174	7	38	12	46	23	59	12	73
175	60	15	159	16	132	38	158	85
176	139	123	126	110	121	124	85	107
177	55	81	57	87	53	48	39	89
178	41	80	44	58	64	76	40	49
179	96	92	71	67	100	125	53	46
186	15	17	7	6	3	5	16	14
189	157	142	124	27	161	144	138	28
190	105	136	65	107	77	92	117	138
191	138	115	132	134	107	55	107	81
192	54	72	89	96	39	36	57	82
193	160	162	105	109	149	143	115	101
194	146	124	69	51	152	135	91	35
195	19	53	46	85	12	11	19	18
196	51	75	66	104	56	54	93	144
197	150	155	130	143	140	133	92	119
198	32	6	55	53	71	21	63	43
199	35	21	32	21	58	42	28	37
200	5	35	5	29	13	49	4	32
201	22	47	10	66	26	103	27	7
203	115	110	145	114	84	104	140	47
225	153	131	163	153	157	121	161	134
227	127	139	128	113	135	154	136	123
229	8	32	20	81	6	30	15	17
231	4	7	27	43	22	29	30	78
233	28	55	16	28	36	50	14	64
236	79	103	72	92	66	108	48	117
239	143	122	48	41	126	101	70	71
240	162	160	144	89	139	134	157	51
247	74	60	68	48	54	51	55	57
248	81	63	119	115	90	80	127	133
253	3	30	1	4	2	3	1	1
255	20	82	18	65	9	44	20	60
269	142	141	104	94	145	148	121	92
272	61	18	39	26	108	40	64	27
275	145	132	151	147	138	119	119	84
276	36	14	74	63	33	28	60	75
277	118	99	148	137	143	130	135	79
278	114	87	154	146	96	31	153	122
279	108	130	140	152	82	85	148	158
281	16	33	6	9	15	15	5	9
282	149	158	141	157	137	149	152	160
284	39	85	50	91	61	112	52	72
286	140	140	116	77	81	65	146	91
287	106	93	86	72	151	142	109	96
289	101	105	42	33	76	61	34	4
299	56	9	88	14	122	32	126	13
302	24	64	35	62	30	93	37	77
310	33	40	23	13	32	62	29	8
313	86	95	103	120	52	132	67	104

cont.

314	47	54	22	15	45	69	46	31
315	131	125	150	144	112	77	89	86
316	23	2	17	1	19	9	38	30
317	75	66	114	125	104	91	88	58
318	122	127	135	136	136	155	122	128
319	65	31	9	24	35	10	18	11
321	58	34	121	123	48	24	96	45
322	69	45	61	35	46	58	42	39
323	62	74	54	74	16	23	76	108
327	37	90	8	38	10	100	9	21
328	97	146	67	135	113	152	71	147
330	83	116	100	130	57	118	59	118
333	44	10	115	18	89	34	102	102
334	121	96	98	102	99	64	99	53
335	25	11	24	11	20	14	21	36
336	111	100	52	52	109	79	84	62
374	30	71	15	37	11	35	8	25
377	84	67	93	57	88	84	116	65
378	21	68	14	59	31	74	7	23
379	137	129	142	119	141	147	155	106
394	46	59	28	31	28	67	36	34
395	99	108	45	60	105	73	66	61
397	6	26	19	22	7	7	10	26
398	77	12	106	30	129	37	103	29
399	120	121	97	126	131	129	113	149
400	116	138	143	160	123	146	142	157
403	117	112	85	82	110	114	73	69
404	95	118	40	75	65	94	25	19
406	104	62	101	100	94	41	86	76
407	136	148	110	132	125	159	90	109
408	128	137	95	112	119	139	108	136
409	141	119	157	162	154	141	149	153
410	159	149	160	124	159	106	98	99
411	151	145	92	84	95	75	94	42
412	72	44	137	117	55	33	143	151
416	57	23	87	40	62	43	87	67
417	107	128	78	111	111	138	72	139
419	155	147	161	163	148	122	160	150
791	126	152	79	122	38	72	145	152
794	27	58	64	68	47	109	78	98
858	109	133	99	116	97	99	110	87
Correlation coefficient	0.82		0.75		0.72		0.73	

7 Conclusions

7.0 Introduction

In this chapter, I offer some general concluding remarks about the research. The purpose of the exercise is to re-emphasise the findings in light of the research questions.

