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Costing regional and remote education: Report for the National School Resourcing Board

ANU Centre for Social Research and Methods

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Executive summary

- This paper reports the results of research into **the additional costs of providing education in regional and remote schools** and the extent to which these additional costs are adequately reflected in the current funding model and the income actually allocated to schools.
    - The research was commissioned to help inform the National School Resourcing Board (NSRB) 2020-2021 review of the Regional Schooling Resource Standard (SRS) Loadings.
    - The modelling reported in this paper is based on extensive administrative data on school income and expenditure and student outcomes, data from the Programme for International Student Assessment (PISA) and data provided by four jurisdictions (Western Australian, South Australia, Tasmania and Northern Territory).
- **School income per student increases with geographic remoteness**. Part, but not all, of the increase in income with remoteness is explained by school and student characteristics other than location.
- The school funding system is currently in transition with the amount of government funding increasing to meet the amounts of funding determined by the SRS. Comparison of the income received by schools in 2018 to their notional SRS allocation shows that, on average, nationally the **government per student funding is $1,803 less than the SRS allocation.**
    - Across all schools, in 2018 the total government funding provided to schools was $4.04 billion less than the SRS in major cities, $658 million less in inner regional schools, $766 million less in outer regional schools, $159 million less in remote schools, and $262 million less in very remote schools.
- **Schools in remote areas and very remote areas received a substantially lower level of income than the notional SRS allocation**. The gap between the notional SRS allocation and actual per student school income increases with geographic remoteness. The average per-student school income in very remote schools was $9,995 less than the SRS in government schools, $8,311 less in independent schools and $4,636 less in Catholic schools.
- Analysis of NAPLAN student outcome data shows that **students in remote and very remote areas have substantially worse student outcomes in Year 3** at school compared to students in other areas and that as they progress through school **students in remote and very remote areas fall further and further behind**.
    - These differences are only partially explained by other observable characteristics.
- The overwhelming evidence from studies around the world is that **higher school incomes result in better quality schooling and better student outcomes**. Consistent with this research**, analysis of NAPLAN and school funding data shows that also for Australia higher levels of school income improve student literacy and numeracy outcomes, as well as school attendance, student experience, and student wellbeing.**

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1 Introduction

This report provides a summary of research undertaken by the ANU Centre for Social Research and Methods into the additional costs of providing education in regional and remote schools as compared to in major cities. The research was commissioned by the Department of Education, Skills and Employment to help inform the National School Resourcing Board (NSRB) 2020-21 review of the Regional Schooling Resource Standard (SRS) Loadings.

The SRS is an estimate of the amount of government funding a school needs in order to meet its students' educational needs. The SRS is made up of a per-student base amount (adjusted for capacity to contribute for non-government schools) and six needs-based loadings. Four of the loadings are based on the characteristics of students and two are based on the school level characteristics of geographic remoteness and size (number of students enrolled). Of main relevance to this paper are the two school level loadings.

This report provides estimates of the adequacy of the current school location and size loadings to meet students' educational needs in regional and remote areas and the extent to which the current government funding provided to schools reflects the SRS and whether this varies by remoteness and school size.

In order to assess the adequacy of the current location and size loadings three specific questions are addressed:

- What are the additional costs incurred by schools in regional and remote Australia compared with schools in major cities with similar characteristics?
- Are the additional costs associated with location adequately addressed through the SRS location and size loadings?
- How does the level of public funding received by schools compare to the SRS location and size loadings and the estimated additional funding required by schools due to their location and size?

The approach taken to estimating the additional costs incurred by schools in regional and remote areas is to estimate how much additional school income is required in order for a school in different locations to achieve equivalent educational outcomes.

Estimating the additional cost associated with location requires taking into account differences in the family background of students at major city, regional and remote schools that may impact educational outcomes and the costs of delivering school education.

In order to estimate the additional costs associated with remoteness and to compare how this compares to current government funding, data from a range of sources is drawn upon, including:

- school level data on school, a range of characteristics of students, student attendance rates and student outcomes for school Years 3, 5, 7 and 9 (where applicable) as measured by data from the National Assessment Program - Literacy and Numeracy (NAPLAN) assessment process.
- Student level data on student outcomes from NAPLAN (similar to the school level data) which includes a school identifier so that students attending the same school can be linked, total school income per student and school location and size.

- School expenditure data for government schools in Western Australia, South Australia and Tasmania.
- Individual-level data from the Programme for International Student Assessment (PISA) for a sample of 15 year-old students across Australia, as well as data from a questionnaire completed by the school Principal, and the income of the school.

In interpreting the current patterns of school income, it is important to understand that the average amount of government provided income is less than the SRS allocation (as determined by the funding formulae) for two reasons. First, the system is currently in transition from the previous funding model to the new SRS model with most (though not all) schools transitioning to a higher SRS amount. The Commonwealth is moving towards fully meeting its SRS commitment of consistently funding at least 20 per cent of the total SRS for government schools and 80 per cent of the total SRS for non-government schools.[1] These proportions reflect the states' and territories' role as the majority funder of government schools and the Commonwealth's role as the majority public funder of non-government schools. Second, some school systems retain some of the SRS funding to fund centrally provided services to schools.

The remainder of this paper is structured as follows. Section 2 provides a brief summary of the existing literature, as well as a summary of the operation of the SRS. In Section 3 the data used in the analysis is described. Section 4 provides a descriptive analysis of school income and how it varies by geographic location, school size, school sector and other characteristics of the school. Sections 5 and 6 report on the analysis of the differences between school income and the SRS allocation. The paper then provides an analysis of student outcomes and how they vary by school and student characteristics (Section 7). In Section 8 the results of the analysis are brought together to address the question as to whether the level of government funding being allocated to schools in regional and remote areas is sufficient to allow students in regional and remote areas to have the same standards of education as those in major cities. In answering this question, the adequacy of the SRS location and size loadings are considered as well as the extent to which the government funding received by schools reflects the SRS allocation. The final section provides a summary of the main findings and implications, with Appendix 1 providing a more detailed summary of the existing literature, a model of school performance, and an analysis of expenditure data for a limited number of jurisdictions.

2 Overview of the Schooling Resource Standard

A number of countries use school funding formulae to determine the funding provided to individuals schools, including Australia. This approach, which was first implemented in the US in the late 1950s, generally involves a base amount of funding per student which is then supplemented with additional funding which reflects additional costs associated with student characteristics or school characteristics (such as geographic location) (Baker 2009; Fazekas 2012; Mort and Reusser 1951). These formulae recognise that the amount of funding required depends upon school characteristics and student needs.[2] While the school funding formulae approach is widely used, there are significant differences in how the funding formulas are

1 https://www.dese.gov.au/quality-schools-package/fact-sheets/what-schooling-resource-standard-and-how-does-it-work

2 For example, Baker and Duncombe (2004) using US data find that spending in the highest need school districts would have to be two to three times that of the average district to reach the same education performance.

applied and what variables and loadings (weights) and adjustments are made (e.g., Ross and Levacic 1999; Toutkoushian and Michael 2008).

For each school the SRS is made up of a per-student base amount, which in 2020 was $11,747 per primary school student and $14,761 per secondary school student. For most, but not all non-government schools, this base amount is adjusted by the capacity to contribute, or the ability of the school community to cover education expenses through school fees. The higher the socioeconomic status of parents and guardians, the greater the reduction, up to a total of 80 per cent of the base amount. This adjustment is not applied to government schools, nor is it applied to non-government special schools or special assistance schools, non-government majority Aboriginal and Torres Strait Islander schools, or non-government sole-provider schools.

The four student loadings are:

- Student with disability loading
- Low English language proficiency loading
- Aboriginal and Torres Strait Islander student loading
- Socio-educational disadvantage loading.

The two school level loadings, location and size, interact with each other and provide schools with additional funding based on the school's location and size. First, small schools receive an additional amount compared to larger schools, regardless of their location. Second, schools in regional and remote areas receive an additional amount regardless of their size. There is an additional top-up reflecting the interaction between size and location, with an even larger amount allocated to very small schools in more remote parts of the country.

According to DESE, 'It is estimated the location loading accounts for 2.1% of Commonwealth recurrent school funding expenditure in 2020 [and] it is estimated the school size loading accounts for 1.6% of Commonwealth recurrent school funding expenditure in 2020.'[3]

The location loading is based on a school's 2011 Accessibility/Remoteness Index of Australia (ARIA+) score, a measure of the remoteness or accessibility of every location in Australia on a scale of 0 to 15, with five threshold categories (calculated slightly differently to the Australian Bureau of Statistics thresholds) and a linear increase within the ranges. Specifically, loadings and thresholds are as follows:

- Major city schools (ARIA+ value of 1, or less than 1) – No regional loading.
- Inner regional schools (ARIA+ values of more than 1 and less than 2.4) – A loading of 1 to 1.1 times the base amount.
- Outer regional schools (ARIA+ values of at least 2.4 and less than 6) – A loading of 1.1 to 1.3 times the base amount.
- Remote schools (ARIA+ values of at least 6 and less than 10) – A loading of 1.3 to 1.7 times the base amount, and
- Very remote schools (ARIA+ values of at least 10 and less than or equal to 15) a loading

[3] https://www.dese.gov.au/quality-schools-package/fact-sheets/what-schooling-resource-standard-and-how-does-it-work

of 1.7 to 1.8 times the base amount.

The size loading as part of the SRS provides extra funding for medium, small and very small schools, in order to meet the additional costs of providing education when economies of scale are more difficult to achieve. Unlike the location loading (and all other loadings), this is the only loading that is calculated as a set dollar amount for the school, rather than as a proportion of the SRS funding amount per student. School size is treated differently for primary and secondary schools, with the following thresholds in the legislation:

- A very small school is less than 15 students for a primary school and less than 100 students for a secondary school
- A small school is 15 students to less than or equal to 200 students for a primary school and 100 students to less than or equal to 500 students for a secondary school, and
- A medium school is more than 200 students and less than 300 students for a primary school and more than 500 and less than 700 students for a secondary school.

Primary schools with up to 300 students and secondary schools with up to 700 students attract a size loading. The size loading is scaled such that:

- primary schools with between 15 and 200 students attract the maximum loading of $185,245 in 2020, and
- secondary schools with between 100 and 500 students attract the maximum loading of $296,392 in 2020.

There are additional loadings based on school size outside of major cities, and additional loadings based on location for small schools.

Individual schools may receive less or more than the SRS allocation for a range of reasons. First, as noted above, there are transitions that are currently in place with DESE stating that ‘Schools currently funded below their target Commonwealth share of the SRS will transition to the target by 2023. Schools that are currently funded above their target Commonwealth share will transition to it by 2029 at the latest.’[4] The data on SRS allocations used in this paper is for the SRS that the schools are transitioning towards, not what they are transitioning from. Second, the Commonwealth contribution to the SRS is, for the vast majority of schools, provided to the approved system authorities which then allocate income to individual schools based on their own criteria and weightings, and taking into account knowledge about local circumstances. Funding is provided directly to non-systemic independent schools.

According to the Review of Needs-based Funding Requirements undertaken by the National School Resourcing Board[5] ‘nearly 90 per cent of schools receive Australian Government recurrent funding through a System and more than 86 per cent of students are enrolled in those schools, the majority of which are government schools funded primarily by State and Territory governments.’ In addition to funding through the SRS, there are a range of other policies that provide support to regional and remote education in Australia (see, for example, Holden and Zhang 2018).

4 https://www.dese.gov.au/quality-schools-package/fact-sheets/what-schooling-resource-standard-and-how-does-it-work

5 https://www.dese.gov.au/national-school-resourcing-board/resources/review-needs-based-funding-requirements-final-report-december-2019

3 Data sources

A large amount of data on schools including school income, expenditure and student outcomes were made available for the purposes of this research. The data sets used in this paper include:

- individual school level and individual student level administrative data, with students linked to the school they were attending and linked to their student outcomes at younger ages.
- school expenditure for government schools in some states/territories, and Programme for International Student Assessment (PISA).

3.1 Individual school and student level administrative data

The school level data includes: geographic location; size (number of enrolments); a range of characteristics of students including those used to determine the SRS; school income; source of income; and the SRS allocation; student outcomes from NAPLAN; and student attendance. The NAPLAN data used in this report is for literacy and numeracy outcomes for Year 3, 5, 7, and 9 students (where applicable in that school) for a given year, and the literacy and numeracy outcomes for the same students from previous NAPLAN assessments.

Data was available on students who undertook the 2018 and 2019 NAPLAN rounds, with student-level linkage undertaken to identify NAPLAN outcomes for these students from the 2016 and 2017 rounds. The majority of the school level data was provided by the Australian Curriculum, Assessment, and Reporting Authority (ACARA). Data on the number of students with disability who require a different level of adjustments are from the Nationally Consistent Collection of Data on School Students with Disability (NCCD).[6] Data on the notional SRS allocation amount for each school for 2018 and 2019 is broken down by the Commonwealth and by the state/territory government components of the SRS allocation. This data was provided by DESE.

Student level data on student outcomes from NAPLAN (similar to the school level data) which includes a school identifier so that students attending the same school can be linked, total school income per student and school location and size. Schools (or individuals) cannot be identified with this data. This data includes student characteristics that feed into the SRS with the exception of requirement adjustments as a result of disability. This data was provided by ACARA.

3.2 School expenditure data for selected state/territories

School expenditure data was made available for a limited number of jurisdictions (Western Australia, South Australia, and Tasmania and the Northern Territory), with expenditure disaggregated into different categories, income information for those schools, and a limited amount of school demographic characteristics available for the first three jurisdictions listed above.

3.3 Programme for International Student Assessment (PISA) data

Individual-level student data from the 2018 Programme for International Student Assessment (PISA) which collected data from a sample of 15 year-old students across Australia, as well as data from a questionnaire completed by the school Principal.[7] Per-student income of the

6 Appendix Table B1 and B2 give the number of schools and total number of enrolments used in the analysis by state/territory and location.