The chapter is organised as follows. In Section 7.1, the overview of the research is presented. The discussion in the section covers the highlights from each chapter of the thesis. The section also summarises the direction of the foregoing research. In Section 7.2, policy implications of the research are discussed. Based on the estimation results in Chapter 5 and 6, in particular, suggestions on the potential policy plans for Tasmanian schools are offered. A discussion on the limitations and direction for future research is offered in Section 7.3. In the section, there is a discussion of the constraints that were encountered in conducting the research. Some suggestions to future researchers on the potential ways how the research could be improved or refined are also presented in the section. Some final remarks are also provided in the section.

7.1 Overview

This research was motivated by the rising concerns of various interested parties (such as parents, teachers and politicians) in Tasmania in light of the low Tasmanian students' academic achievement. The performance of Tasmanian students from 2000 to 2007 did not meet the targets as set in the Tasmanian Together Goals and Benchmark. With the concern in mind, I embarked on the research with the following objectives: (i) to identify the determinants of students' academic achievement, in particular, the effects of education expenditure on students' academic achievement, (ii) to evaluate the level of technical efficiency of Tasmanian public schools, and (iii) to identify factors that influence schools' technical efficiency.

The seven chapters of the thesis deal with the foregoing broad research issues. In Chapter 2, I discussed the Tasmanian educational system, analysed Tasmanian students' academic achievement and outlined the state government's commitment towards education from year 2000 to 2007. The chapter set the backdrop for the study and provided insight into the issues that had sparked the motivation behind the research. To model the educational production technology, the discussion in Chapters 3 and 4 proceeded with a review of the extant literature on educational production function and schools' efficiency evaluation. The two chapters provided the theoretical foundations of the models to be employed in Chapters 5 and 6, and the practical approaches to employing the models in empirical research.

In Chapter 5, the primary objective of the analysis was to evaluate the effects of school resources, in particular education expenditure, on students' academic achievement. First, I demonstrated, using equations (5.13), (5.14) and (5.15), that the measure based on school financial resource per student (instead of total school financial resource) was the appropriate variable to be employed in estimating the effects of educational expenditure on students' academic achievement. The financial variable employed, *percapita* (educational spending per student) measures the degree to which the educational expenditure acts as a private good for students. From the estimation of educational production function, I found evidence of positive and significant effects of *percapita* on reading, writing and numeracy performance. A 1% increase in *percapita* spending has a 1.22% increase on reading, 0.84% increase on writing and 1.12% increase on numeracy scores, *ceteris paribus.*

Parental education was another factor found to affect literacy and numeracy in a positive direction. The variables with significant negative effects on literacy and numeracy, on the other hand, were the gender of a student (male students on average performed less well than female students); the indigenous status of a student (an indigenous student on average scored lower than the non-indigenous student); the number of days a student absent from school; the number of students who had English as a Second Language in a school, and the level of suspension rates. With the identification of the variables that significantly affect a student's academic achievement, a recommendation to the DoE, Tas, is to evaluate the existing policies in light of the findings. In Section 7.2, I discuss some tentative policy recommendations based on the findings.

As found in Chapter 5, school resources significantly affect students' academic achievement. The analysis in Chapter 5 however, did not provide any insight as to whether resources were efficiently utilised. The analysis in Chapter 6 investigated the matter of efficiency. In Chapter 6, I estimated the technical efficiency of the 163 public primary schools in Tasmania, using the Stochastic Production Frontier (SPF) and Data Envelopment Analysis (DEA). The average level of technical efficiency of Tasmanian public primary schools was high and stable across the study periods 2003, 2005 and 2007. Based on the estimation of SPF, the average technical efficiency was constant at 96%, while based on the DEA method, it was 95%. The constant average technical efficiency score implies no technical efficiency change in the educational sector over the period.