7 This data was provided by ACER.

school (from the ACARA database).

4 School income by school size and location

This section reports data on how school income varies according to the geographic remoteness of the school (school location). The data is from the ACARA School Profile data base.[8] In order to take into account size of school, school income data is presented on a per-student basis.[9] All income data reported in this section is for 2018.

Across all schools in Australia (primary, secondary, combined, and special schools) in 2018, the mean school income per student per annum from all sources was $20,343, the median income was $15,952, and the standard deviation of income was $15,359. When special schools, which have a higher average per-student funding due to having a high proportion of students with disability, are excluded the average per-student funding declines to $18,518.

An alternative way of calculating the average and median level of funding is to weight by the number of students enrolled in each school. This means that schools with larger numbers of students have a bigger impact on the average per-student funding than schools with smaller numbers of students. Weighting by school size thus provides a better measure of the income of the school as experienced by the average student, rather than for the average school. Using this measure, the mean income per student is $16,084.

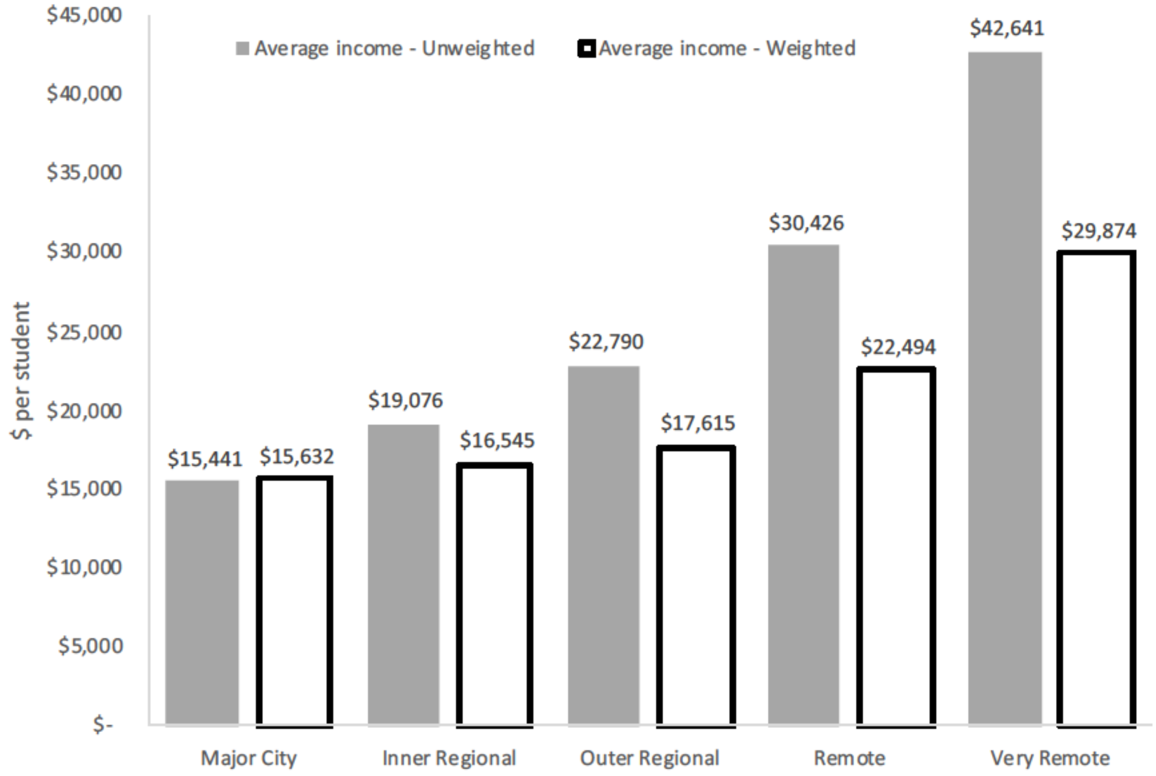
Using the five-category remoteness classification (major city to very remote), average income per student when weighted by student numbers is similar in major cities ($15,632) and inner regional areas ($16,545), and then increases substantially with remoteness to be $17,615 in Outer Regional areas, $22,494 in Remote areas and $29,874 in Very Remote areas (Figure 1). When the unweighted data is used (i.e., each school carries equal weight) the pattern of average per-student income increasing with geographic remoteness is similar to those based on the weighted data, although the increase in income with geographic remoteness is larger when the unweighted data is used. This reflects the fact that small schools tend to have higher incomes, particularly in remote and very remote areas.

8 The ACARA School Profile database for 2019 incudes 9,562 schools. Of these 6,224 were primary schools, 1,465 secondary schools, 1,368 combined schools and 505 special schools. By school sector, 6,714 were government schools, 1,702 Catholic schools and 1,146 were independent schools. The major differences in school type by school sector is that there are more Catholic and Independent schools that are combined schools, with government schools more likely to be separate primary or secondary schools.

9 This is calculated by dividing the school income by the number of full-time equivalent student enrolments.

Regional and remoteness funding loading

Figure 1 Average income per student from all sources per annum, by remoteness classification, 2018



Source: ACARA School Profile data.

Note: Weights are based on student enrolments. Special schools are excluded.

The differences in school income by remoteness reflect, in addition to location, a range of other factors including student characteristics and school size that are used to determine the allocation of government funding to schools as well as differences in non-government funding (largely fees paid by parents). In order to estimate how remoteness affects school funding independent of other characteristics of schools a regression model with per-student school funding as the dependent variable is estimated.[10,]

The key results are summarised in this section. The full regression results are provided in Appendix Table B3. While the primary interest for the Review of the location and size loading is the relationship between location and per student school income holding constant other school characteristics, the differences in per-student funding for other characteristics is useful contextual information.

10 The dependent variable, school income, is log transferred in order that it better approximate the normal distribution. Schools which have zero income for a particular source of income are given a value of the natural log of $1, in order to allow them to be included in the analysis. Because we control for special schools explicitly in the analysis, they are included in the sample. On the dataset available for analysis in this paper, all Western Australian Government Schools have missing data for the per cent of the sample who speak a language other than English at home. We use a regression-based imputation procedure to impute values for Western Australian government, but also check robustness using case deletion and multiple imputation. Imputation changes the results for Western Australia (as without imputation only Catholic and Independent schools in Western Australia are able to be included in the analysis), but does not change the results for language background other than English or other independent variables.

Regional and remoteness funding loading

ss 47B(a), 47E(d)

The total income of government schools is substantially lower than an otherwise equivalent independent school, and to a lesser extent an otherwise equivalent Catholic school.
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. As will be described below, this reflects the higher level of fees and charges in the Catholic and Independent school, which in the current system more than make up for the lower levels of public-sector income received by these schools due to the capacity to pay adjustment.

Reflecting the application of the size loading, there is a higher income (per student) in very small schools in particular, but also small and medium schools (relative to large schools). Compared to schools that cater to primary students only, income is higher in combined schools; secondary schools, and special schools. Schools with a large proportion of students outside of the top socio-educational advantage (SEA) quartile but in the middle two quartiles have lower income than those with a high proportion of students in that quartile, with the biggest difference being for those students with a high percentage of students in the upper-middle quartile.

There is a strong positive relationship with the proportion of students in the school that identify as being Aboriginal or Torres Strait Islander, but a weak and negative relationship with the proportion of students from a Language Background Other Than English (LBOTE). Finally, there is a strong positive association with the proportion of students with disability in that school.

Holding constant the above characteristics, there is a smaller relationship with remoteness category than when these characteristics are not controlled for (Table 1). That is, part of the difference in income by remoteness is due to other characteristics of those schools, as captured in the SRS.

This does not necessarily mean that schools are receiving too little or too much based on either the SRS or the needs of school students (this issue is covered in a subsequent section). What it does show, however, is that the location loading isn't the only factor that influences the level of income received by schools in regional and remote areas, but that other aspects of the SRS and the capacity of parents/guardians to contribute is pulling in different directions.

11 The prediction of per-student income is made holding other student characteristics at their approximate mean value.

Table 1 Differences in per-student income by remoteness category relative to a major city school, unconditional and conditional on holding constant student and school characteristics, 2018

	Difference in per-student income to a major city school		Difference in per-student income explained by other characteristics
	Not holding constant differences in student and school characteristics	Holding constant differences in student and school characteristics	
	Per student per annum		
Inner regional	$1,438	$738	48.7
Outer regional	$5,370	$1,949	63.7
Remote	$12,203	$4,724	61.3
Very remote	$21,217	$6,261	70.5

Source: ACARA School Profile data.

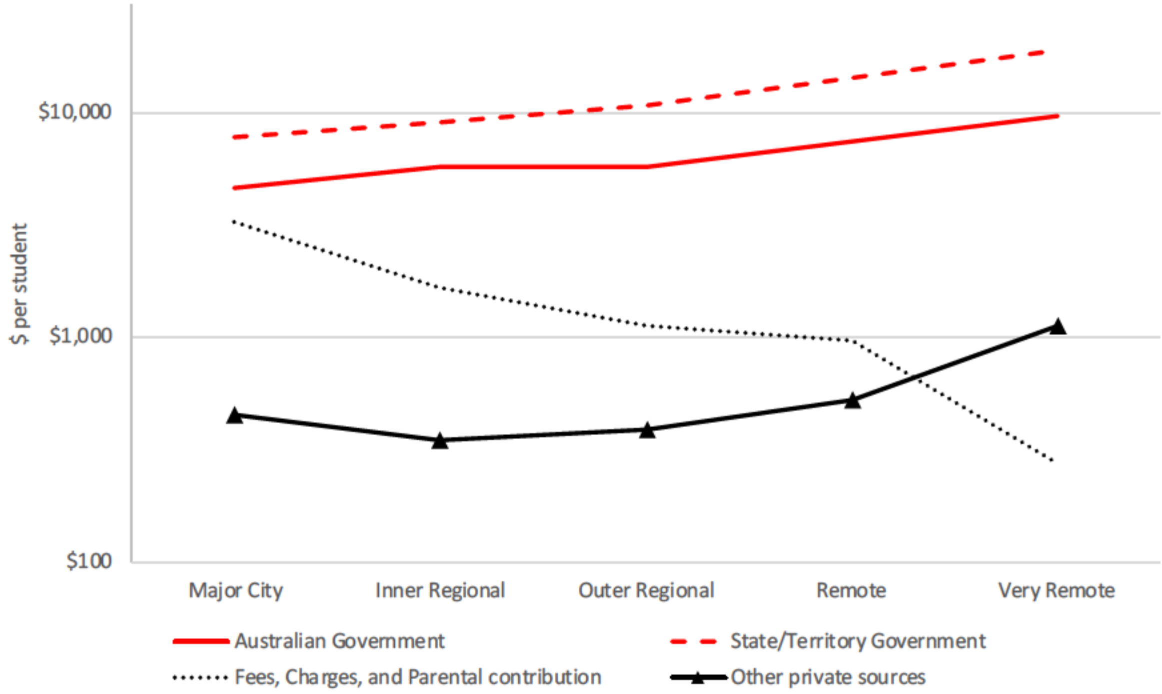
Note: Unweighted data. Results differ from those presented in Figure 1 due to the inclusion of special schools in the analysis.

Data on school income by source of income and geographic remoteness is reported in Figure 2 (and regression analysis available in Appendix Table B4). The four sources of income are Australian Government; state/territory government; fees, charges and parental contributions and other private sources.

Using a log scale to better capture the very different levels of income for each of the four sources, it can be seen that the slope of the line is positive and similar for Commonwealth Government and state/territory government income, negative and then positive for 'other private sources' (beyond inner regional areas) but negative for 'Fees, Charges and Parental contributions.' That is, contributions from parents and guardians to school education declines in absolute terms as schools become more remote, and decline to an even greater extent in relative terms.

Regional and remoteness funding loading

Figure 2 Average income by source per student, by five-category remoteness classification, 2018



Source: ACARA School Profile data.

Note: Weighted by number of students enrolled in each school.

A number of additional insights can be taken from the estimates of the factors associated with the different types of school income (Appendix Table B4). Reflecting the way the funding of schools is allocated differently across school sectors, Catholic and independent schools receive a higher amount of income from the Commonwealth Government compared to government schools (Catholic schools in particular), whereas they receive a lower amount of income from State/Territories. These schools receive a significantly and substantially higher income from fees and charges, with independent schools receiving a greater amount than Catholic schools.

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Small schools and particular very small schools receive less income from fees and charges on average than large and medium sized schools, as do schools with a high proportion of students outside of the top SEA quartile, schools with a high proportion of students who identify as Aboriginal or Torres Strait Islander, and schools with a high per cent of students who speak a language other than English.

4.1 Summary of findings

Schools in regional and remote areas receive substantially more income than schools in major cities. The increase in income with remoteness is explained, in part, by other characteristics of those schools and students.

There are large differences in income between small/very small schools and large schools, and smaller differences between medium schools and large schools.

Consistent with the SRS allocation formulae, schools with a high proportion of Aboriginal and Torres Strait Islander students, a high proportion of students with disability, a high proportion of students with socio-educational disadvantage, and a small absolute number of students receive higher incomes. After controlling for these differences, independent and Catholic schools receive a higher income than government schools, and schools in certain jurisdictions receive a higher income than other jurisdictions.

Although there is an increase in government income by remoteness, income received from fees, charges and parental contributions decline as remoteness increases.

5 Comparison of the amount of government income schools receive and the Schooling Resource Standard by location

5.1 National level

In addition to the school location loading and school size loadings which increase the per-student income of schools as remoteness increases, the fact that for several of SRS student loadings the proportion of students with the particular characteristic increases with remoteness[12] results in the SRS allocation to school increasing quite substantially as the remoteness of schools increases.

The dataset provided to the ANU for the purposes of this research include the income allocated to each individual school as part of the total SRS, as well as two components of the SRS – the size loading and the location loading. This section uses this data to look at the extent to which there is a gap between the SRS and the total public sector income received by schools and the extent to which this differs by remoteness.

According to the ACARA data that was able to be linked, the total income received from government (Commonwealth, state and territory governments) was around $50.6 billion which is about 89.6 per cent of the total SRS amount of $56.5 billion. Across all schools, the total funding gap in 2018 equated to $4.04 billion in major cities, $660 million in inner regional schools, $766 million in outer regional schools, $157 million in remote schools, and $262 million in very remote schools.

As noted above, the SRS arrangements are moving towards the Commonwealth contributing 80 per cent of the SRS amount for non-government schools and the state and territory governments contributing 20 per cent. For government schools it is moving towards the Commonwealth contributing 20 per cent of the SRS amount and the state and territory governments contributing 80 per cent. According to the ACARA data, in 2018 the Commonwealth contribution to the SRS averaged 35.3 per cent for all schools, 17.5 per cent for government schools, 78.8 per cent for Catholic schools and 74.0 per cent for independent schools. While these are an increase from earlier years, they are still well below the 20/80/80 ratio that the funding agreements are working towards.

There is no major difference in the proportion of the SRS contributed by the Commonwealth by geographic remoteness within the different school sectors, with the exception of independent schools, where the per cent of the SRS funded by the Commonwealth is higher in major cities (75.0 per cent) compared to inner regional schools (71.9 per cent), outer regional schools (70.5 per cent), remote schools (68.4 per cent) and very remote schools, in particular (61.8 per cent). This reflects in part the different point on the transition to the complete application of the SRS (discussed in the introduction) across sector and region with the Commonwealth having provided a far lower share of the funding amount in very remote schools in 2014 (45.7 per cent according to data provided by the DESE) and remote schools (52.1 per cent).

The combined contribution of the location loading and the size loading (which interact with each other) to the total SRS amount is 3.4 per cent for major city schools, 13.9 per cent for

[12] Proportion of students with disability, who are Aboriginal or Torres Strait Islander and who experience socio-educational disadvantage increase with remoteness.

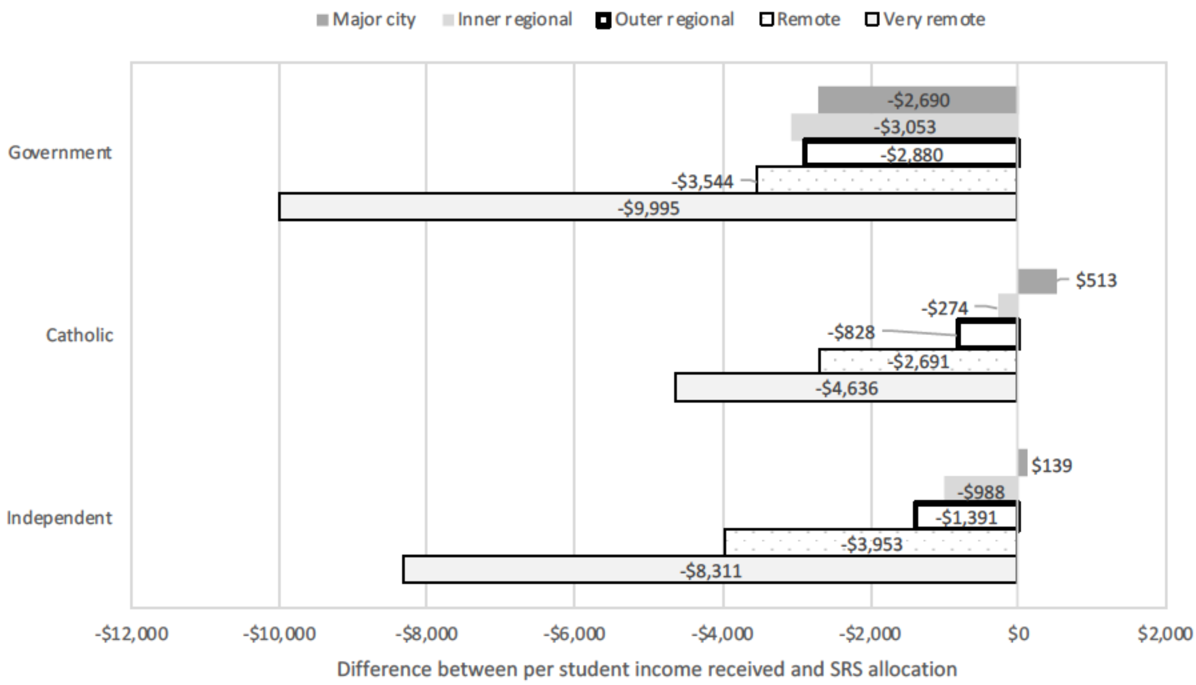
inner regional schools, 23.6 per cent for outer regional schools, 38.2 per cent for remote schools and 43.7 per cent for very remote schools.

Because school income increases with remoteness, and there is significant variation in the number of schools and students across the combination of remoteness areas/sectors, it is important to consider the difference between the SRS and the actual income received in dollars per student. If the number of students in each school is not taken into account, then the average gap across all schools is -$566 (an underpayment). However, when weighted by the number of students in each school, or the 'funding gap' as experienced by the average student, this rises to -$1,803. This difference is because the greatest gap in funding occurs in larger schools (as described below).

Looking separately by sector and weighting by enrolments, the average gap is largest in government schools, with a total of -$2,822 gap. There is a slight over-payment in Catholic schools ($275), and a slight under-payment in independent schools (-$34). Figure 3 shows the difference between per-student government funding received by schools and the SRS allocation across remoteness categories. A negative value indicates that schools receive, on average, less per student from government sources than the SRS allocation and a positive value indicates that type of school receives more per student.

The largest 'over-payment' relative to the SRS occurs in Catholic schools in major cities (an average of $513 extra per student relative to the SRS). The largest 'under-payment' is for government schools in very remote areas (-$9,995) followed by independent schools in very remote areas (-$8,311). There are very few independent schools in very remote areas (18 schools in the database with SRS and income information), which means that the 'under-payment' to government schools in very remote areas impacts on far more students than the 'under-payment' to independent schools.

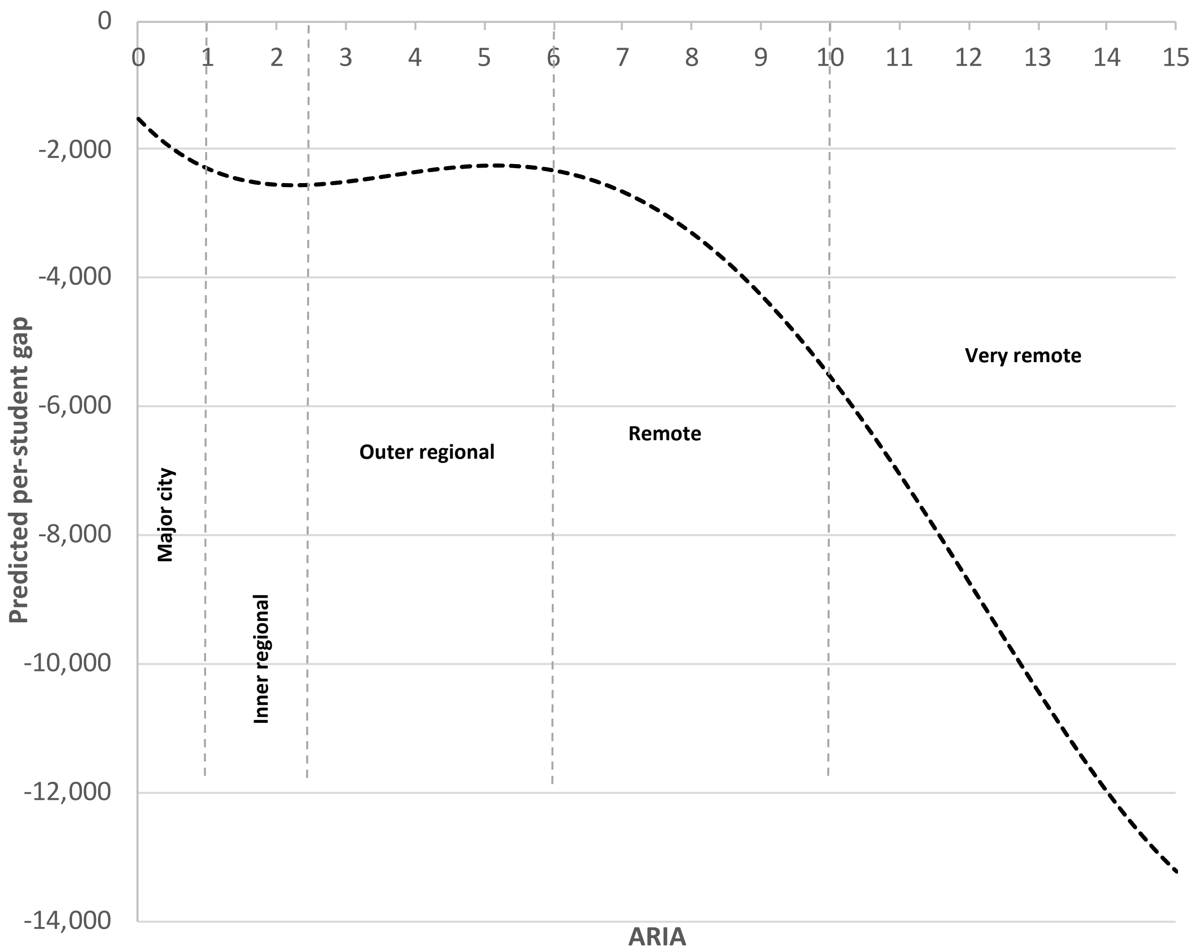
Figure 3 Average per-student gap between total income received from government sources and SRS, by remoteness and school sector, 2018



Source: ACARA School Profile data.

Figure 4 summarises the relationship using the more detailed ARIA+ remoteness classification which is used in the SRS location loading formulae and the average difference between per-student government income received and the SRS loading (weighted and unweighted).[13] The underlying data has some "noise" due to relatively small numbers of schools in some of the more remote categories and so a curve has been fitted using a regression model to describe the relationship between remoteness and the difference in per-student funding provided and the SRS allocation. This shows that the gap in the amount of funding provided (in dollar terms) increases quite rapidly from about an ARIA+ score of about 8.5 which is around the mid-point of the "remote" category.

Figure 4 Modelled average per-student gap between total income received from government sources and SRS, by continuous ARIA+



Source: ACARA School Profile data.

Note: Weighted by number of students enrolled in each school.

The gap identified in Figure 4 is estimated for 2018. As mentioned previously, this was at a time when the Commonwealth and State/Territories were transitioning to a new funding model, and it is likely that some of the gaps above will be closed through time. However,

13 The coefficients for the unweighted model are: linear -897.3648; quadratic 455.2818; cubic -57.34227; quartic 1.93843; and constant -371.3244. The coefficients for the weighted model are: linear -1123.102; quadratic 392.9557; cubic -46.90273; quartic 1.481368; constant -1509.037

these historical gaps have the potential to have impacted on a large cohort of students over a number of years, which may mean that even by the time the funding gap has closed, a significant achievement gap is likely to remain.

5.2 State and Territory differences

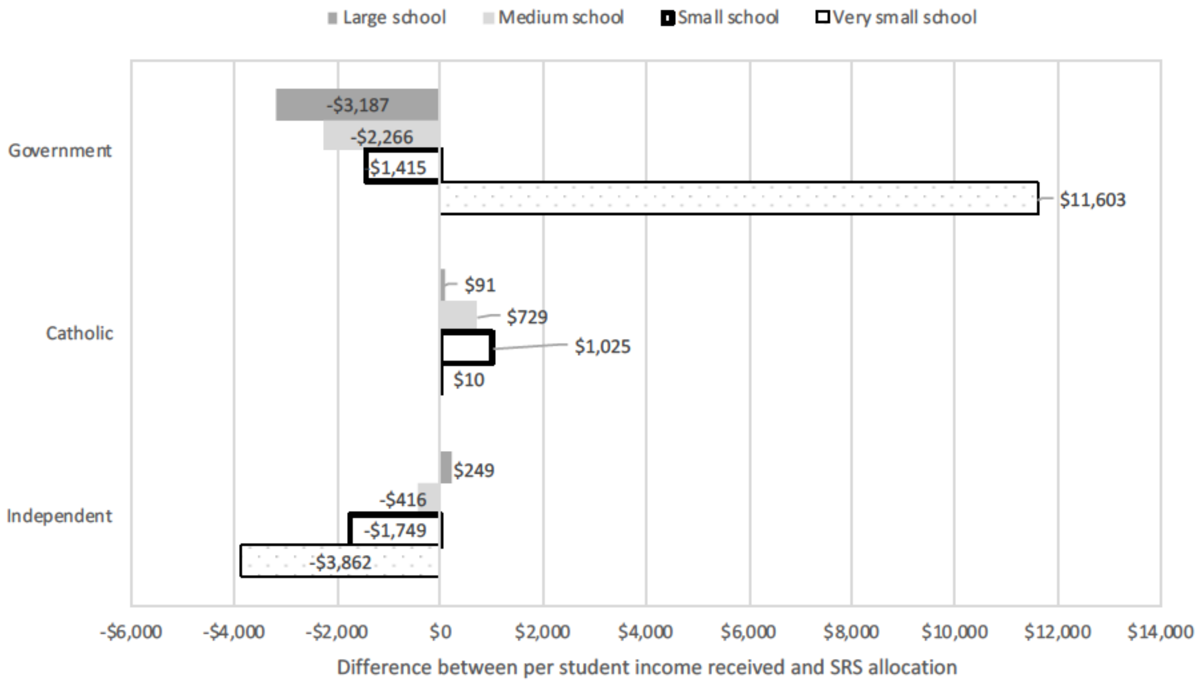
As mentioned in the introduction to the paper, the funding allocated to most schools is administered by approved system authorities (systems). State/territory governments are systems, and a number of the non-government systems are constituted at the state/territory level. Appendix Table B5 provides the average weighted per-student gap by state/territory and school sector for Major Cities through to Very Remote areas.

ss 47B(a), 47E(d)

5.3 School size differences

In addition to remoteness, a key component of the SRS calculation is the size of the school. Not only do small and very small schools receive an additional allocation, but there is also an interaction with remoteness with small and very small schools outside of major cities receiving an additional loading. Figure 5 shows that, within the government system, large schools receive a substantially lower amount from the Commonwealth and state/territory combined than the SRS, whereas medium and small schools have a smaller but still negative gap. Very small schools, on the other hand, receive a much higher amount than the SRS. In Catholic schools, the relativities are similar (more positive gap the smaller the school), whereas in independent schools the relativities go in the opposite direction with very small schools having a very large gap in income per student.