In analysing the level of technical efficiency of schools in Tasmania, socio-economic factors of students in a school need to be considered. Technical efficiency of public primary schools in Tasmania has been negatively affected by the number of Aboriginal and Torres Strait Islander students (*atsi*); the number of students who had English as the Second Language (*esl*); the number of students with severe disability (*disable*); suspension (*susprate*) and absenteeism (*absent*) rates; the percentage of fathers with tertiary qualification (*dadedu*); and rural schools (*d_rural*). The only factor that had a positive effect on technical efficiency from the eleven environmental variables considered in the SPF and Tobit regressions is *mumwork* (the number of mother who worked in professional and management jobs).

In the remainder part of this chapter, I discuss the policy implications and recommendations of the research to Tasmanian schools, limitations of the research, recommendations for future research and the overall conclusion of the study.

7.2 Policy Implications of the Findings

In this section I discuss the policy implications of the results generated in Chapters 5 and 6. The purpose of the discussion is to shed some tentative suggestions on potential policy plans for Tasmanian schools. In considering the suggestions made, note that the costs that may involve in the pursuit of any suggested policy are not part of the analysis of this research. To do so would make an already long thesis unfashionably longer. I therefore caution the need for a thorough cost-benefit justification for an implementation of any suggested policy.

Based on the estimation of educational production function in Chapter 5, two strands of policy to improve Tasmanian students' literacy and numeracy performance are suggested. First, short-run policy can be derived from the evidence of positive effects of educational expenditure on students' academic achievement. An immediate response is possible since the variable *percapita* is directly under the control of the Department of Education, Tasmania (DoE, Tas). Based on the FE polynomial estimations (Appendix 5.2), at the 2006 average *percapita* of $248.02, a 1% increase (which is equivalent to $2.48 real dollar increase per student) in *percapita* affects reading, writing and numeracy scores by 1.18%, 1.12% and 0.88%, *ceteris paribus*. Since I have found a diminishing effect of more monies under the *percapita* category on a student's reading and numeracy scores, the DoE, Tas needs to note that the marginal benefit of spending per student is diminishing for every dollar increase per student. Increased educational expenditure therefore, is indispensable but there are limitations of the effect of the variable on students' academic achievement.

A policy that aims at a reduction in the disciplinary problem of students seems to be warranted to improve Tasmanian students' academic achievement. The data suggests a negative relationship between low disciplinary level and students' academic achievement as captured by the variables *absent* and *susprate*. From the results in Table 5.10, a 1% reduction in the the number of days absent from school is associated with an increase in a student's reading, writing and numeracy scores by 0.18%;, 0.22% and 0.17%, *ceteris paribus.* A reduction in serious disciplinary problems (that lead to suspension from school) by 1% has a positive effect on reading, writing and numeracy scores by 0.07%, 0.09% and 0.07%, *ceteris paribus*.

Second, the variables *d_male* (the gender a student), *d_indig* (the indigenous status of a student), *esl* (the number of students who had English as a Second Language), *mumedu* and *dadedu* (parental education) are simply out of reach of the DoE, Tas. policy. An intervention policy to tackle the above socio-economic variables is simply not feasible. To suggest a social re-engineering that involve *d_male*, *d_indig*, *esl*, *mumedu* and *dadedu*, for example, is either politically unacceptable or ethically dubious. Further, the effects of the variables are small for such a policy to be considered. The findings nevertheless remain crucial as evidence of the need to take into account of disadvantages in socio-economic conditions in funding allocations to schools.

In Chapter 6, the results of high and stable level of technical efficiency of schools in Tasmania imply that the room for improvement is small. Schools therefore need to sustain the high level of technical efficiency.

The estimates of the inefficiency model and Tobit regression in Chapter 6 identified the negative effects between the disadvantaged socio-economic environment (such as *atsi*, *esl*, *disable* and *d_rural*) and technical efficiency. In comparing school performance, it is therefore necessary to take into account the influence of the socio-economic environment attributed to the school. Once the technical efficiency has been adjusted according to the influence of the socio-economic environment, the measure is no longer confounded by the environmental effects. As a result, the performance of schools is more comparable. The DoE, Tas. therefore should take into account the socio-economic conditions surrounding schools in making a ranking-based comparison of schools' performance.