Figure 5 Average per-student gap between total income received from government sources and SRS, by school size and school sector, 2019



Source: ACARA School Profile data.

5.4 Key findings

When the actual income received by the school is compared with either the SRS for that school or the location loading specifically, certain schools receive less than the formula suggests they should. The total income received from government (Commonwealth, state and territory governments) was around $50.8 billion, about 89.6 per cent of the total SRS amount of $56.7 billion.

Across all schools, the total funding gap in 2018 equated to $4.04billion in major cities, $658 million in inner regional schools, $766 million in outer regional schools, $159 million in remote schools, and $262 million in very remote schools. The 'funding gap' as experienced by the average student, is estimated to be -$1,799 per student, per school.

Government schools receive the least as a proportion of their SRS allocation, whereas Catholic schools receive the most.

Across all three school sectors, schools in very remote areas receive a substantially lower level of income than suggested either by the SRS or by the model of school income distribution. The per-student gap experienced by the average student in very remote schools is -$9,995 in government schools, -$8,311 in independent schools and -$4,636 in Catholic schools. Across all schools, the total funding gap in 2018 equated to -$159 million in remote schools, and -$262 million in very remote schools.

6 Modelled national location loading

A more direct estimate of the how much additional government income (from the Commonwealth and state and territory governments) is provided, on average, as remoteness increases can be obtained using regression modelling which hold constant other characteristics of the school that feed into the SRS formula.

This section reports the results of modelling the relationship between geographic remoteness and per-student government income, while holding constant characteristics of the school and the school students that are likely to impact on the income allocated to that school through the various funding formulae.[14] In addition to remoteness, the effects of which are captured by including a flexible non-linear remoteness specification, with ARIA+, ARIA+ squared, ARIA+ cubed, and ARIA+ to the fourth power, the explanatory variables included in the model are:

- school size (medium-sized, small, and very small, with large schools the omitted category)
- school type (combined, secondary, and special, with primary schools the omitted category)
- socio-educational disadvantage loading (per cent of student in the school in the bottom and lower middle socio-economic quartile)
- capacity to pay adjustment (Index of Community Socio-Educational Advantage (ICSEA) score as a proxy for SES score (not available on dataset))
- per cent of students who were identified as being Aboriginal or Torres Strait Islander
- per cent of students who spoke a language other than English
- per cent of students with disability at extensive, substantial or supplementary NCCD levels (from the NCCD database)
- whether the school had boarding-students.

To take into account the different application of the capacity to pay adjustment in non-government schools, and the fact that there were no government boarding schools identified in the dataset (though there were a number of non-government boarding schools), a separate model was estimated for government, Catholic and non-government schools (ICSEA was not statistically significant for government schools, positive and significant for Catholic schools, and negative and significant for independent schools).

Using the results of these regression models, a predicted value of per-student government income was generated for each school, based on the school's values for the independent explanatory variables included in the model, but with an ARIA+ score of zero. That is, this is an estimate of the government income that that school would receive if it had exactly the same characteristics as it currently does, but was located in a major city.

To calculate the actual application of the location loading for that particular school, the school's actual government income was divided by the predicted government income if that school had an ARIA+ score of 0, but otherwise identical characteristics. Any difference between the predicted and the actual value is therefore a reflection that either the school received a different income due to other characteristics not included in the model, or the actual location loading used by that school system differed. The final step was to calculate the SRS formula value for the remoteness loading in the SRS, based on the school's ARIA+ score.

The model fit is quite high for the econometric model used to estimate the funding formula. Specifically, the adjusted R-Squared of the model (or the proportion of variation in income

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[14] The dependent variable, school per-student government income, was converted to natural log to improve goodness of fit and assumptions of normality that sit underneath linear regression analysis.

explained by the model) is 0.7961 for the model for government schools, 0.7959 for Catholic schools and 0.8042 for independent schools.

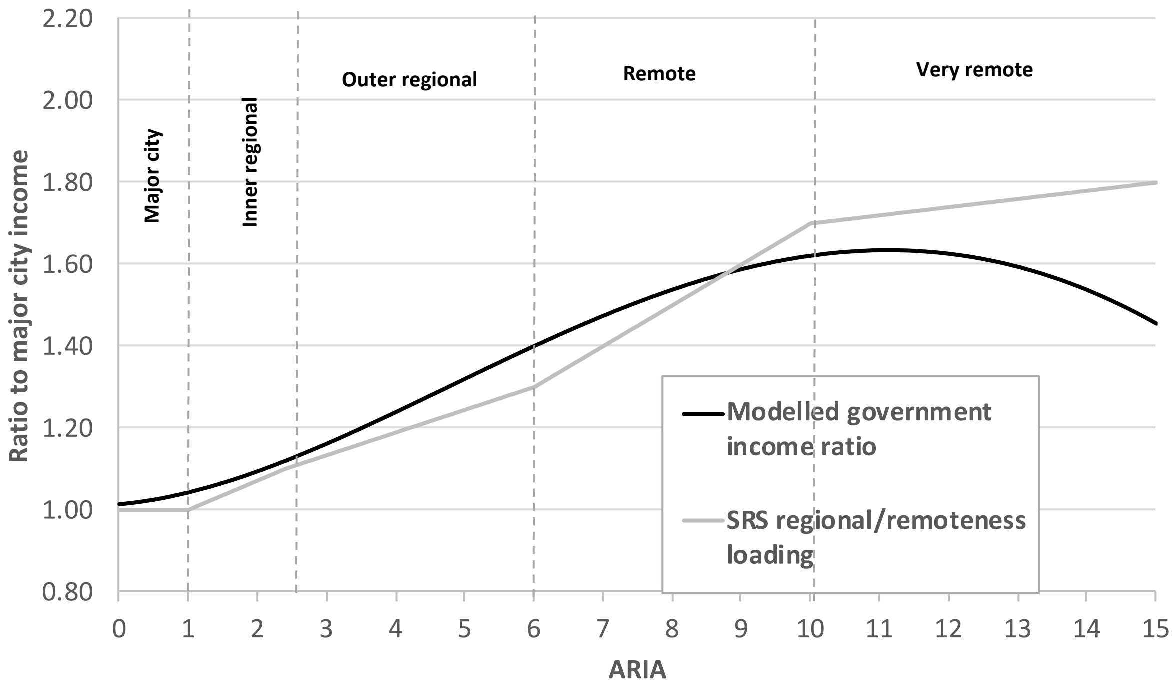
Using individual schools as the unit of analysis, there is a positive correlation between the schools' observed income ratio (actual income divided by predicted income if ARIA+ equals zero) and the SRS-based location-loading for that school. For all schools combined, there is a correlation coefficient of 0.4285. There was, however, a stronger relationship between the observed ratio and the SRS value for Catholic schools (0.5357) than for government schools (0.4197) and independent schools (0.3087). For all schools, this shows that the location loadings are followed reasonably closely within school systems, but that the formula is more closely followed in Catholic schools.

Having estimated an actual difference between the predicted value for a major city school and the observed income for that school, it is straightforward to calculate the extent to which that varies from the SRS location formula. This is termed the 'ratio of ratios.' In a simple model of the factors associated with the relative difference between the observed income ratio and the SRS value (ratio of ratios) inner regional schools on average have a slightly higher additional income due to their remoteness than the formula predicts (coefficient of 0.036). There is no difference between outer regional/remote schools and major cities, but there is a lower income relative to the prediction for very remote schools (coefficient of -0.112).

Using a continuous ARIA+ set of independent variables (as a linear, quadratic, cubic, and quartic), a continuous prediction of the actual government income ratio across the entire distribution of ARIA+ scores can be obtained which can then be compared to the SRS location loading.[15] It is apparent from Figure 6 that the ratio of income to an otherwise equivalent school in a major city was greater than the regional/remoteness loading in schools with an ARIA+ value up until 8.8, and then lower for ARIA+ values beyond then.

[15] The estimated coefficients are: linear 0.0149182; quadratic 0.0149417; cubic -0.0012517; quartic 2.13 x10^{-05}; constant 1.015482.

Figure 6 Modelled ratio of school government income relative to major city income and the SRS loading by ARIA+, 2018



Source: ACARA School Profile data.

A more complicated model which also controls for state/territory and other characteristics of the school is estimated. The dependent variable for this model is the 'ratio of ratios' or the difference at the school level between the estimated additional income received for that school compared to a school in a major city with otherwise identical characteristics (the black line in Figure 6) and the SRS regional/remoteness loading (the grey line). This model is not an estimate of whether schools with those characteristics receive more or less income based on the combined funding formulae (that is, based on Aboriginal and Torres Strait Islander status, socio-educational advantage, etc.), but rather whether schools with those characteristics receive more or less of an income boost due to their ARIA+ level.

ss 47B(a), 47E(d)

Very small schools have higher remoteness loadings, capturing the interaction between size and remoteness in the funding formula but not captured in the model. There are no differences by school type showing that although funding levels vary between primary and secondary schools, the taking into account of remoteness does not appear to.

There is a complicated relationship with socioeconomic status, with schools with a higher proportion of low and upper-middle quartile SEA students (relative to top quartile students) having a high remoteness loading, but schools with a high percentage of lower-middle SEA quarter students having a lower remoteness loading.

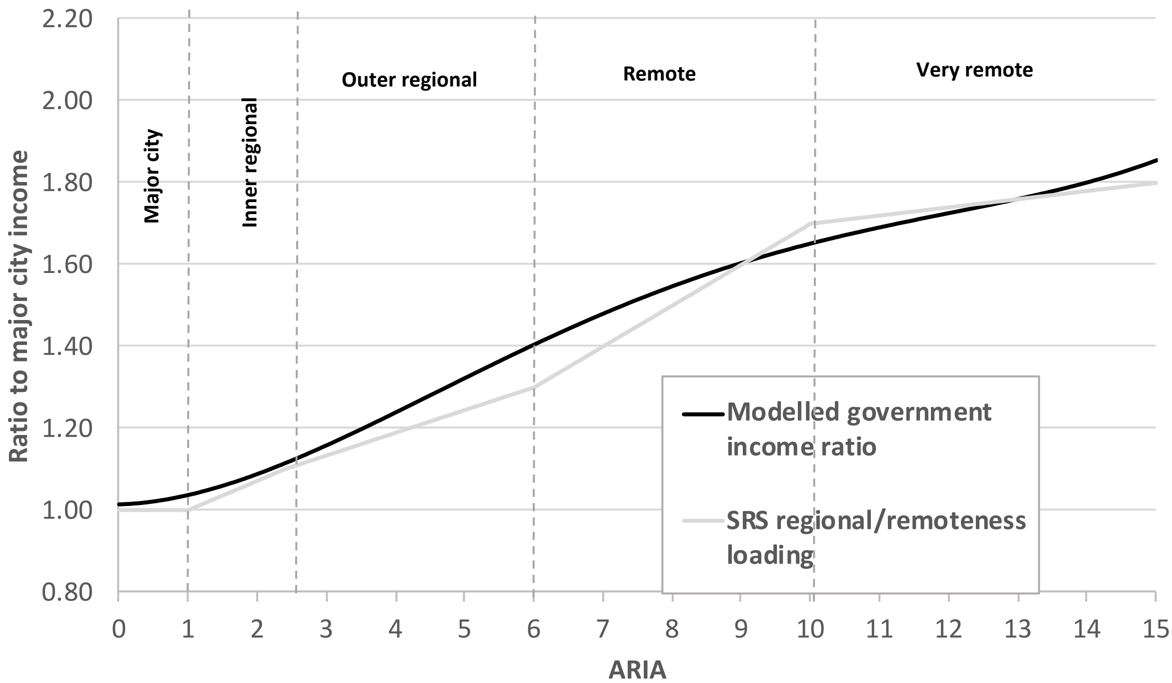
Regional and remoteness funding loading

One of the key findings from this more complicated model though is that schools with a high proportion of students who are Aboriginal or Torres Strait Islanders have a lower location loading than schools with a relatively low proportion of students who are Aboriginal or Torres Strait Islanders. To put this another way, location seems to factor into school funding less for schools with a high proportion of Aboriginal and Torres Islander students.

In the discussion presented in the previous sub-section, the data shows that for remote and very remote schools in general, and for government schools in particular, there were very different gaps by state/territory between the SRS funding allocation and the reported income received by the schools from government sources. ss 47B(a), 47E(d)

ss 47B(a), 47E(d)

Figure 7 Modelled ratio of school government income relative to major city school income and the SRS loading by ARIA+, excluding the Northern Territory, 2018



7 Student outcomes

Schools have a range of outcomes that they attempt to achieve for their students. In addition to providing a safe and supportive environment, schools aim to develop students' cognitive ability (including but not limited to literacy and numeracy), non-cognitive ability, and knowledge across a range of subject matter areas. In addition, schools aim to provide a rounded experience for students across sports, the arts, and cultural enrichment.

Achieving these outcomes requires a range of school inputs. There is extensive literature that attempts to estimate school cost and production functions. Education production functions estimate the underlying determination of skills and link inputs[17] related to the teaching and learning environment to outputs which are related to student achievement and are often measured in terms of test scores (Deutsch et al. 2013). Because of a historic lack of available data in Australia (the data has been collected but not made available to independent researchers), much of the literature is based in the US. According to Hanushek (2020), there is generally only weak evidence that simply increasing school funding and teacher salaries will lead to improved student performance. However, the literature suggest that this is because it is more important *how* money is spent rather than *how much* is spent.

17 These inputs include: family background (socio-demographic characteristics such as parental education, income, and family size); (2) peer inputs (usually aggregates of student socio-demographic characteristics or achievement for a school or classroom); (3) school inputs, such as teacher background (education level, experience, sex, race, etc.), school organization (class sizes, classroom resources, facilities, administrative expenditures), and district or community factors (average expenditure levels) (Hanushek 2020).

Jackson et al. (2016) also argue that a focus on test scores as the main outcome does not capture all of the positive effects on learning and subsequent life outcomes. They address this limitation by looking at the effect of school spending on long-run outcomes such as educational attainment and labour market success (earnings), and they use panel data and state finance reforms in the U.S. to study the causal effect of school spending on outcomes. They show that schools used these additional school funds to reduce student-to-teacher ratios, to have longer school years, and to increase teacher salaries. Increased school spending improved student outcomes and helped reduce the intergenerational transmission of poverty. Low-income families benefitted the most from these reforms, with large improvements in educational attainment, wages, family income, and reductions in adult poverty. Their results imply that a 25 per cent increase in per-student spending throughout one's school years could eliminate the average attainment gaps between children from low-income and higher-income families.[18]

Lafortune et al. (2018) use a similar event study framework and confirm that schools used these additional funds to increase instructional spending, reduce class size, and spent it on capital outlays. Most importantly, they show that these reforms had a positive effect on student achievement in low-income districts and on students' eventual earnings. Their findings imply that a $1 increase in funding to low-income school districts raises students' eventual earnings by more than $1 in present value.[19]

A more recent meta-analysis (which pools findings from a range of studies) provided very strong evidence that a school's income directly affects school outcomes. Jackson and Mackevicius (2021) find that across all "credibly causal" studies 'a $1000 increase in per-pupil public school spending (for four years) increases test scores by 0.044 standard deviations, high-school graduation by 2.1 percentage points, and college-going by 3.9 percentage points'.[20] To reinforce the point, the authors stated up front that 'Speaking first to the "does money matter?" question, we show that 94 percent of all included studies find a positive overall effect of increased school spending (irrespective of significance). If positive and negative impacts were equally likely (as is the case if school spending did not matter), the likelihood of observing this many positive estimates or more is less that one in 4.3 million.'

Such studies have not been publicly available in Australia, because the data to undertake them has not been made available previously (or the results have not been released). It is tempting to dismiss the findings and assume the positive results are particular to different points on the income distribution. However, the most plausible assumption is that returns are highest at the bottom part of the school-income distribution, with Australia in recent history having on average lower levels of spending on elementary and secondary education than the US (around 20 per cent lower in 2016)[21] Perhaps more importantly though, there do not appear to be diminishing returns in the studies available, with Jackson and Mackevicius (2021) stating that 'Some have argued that while school spending may have mattered when baseline spending

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18 More precisely, they find that for low-income children, "a 10% increase in per pupil spending each year for all 12 years of public school is associated with 0.46 additional years of completed education, 9.6% higher earnings, and a 6.1 percentage point reduction in the annual incidence of adult poverty".

19 "Ten years after a reform, relative achievement of students in low-income districts has risen by roughly 0.1 standard deviation, approximately one-fifth of the baseline gap between high- and low-income districts. The implied impact is between 0.12 and 0.24 standard deviations per $1,000 per pupil in annual spending. This is at least twice the impact per dollar that is implied by the Tennessee Project STAR class size experiment." (Lafortune et al. 2018).

20 This is equal to an Australian amount of $1,286 based on the exchange rate on 2 March 2021.

21 https://nces.ed.gov/programs/coe/indicator_cmd.asp

levels were low, the marginal impacts may be smaller at current spending levels … Precision-weighted models reveal that the marginal impacts are remarkably stable for a wide range of baseline per-pupil spending levels'

It was not possible to undertake the type of causal analysis described in Jackson and Mackevicius (2021) due to a lack of available data on the outcomes used in their analysis (school completion, post-school attainment), the challenge in identifying instrumental variables (measures that are correlated with income, but not directly correlated with outcomes) and the availability of only two years of NAPLAN data. However, the analysis in this section describes the extent to which student outcomes vary across different characteristics of schools (in particular locations), as well as whether some of the differences in school income presented in the previous sections may be explaining some of these differences in student outcomes.

The section first describes average literacy and numeracy outcomes in a school, and then presents the results of statistical analysis of the determinants of literacy and numeracy outcomes. The final two parts of this section consider a broader range of student outcomes and their relationship with location, school size, and income (amongst other things), beginning with student attendance and then the broader school experience.

7.1 School-level literacy and numeracy

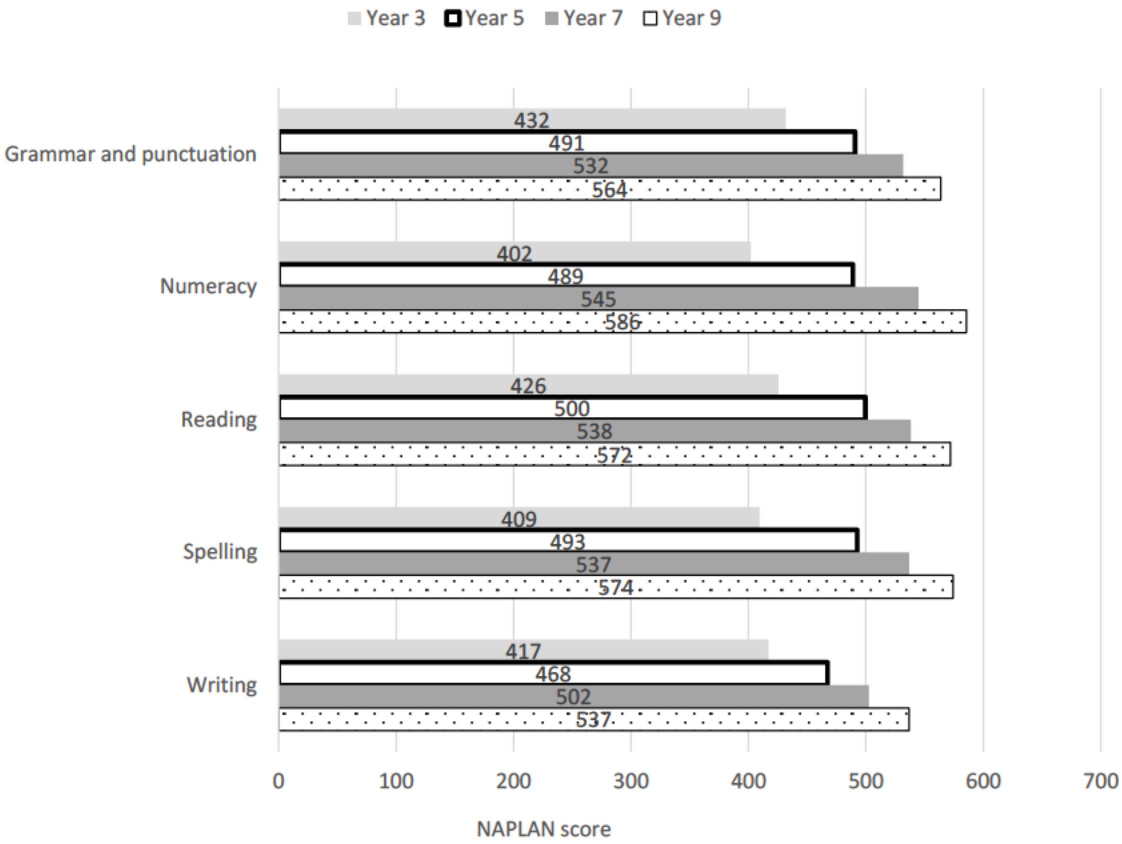
7.1.1 Relationship between NAPLAN and student age

For all five areas of student performance tested in NAPLAN, the average student performance improves as students' get older and progress through school, but the average improvement is smaller as students get older (see Figure 8).[22]

[22] There have been some changes made to the NAPLAN assessment process for the writing domain which has led to some concerns about the comparability over time for this domain (Thomas, 2019). The sensitivity of the result to the inclusion of the writing domain has been tested by replicating the analysis excluding the writing domain. All of the results presented in this paper are consistent whether the writing domain is included or excluded.

Regional and remoteness funding loading

Figure 8 Average levels of literacy and numeracy by school year, 2019



Source: ACARA school level data.

In a simple regression model controlling for Year level, test domain, and whether or not the test was done online, there is a negative relationship between income and average test scores. That is, as income of the school goes up, average NAPLAN in the school goes down. Given the current funding approach to schools (described in detail in the previous section), the above relationship likely reflects the net effects of selection biases, counterbalanced to a certain extent by the direct effect of school income on student outcomes.

In one direction, because governments target schools that are likely to require additional resources, there is also likely to be a strong negative selection effect of income from government sources and student outcomes. However, to counterbalance this to a certain extent, because parents who are able to pay fees towards their child's education are also more likely to be able to fund other investments in their child's human capital, there is likely to be a positive selection effect of fee income and self-selection of relatively advantaged students into high performing schools.

These selection effects are demonstrated by a regression model with NAPLAN scores as the dependent variable (controlling for Year level, test domain, and whether or not the test was done online) with the four sources of income as separate explanatory variables. Specifically, the coefficients and p-values for the sources of income divided by $1,000 are as follows:

- Commonwealth government income – coefficient = -3.66, p-value = 0.00
- State/territory income – coefficient = -4.07, p-value = 0.00
- Fees, charges, and parental contribution – coefficient = 1.45, p-value = 0.00, and
- Other private sources of income – Coefficient = 0.13, p-value = 0.33.

Controlling for Year level, test domain, and whether or not the test was done online, there is a negative relationship between remoteness and average test scores. That relationship becomes less negative when income of the school is controlled for, suggesting that part of the difference in average test scores by remoteness is due to variation in income, with coefficients from the two models as follows:

- -18.6 coefficient in inner regional areas unconditional on income, -17.8 conditional on income
- -27.0 coefficient in outer regional areas unconditional on income, -25.0 conditional on income
- -46.1 coefficient in remote areas unconditional on income, -40.8 conditional on income, and
- -121 coefficient in very remote areas unconditional on income, -112.2 conditional on income.

7.1.2 Student growth analysis

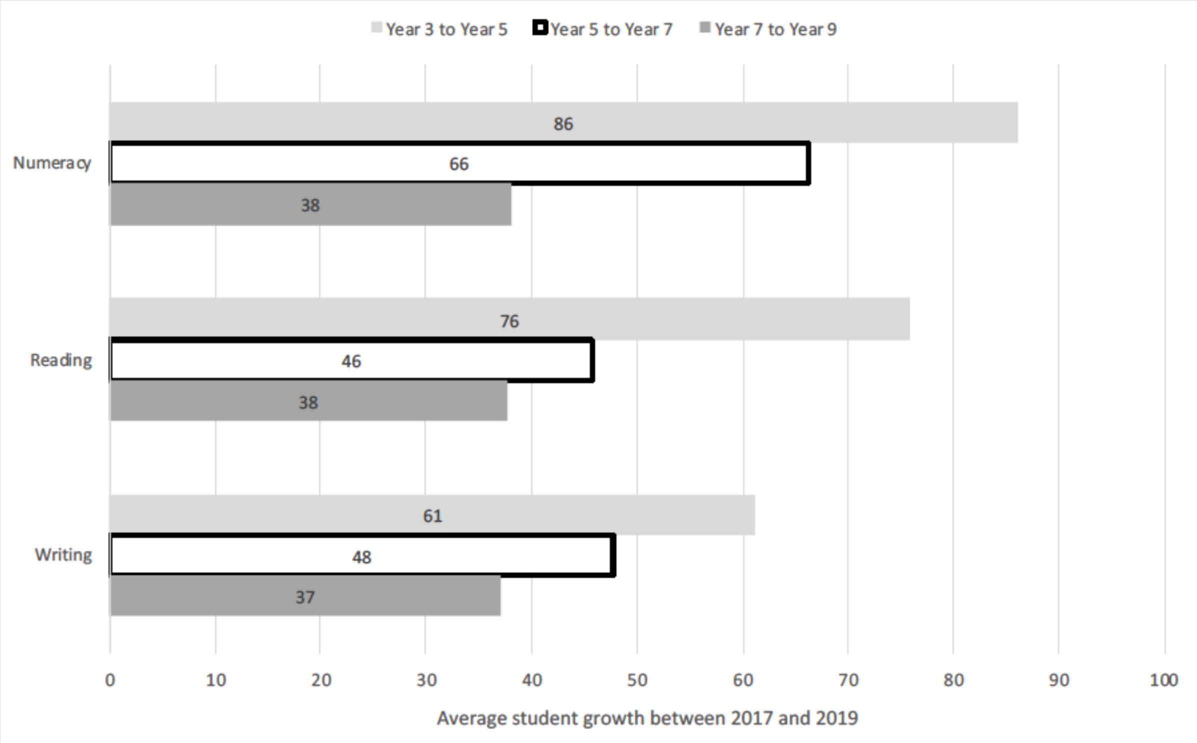
In order to control for some of the selection effects described above, as well other unobserved characteristics of students that impact on their literacy and numeracy, one option is to focus on growth in student outcomes between years. Many of the selection effects will be captured by baseline NAPLAN, with change through time in student outcomes potentially more closely capturing the direct impact of income on student outcomes. The literature emphasises the advantages of using growth measures (change in test scores between two time periods for the same cohort of students) as opposed to test scores at one point in time. Growth measures control for the skills and knowledge a student already possesses and the home environment prior to the first examination time-point, and therefore it is a better representation of the contribution of the current school. There are further methodological advantages of using the growth measures which we discuss in the literature review in Appendix A.