The estimation based on the Tobit model also found rural schools were relatively inefficient as compared to urban schools. In an effort to improve the technical efficiency of rural schools, the following suggestions merit consideration:

i) The analysis of Table 6.19 in Section 6.2.3 gives the projected output (numeracy score) for each rural school in order for them to improve their technical efficiency. Since the figures are computed based on the role-model schools that act as peers to the identified inefficient schools, the projected output figures give a measurable and achievable target. The figures can be used as a key performance indicator.

ii) Policies that address the issue of non-optimal school size, particularly prevalent among rural schools (refer to Section 6.2.3 for the analysis) needs to be considered. Low population density in the rural area is the reason why rural primary schools in Tasmania are scale inefficient as compared to urban schools.

I also caution of the use of school ranking as a way to measure school performance. As shown in Tables 6.22 and Appendix 6.2, the ranking position of schools varies, depending on the techniques employed to measure technical efficiency. Even after adjusting for the socio-economic conditions surrounding schools, the difference in the ranking position across the various estimation techniques remains significant. As such, prior knowledge of the technique used to construct the school ranking is important in order to avoid any misleading conclusion about school performance. The explanation for the significant difference in the rankings can be attributed to: (i) the different ways how the SPF and DEA techniques discriminate schools in the construction of the production frontiers, and (ii) the different approaches how the SPF and DEA control for the environmental factors. With the above suggestions in mind, I discuss the limitations and direction for future research in the next section.

7.3 Limitations and Direction for Future Research

The underlying theoretical foundation of the study assumes the existence of an educational production function. The estimation of the function in the study is limited by the availability of input data in the area of education. Although I have used panel data for the estimations, caution needs to be exercised when interpreting the results. The use of test scores as an output of education is narrow in representing the scope and objectives of education. Much broader objectives of education, such as in producing a resilient, happy, active and law-abiding citizen, may not be captured by the test scores. The implication of employing such a narrow measure of performance is that excellence performance in non-academic areas is ignored by the analysis. In terms of input data, I had exhaustively employed the available input data at hand. The data on teacher characteristics (such as teacher experience and qualification) however, were not available even though I had requested such data from the DoE, Tas. The data on teacher characteristics is important because as shown in research elsewhere, knowledge transmission depends on the quality of teacher (in terms of the teaching techniques, attitude towards students and motivation). Whether that is also true in the Tasmanian case is still an open question.

Caution needs to be exercised when interpreting the results of the Tobit regression (method A of DEA) found in Chapter 6. Since the first-stage variables (the various categories of educational expenditure) used in the first-stage (DEA) are to a certain degree, correlated with the second-stage variables (socio-economic variables), the estimation results may be biased (Simar & Wilson, 2007). The correlation is a consequence of the way the DoE, Tas chose to allocate the educational expenditures (used in the first-stage) to schools in Tasmania. Factors associated with socio-economic disadvantaged had been considered in how schools received the funding. An alternative estimation of DEA based on method B has been then considered. Under the method, the environmental variables have been accounted by categorising the schools into rural and urban schools. Then, two separate DEA estimates have been undertaken under method B. One limitation of the method (method B of DEA) is the reduction in the comparison set of schools, resulting in low discriminating power of the analysis. The consequence is that many schools have been found to be efficient. Another limitation of the method is that only one environmental variable (rural or urban school) has been considered in accounting for the heterogeneity in the production environment. As such, the characteristics of the other socio-economic variables are assumed to be sufficiently captured by the rural or urban status of the schools.

One general limitation of this research is that the findings are based on the curriculum of schools from 2000 to 2007. In 2008, a new curriculum to schools, known as the National Assessment Program – Literacy and Numeracy (NAPLAN) was introduced into schools in Australia. In order to understand the dynamic and changeable nature of the education production process, future research should be based on the impacts of the new curriculum. A study based on panel dataset of NAPLAN should be the direction of the future research in education economics based on Tasmanian case. In addition, an analysis involving all states and territories in Australia is another potential avenue of research. A perception that Tasmanian students' academic achievement is on average lower than the other states and territories need to be investigated. Such research should identify the factors that may explain the discrepancy in Tasmanian students' performance vis-à-vis the other states and territories in Australia.

In conclusion, I hope the findings and suggestions made in this research will contribute to a more informed debate and decisions when formulating future policies for Tasmanian education. This study also hopes to spearhead more economic research in education based on Tasmanian case.

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