For primary schools, growth can be measured from Year 3 to Year 5, whereas for secondary schools, growth can be measured from Year 7 to Year 9. For combined schools, growth can be measured across those year ranges, as well as between Year 5 and Year 7.

Using the school-level data, growth is only available for students who stay within a particular school over the two years between tests. That means that not all students are able to be matched across those year levels. Average growth between 2017 and 2019 was greater for Year 3 to Year 5 for all three available test domains, with growth lowest for Year 7 to Year 9.

As shown in Figure 9 between Year 3 and Year 5, growth was greatest for numeracy, followed by reading and writing. Between Year 5 and Year 7, growth was greater for numeracy, but similar for reading and writing. For Year 7 to Year 9, growth was similar across all three domains.

Figure 9 Average student growth over a two-year period, 2017 to 2019



Source: ACARA school level data.

When analysing the factors that predict growth in student outcomes, it is important to take into account the baseline NAPLAN result. This is in part because of floor/ceiling effects where students at the bottom and top (respectively) of the distribution have less space to decrease or increase (respectively) their scores between waves of testing. Another reason to control for baseline scores is the process known as 'regression to the mean', whereby random variation for individuals in their NAPLAN scores in a given year means that those students who (by chance) have a higher/lower score in one year than their true level of literacy or numeracy would suggest will have a relative decrease/increase in their NAPLAN score before the next wave of testing.

Without controlling for baseline NAPLAN, or the year levels that growth is being measured across, schools in major cities have the lowest level of average growth, with schools in remote and very remote areas having the greatest growth. When the models control for baseline NAPLAN (which is higher in major cities) and the grade range (with schools in major cities being more likely to have the same students in Year 7 and 9), conditional student gain is greatest in major cities, with a steady reduction in gain between Inner Regional, Outer Regional and Remote schools, and then a very large relative decline in Very Remote schools.

Controlling for baseline NAPLAN and a range of other factors that have a direct effect on student growth, it is also possible to look at school level factors that predict student growth. In particular, there are a number of characteristics that are available on the school-level dataset that are not available on the individual-level data described below that are of relevance to this research project, in particular school size and disability.

There is no evidence that medium, small and very small schools have lower growth in NAPLAN than large schools. By contrast, the coefficient for small schools is positive (1.77) and statistically significant. The coefficient for very small schools is even larger (9.26), however because of very small sample sizes it is not statistically significant.

Looking at other results from the table, growth in NAPLAN is higher for boarding schools, schools with a relatively high level of socio-educational advantage, and those with a high proportion of students who speak a language other than English at home. Growth is, however, lower for schools with a high proportion of students who identify as Aboriginal or Torres Strait Islander or who have disability.

7.2 Individual student level growth analysis

The analysis reported in the previous section shows that growth in student outcomes after controlling for baseline NAPLAN becomes smaller as the school they attended becomes more geographically remote. This section uses the individual student level data to estimate the relationship between geographic remoteness and growth in student outcomes while controlling for as many of the other student level factors that may be related to growth in student outcomes and geographic remoteness.

7.2.1 Constructing the student-level dataset

The ACARA dataset provided to the ANU includes all students who undertook the NAPLAN assessment for a given year. The data set used to estimate the models of growth in student outcomes excludes students who did not complete the previous NAPLAN assessment because it is not possible to measure student growth. Also excluded are students who moved schools because, while NAPLAN scores are available, we do not know which school they previously attended and by extension the income they were exposed to.

Given that Year 7 is the first year of secondary school, many students change schools between Years 6 and 7 (only 14.9 per cent of Year 7 students in the dataset had NAPLAN data for Year 5, had not changed schools over the period, and had income data available for their school) The analysis is therefore based on growth in student outcomes between Year 3 and Year 5 and Year 7 and Year 9. Of the students who completed NAPLAN in Year 5, 71.0 per cent also completed NAPLAN in Year 3 and were attending the same school in Year 3 and 5 and for whom school income data was available for both points in time and are thus included in the model. For those who completed NAPLAN in Year 9, 69.4 per cent had both NAPLAN data for Year 7, had not changed schools and school income data was available.

The exclusion of students who changed schools between Years 3 and 5 or between Years 7 and 9, the exclusion of those with missing income data and those who missed the previous NAPLAN assessment has the potential to bias the results. In order to ameliorate such a potential impact inverse probability weights based on the chance of having complete information, conditional on a range of demographic, geographic, and socioeconomic measures have been created.[23] For details of this approach see Langkamp, Lehman and Lemeshow (2010).

[23] The explanatory variables are year level, remoteness, sex, parental occupation, parental education, LBOTE status, Aboriginal and Torres Strait Islander status, state/territory and school sector. The pseudo R-Squared for the estimation is 0.0389 and the average inverse probability is 1.56 for those who are not in the sample, and 1.42 for those within the sample. The within the in-sample population weights are: higher for Year 9 students; very remote, remote, outer regional, and inner regional students (in that order); children whose parents are not employed; Aboriginal and Torres Strait Islander students; South Australian, Northern Territory, Victorian, Queensland, Australian Capital Territory, and Western Australian students (in that order); non-government school students. Lower for females; students with a parent who was a manager

Having constructed a weight for each student in the dataset, the next step is to create the measure of growth in student outcomes, which based on the discussion above, is the change in NAPLAN test scores for a given domain, over a two-year period (student gain).

When estimating the relationship between student gain and other school inputs, the effect of baseline NAPLAN is controlled for using a modelling approach. This involves modelling student gain as the dependent variable (Year 3 to Year 5; or Year 7 to Year 9) and including baseline NAPLAN (Year 3 and Year 7 respectively) as a linear and squared term in the model. This allows estimation of the factors associated with student growth, holding constant where each student was on the distribution of academic performance in the preceding year.

7.2.2 Analysing student gain

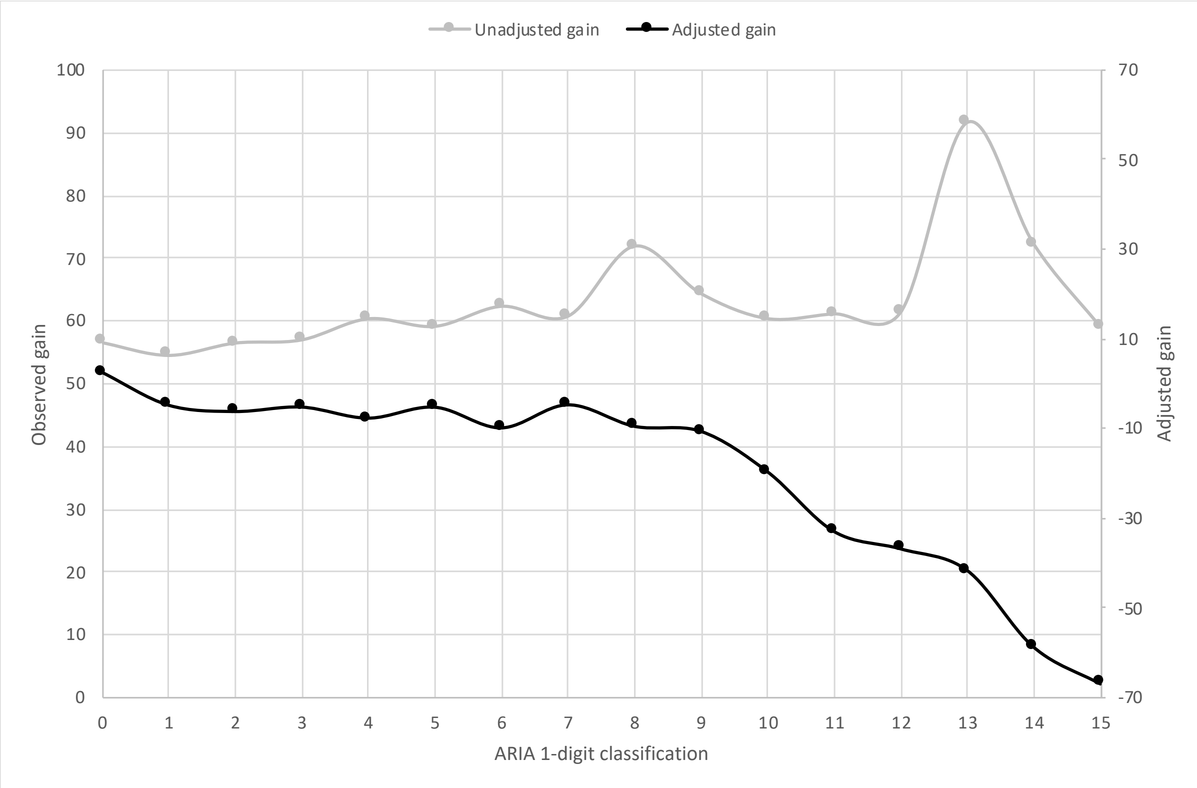
Combining data from 2018 and 2019 the individual student level dataset has 3,959,587 usable observations, with a maximum of five observations per individual student (one for each domain). Across the entire sample there is an average student gain of 56.62, and an average adjusted gain of close to zero (0.64), weighted for selection into the final dataset.

Figure 10 shows the student gain (with and without controlling for baseline levels). Unadjusted gain is higher in all 1-digit ARIA remoteness categories compared to major cities (ARIA = 0) apart from those with an ARIA value of 1 to less than 2. The largest average student gain was for those with an ARIA value of 13 to less than 14.

Similarly to the school-level NAPLAN data presented in the previous sub-section, unadjusted gain is not a useful measure of student performance. Adjusted student gain (that is, controlling for baseline levels) was highest in major cities (ARIA = 0) and lower for all other 1-digit ARIA categories. The smallest adjusted gain was for those in the most remote category, with gains of 66.8 points lower (on average) once baseline NAPLAN has been controlled for.

or professional; students who had a parent who had completed Year 12; and students who had a parent with a post-school qualification.

Figure 10 Unadjusted and adjusted NAPLAN gain, Years 5 and 9 students, 2018 and 2019, by ARIA 1-digit remoteness classification



Note: The adjusted student gain reported in this figure is based upon the dependent variable adjustment approach which reflects the extent to which each student has a greater (or smaller) growth in that particular domain, based on their test score for that domain two years previously. The steps to estimate the outcome measure of 'adjusted gain' are: (i) Calculate the difference in test score for that domain from two years previously; (ii) for Year 5 and Year 9 students separately, estimate a model of student gain as a function of baseline NAPLAN (as a linear, quadratic, cubic, and quartic variable); (iii) predict the gain for that student in that domain, based on their own baseline NAPLAN; and subtract their predicted gain from their actual gain

Source: ACARA individual student level data.

Before looking at the relationship between income and student growth (in the subsequent section), the extent to which the gaps observed in Figure 10 are due to differences in demographic and socio-educational characteristics of students, and the extent to which gaps remain after these characteristics are controlled for is documented.

A modelling approach is used, with adjusted gain the dependent variable. Because of the interest in student background characteristics only as control variables, a very flexible specification is used. The specification controls for calendar year, test domain, year level, and the student's age, gender and Aboriginal and Torres Strait Islander status. The models also include each category of the following variables as separate dummy variables, with the base case chosen to be the modal category and given in brackets:

- Father's occupation (base case = tradesperson)
- Mother's occupation (tradesperson)
- Mother's school education (Year 12)
- Father's school education (Year 12)

- Mother's non-school education (bachelor's degree or above)
- Father's non-school education (bachelor's degree or above).

It should be noted that those students for whom characteristics of their mother and father are not known (including single parents) are still included in the analysis with a separate dummy variable for missing data, and that children with two parents of the same gender are likely to have one parent mis-classified as a father or mother.

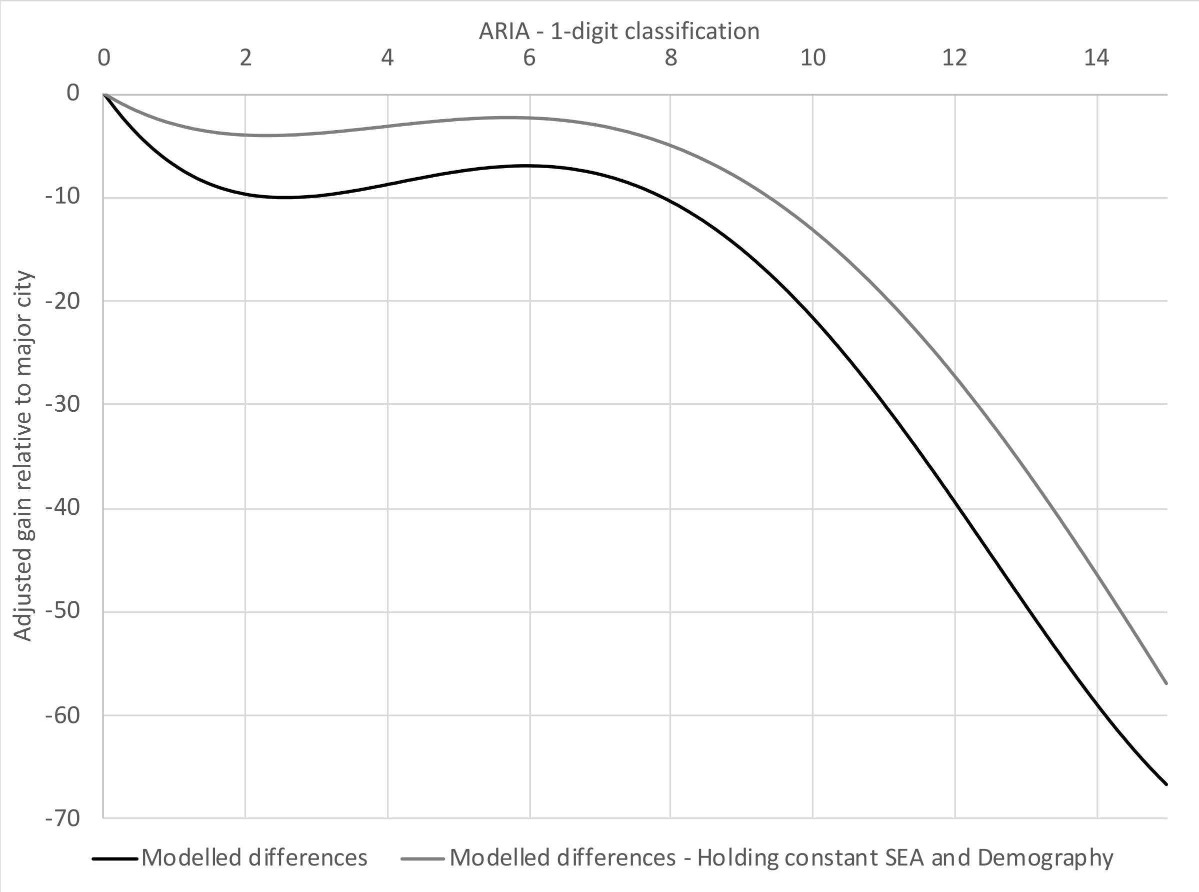
The final set of variables in the model is a very flexible specification of remoteness, with a linear, squared, cubic, and quartic term for the continuous remoteness classification. Figure 11 shows the predicted difference in adjusted gain between major cities and each point on the remoteness distribution. The black line is essentially the smoothed distribution from the previous Figure, setting the major city value to zero. The grey line is the best estimate of what the gap would be, if children in regional and remote areas had the same demographic and socio-educational outcomes as those in major cities. It should be noted that income is not controlled for in either model. This means that the distributions reflect the current allocation of income across schools, not a counter-factual situation where all schools receive the same income, or where schools receive the SRS allocation (or some other hypothetical allocation).

For all points on the distribution, the grey and black lines are below zero, showing that predicted adjusted gain in NAPLAN is lower outside of major cities. However, for all points on the distribution, the grey line is closer to zero than the black line, showing that at least some of the difference in student growth is explained by socio-educational and demographic characteristics. The point on the remoteness distribution where the two lines are furthest apart, or where socio-educational and demographic characteristics explain the greatest proportion of the distribution is an ARIA+ value of 5.5, where around two-thirds of the difference between a student in that type of area and one in a major city is explained by other observed characteristics.

The final point to note from Figure 11 is that in the most remote parts of Australia, there is still a very large gap in NAPLAN growth compared to a student in a major city, adjusted for the student's starting point. Indeed, beyond an ARIA+ value of 14, only around 15-21 per cent of the difference is explained by observable characteristics. There is nothing mechanical about this finding, and it is as likely that more of the gap would have been explained by observable characteristics at that point on the distribution than less. It is also worth keeping in mind that these differences are in a situation where income levels per student are much higher in very remote areas (Figure 1), albeit not as high as the SRS formula would suggest (Figure 3). Furthermore, these are differences in student growth rather than levels, and reflect a further falling behind in literacy and numeracy, let alone any convergence to major city values.

In sum, there are very large gaps in literacy/numeracy growth between students who live in regional and remote areas compared to those who live in major cities adjusting for starting point, with some but far from all of these gaps explained by demographic and socio-educational characteristics. It may be the case that the inclusion of further controls reduces the unexplained gap in the change in outcomes. However, these controls would need to predict change in NAPLAN, rather than levels and for them to be useful in this paper, would need to not be influenced by remoteness.

Figure 11 Adjusted NAPLAN gain with and without demographic and socio-educational controls, Years 5 and 9 students, 2018 and 2019, by ARIA 1-digit remoteness classification



Source: ACARA individual student level data.

The analysis summarised in Figure 11 is focussed on providing an accurate measure of the relationship between location and student gain, controlling for a range of demographic and socio-educational characteristics. However, the relationship of some of these control variables with student gain are also of interest in their own right. Females have a greater adjusted gain in NAPLAN than males, whereas those who speak a language other than English have a greater adjusted gain than those who don't. Aboriginal and Torres Strait Islander children have lower adjusted gain than non-Indigenous children or those whose Indigenous status is not stated. For the most part, higher socio-educational advantage is associated with greater NAPLAN gain, and it is important to point out that the relationship with characteristics of the child's mother is similar to the relationship with the characteristics of the child's father.

7.3 Student attendance

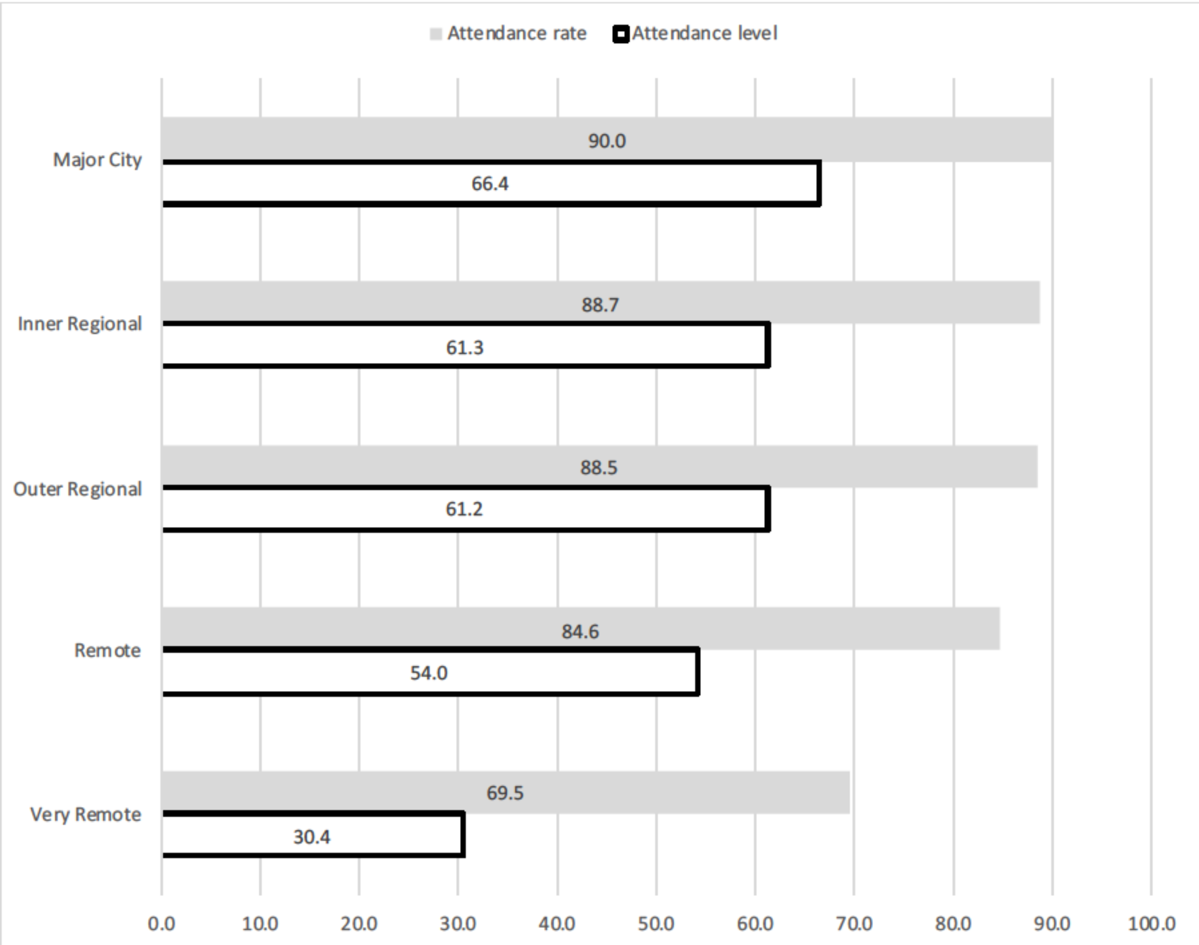
For a school to have an impact on the growth in literacy and numeracy levels on its students, they need to attend school on a reasonably regular basis, ideally for full, rather than partial days. Unfortunately, the individual-level data analysed in the previous sub-section does not have any measures of student attendance. However, the school-level data has two outcomes related to school attendance:

- Attendance rate, or the number of actual full-time equivalent student-days attended by full-time students in Years 1-10 as a percentage of the total number of possible student-days attended
- Attendance level, or the proportion of full-time students in Years 1-10 whose attendance rate in Term 3 is equal to or greater than 90 per cent.

Without weighting by school size, the average attendance rate across all schools was 89.5 per cent, implying that for the average school around nine-in-ten student are attending on a given day. The average attendance level, on the other hand, is only 65.0 per cent, or only roughly two-thirds of students in the average school missing one-tenth or fewer days of school. Not only is the measure of attendance level lower on average than the measure of student rates, there is a greater variation around that mean, with a standard deviation of 5.7 for student rates and 13.1 for student levels.

Figure 12 shows that both the attendance rate and the attendance level decline as remoteness increases, with a particularly large difference between remote and very remote Australia and between outer regional areas and remote Australia for the attendance level measure. Specifically, in Term 3 2019, 90.0 per cent of students in a major city were attending school on a given day and 66.4 per cent of students in a major city attended at least 90 per cent of days throughout the year. For very remote areas, at the other end of the distribution, this falls to 69.5 per cent and 30.4 per cent respectively.

Figure 12 Student attendance rates and attendance levels by remoteness, Term 3, 2019



Source: ACARA School Level data.

In addition to remoteness, and similar to school-level literacy and numeracy, there are a number of other characteristics that are associated with school attendance. A model of school-level factors associated with each of the school attendance outcomes is estimated. Some of the explanatory variables are associated with both attendance measures in similar ways. However, there are important differences that highlight that although the two measures are conceptually quite similar, they are still picking up subtly different aspects of attendance.

ss 47B(a), 47E(d)

Catholic schools have lower attendance than government schools, whereas independent schools have significantly and substantially higher attendance. School size does not correlate in the same way with attendance as with literacy/numeracy. Keeping in mind that the model controls for a range of other characteristics, it would appear that attendance is highest in large schools, declining as school size declines. While there is no evidence that small school size hampers literacy/numeracy development, it would appear that it may negatively impact on school attendance.

Socio-educational advantage correlates with attendance, but in slightly different ways for the two measures. For both measures, having a high per cent of students in the lowest quartile and in the upper-middle quartile (relative to the highest quartile) is negatively correlated with attendance. There is no association between attendance levels and the lower-middle quartile, and a small positive correlation with attendance rates. Schools with a high proportion of students who identify as Aboriginal or Torres Strait Islander or who have a disability have low attendance, whereas there is a small positive association with speaking a language other than English at home.

The final thing to note with regards to the regression analysis is that after controlling for other characteristics, some of the differences in attendance rates and levels by remoteness disappear or move in the opposite direction. Conditional on other characteristics, attendance levels and rates are higher in inner regional and outer regional areas, whereas there is a slightly higher attendance rate in remote areas (no difference in attendance levels). Very remote areas, however, have a negative correlation with both measures of attendance.

While there are benefits of regular school attendance above and beyond the effect it may have on literacy and numeracy, those potential effects are also of particular relevance. It would be close to impossible to establish causality with school-level data for attendance on literacy/numeracy, as it is equally plausible that those students who have relatively low levels of literacy/numeracy or even lower growth in these outcomes may attend school less frequently because either the costs are higher or the benefits are less.

When including both measures of student attendance it is apparent that there is a positive correlation between attendance and student growth. The relationship with the attendance rate is slightly stronger, with a one-unit increase in the per cent of students who are in attendance on a given day associated with a growth in NAPLAN-based literacy and numeracy that is 0.24 points higher.

7.4 School experience

In the previous sub-sections of the paper, the focus has been on the relationship between school location and student literacy and numeracy as well as student attendance. While literacy and numeracy (as measured by NAPLAN) and attendance are key outcome measures, they do not capture all of the important aspects of the school experience. In order to look more broadly at the experience of students across regional and remote areas, the analysis is extended to look at a broader set of outcomes.

7.4.1 Describing the data

The Programme for International Student Assessment (PISA) is a school-based survey, collected most recently in Australia in 2018. Data was collected from 776 schools, with 510 of those schools being in major cities, 246 in regional Australia, and 20 in remote Australia.

Principals are asked a number of demographic questions about their schools, but are also asked questions on: whether their school's capacity to provide instruction was hindered by a range of issues; the school's capacity to enhance learning and teaching using digital devices; other schooling available to students in the location; the extent to which learning is hindered by various phenomena; student-computer ratios; teacher attendance at professional development; activities offered to students; parent-participation in school related activities; study help.

From these schools, data was collected from 14,273 students. The average age of respondents is 15.79 years, with an age range of 15.25 to 16.33 years (unweighted). Across the sample, 82 per cent of respondents were in Year 10, 11 per cent were in Year 9, and 7 per cent were in Year 11. Across the sample 9,866 of these students were attending a school in a major city; 4,202 were attending a school in regional Australia; and 205 were attending a school in remote Australia. While the sample size of remote students is relatively small, there are a large number of regional students and, because the differences between remote and non-remote students are quite large, many of the differences are statistically significant.

This sub-section of the paper looks at the extent to which a range of school-level measures are different in regional and/or remote schools compared to schools in a major city?

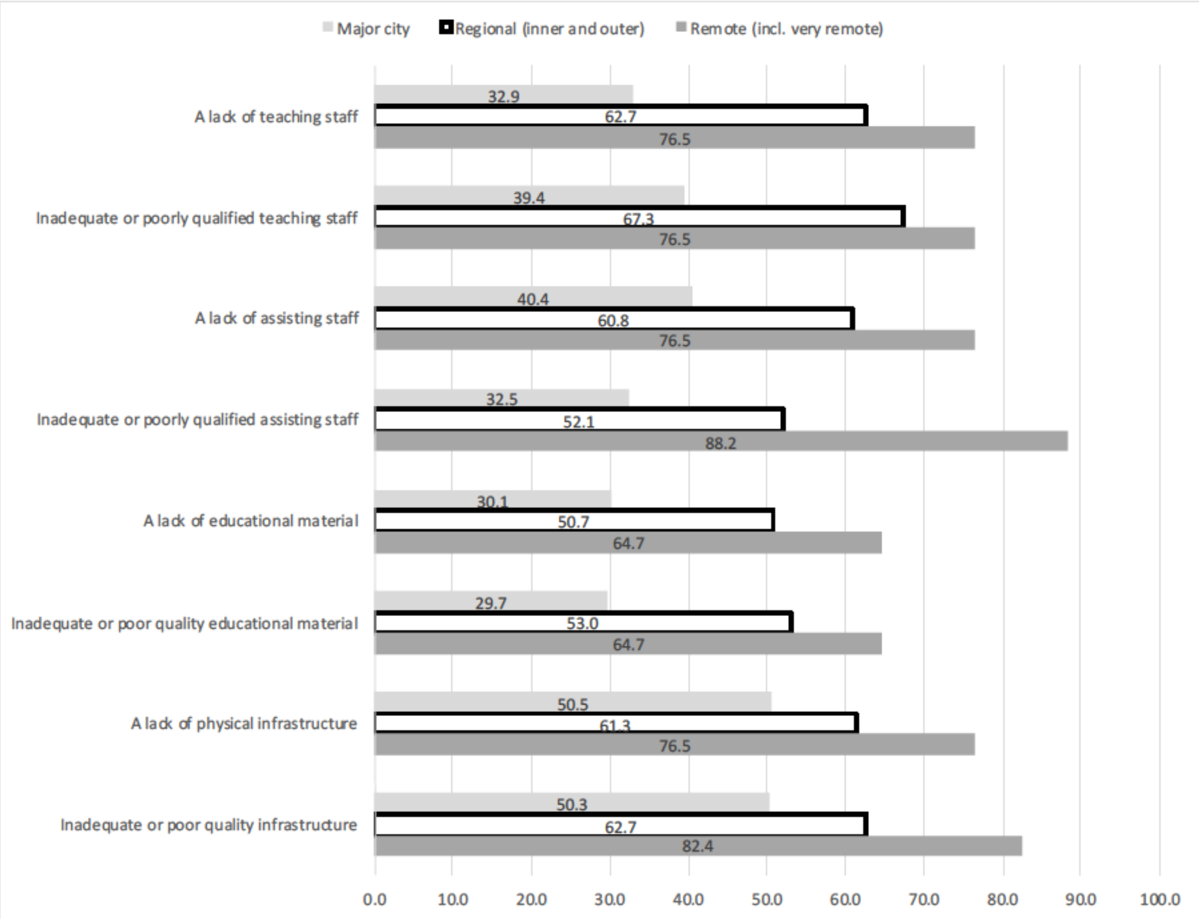
7.4.2 School constraints

Principals were asked about whether their school's capacity to provide instruction was hindered by eight potential issues, with response options ranging from not at all; Very little; To some extent; and A lot. If values of 1, 2, 3 and 4 are assigned to the response options above (higher values = greater constraints), then the average value is 12.20 for major cities; 14.70 for regional areas; and 17.88 for remote areas (theoretical range of 8 to 32). If the threshold is set at least 'very little', then the average number of constraints is 3.06 in major cities; 4.71 in regional areas; and 6.06 in remote areas;

Looking at the individual constraints in Figure 13, regional schools were more likely to report all of the constraints than schools in major cities. The most common constraint reported in regional areas was inadequate or poorly qualified teaching staff (67.3 per cent), whereas the biggest gap with major cities was a lack of teaching staff (62.7 per cent in regional areas compared to 32.9 per cent in major cities) and inadequate or poor quality educational material (53.0 per cent in regional areas compared to 29.7 per cent in major cities);

Remote schools were more likely to report all of the constraints than schools in major cities. The most common constraint reported in remote areas and the one with the largest gap with major cities was Inadequate or poorly qualified assisting staff (88.2 per cent in remote areas compared to 32.5 per cent in major cities).

Figure 13 School constraints for major cities, regional, and remote areas, 2018



Source: PISA 2018.

7.4.3 Hindrances to student learning

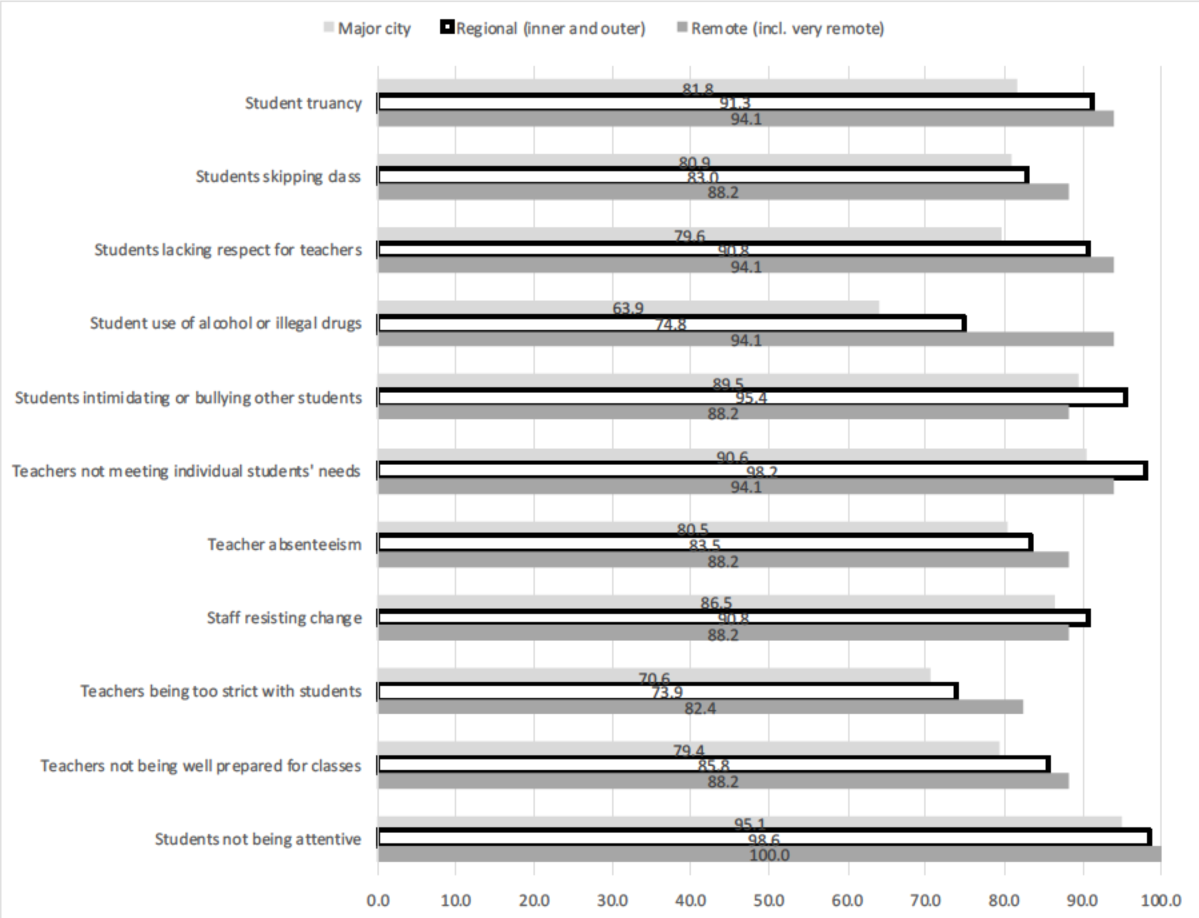
Principals in PISA were asked whether 11 types of phenomena are a hindrance to student learning within their school. Response options were Not at all; Very Little; To some extent; and A lot. If values of 1, 2, 3 and 4 are assigned to the response options above (higher values = greater hindrance to student learning), then the average value is 22.77 for major cities; 24.72 for regional areas; and 27.24 for remote areas (theoretical range of 11 to 44). If a threshold of at least 'very little' is set, then the average number of hindrances is 8.98 in major cities; 9.66 in regional areas; and 10.0 in remote areas.

Regional schools were more likely to report all of the hindrances than schools in major cities. The most common hindrance reported in regional areas was teachers not meeting individual students' needs (98.2 per cent) and students not being attentive (98.6 per cent), whereas the biggest gap with major cities was student use of alcohol and other illegal drugs (74.7 per cent in regional areas compared to 63.9 per cent in major cities).

Remote schools were more likely to report all but one of the hindrances than schools in major cities. The most common constraint reported in remote areas was students not being attentive (reported by all schools) whereas the biggest gap was student use of alcohol and other illegal drugs (94.1 per cent in remote areas compared to 63.9 per cent in major cities).

Importantly, there were three hindrances more likely to be reported in regional areas compared to remote areas - Students intimidating or bullying other students; Teachers not meeting individual students' needs; and Staff resisting change.

Figure 14 Hindrances to learning for major cities, regional, and remote areas, 2018

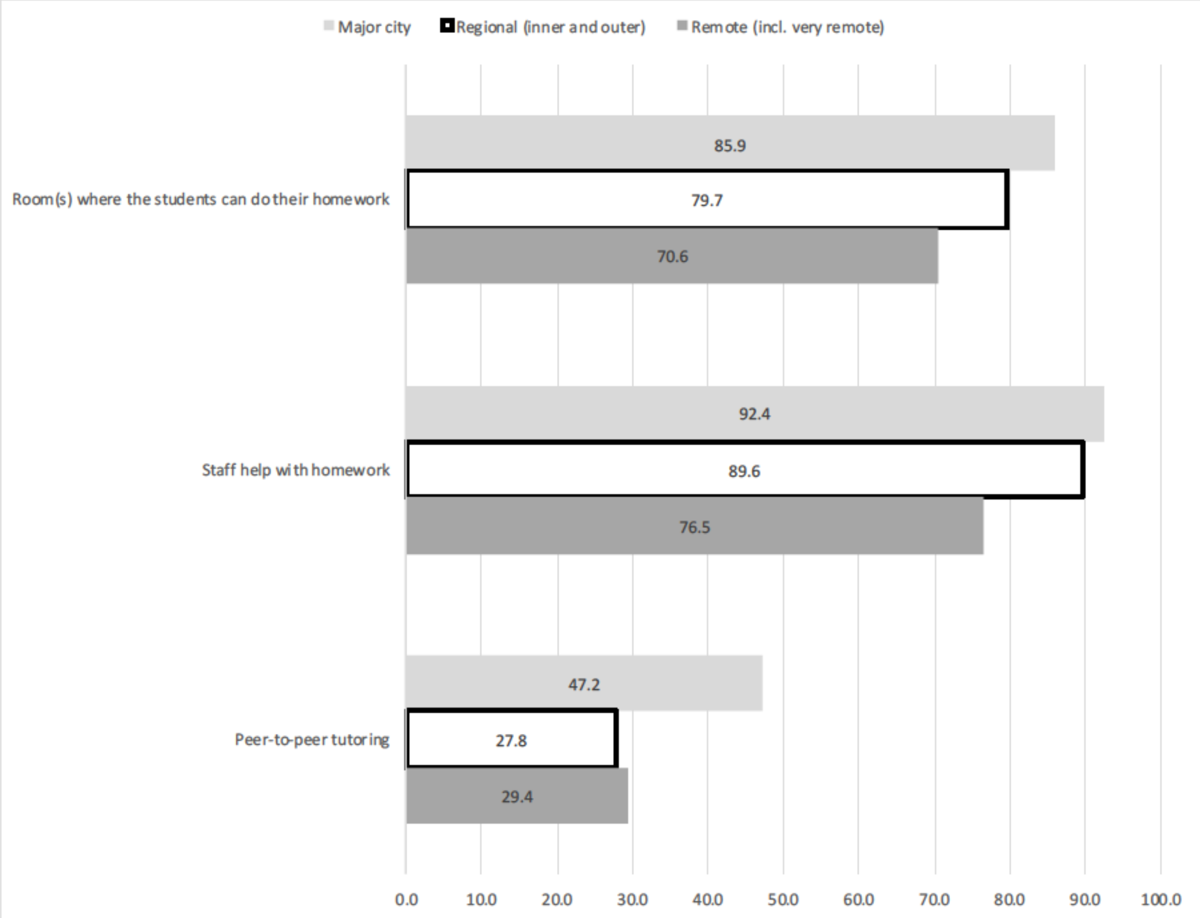


Source: PISA 2018.

7.4.4 Study help and school activities

Principals were asked whether 'For 15-year old students, does your school provide the following study help?' with three types of study help asked about. Compared to those in major cities, (Figure 15) principals in regional and remote schools were less likely to say that their schools had Room(s) where the students can do their homework; Staff help with homework; and Peer-to-peer tutoring. The last of these forms of study help had the largest gap between regional/remote schools and major cities.

Figure 15 Study help for major cities, regional, and remote areas, 2018



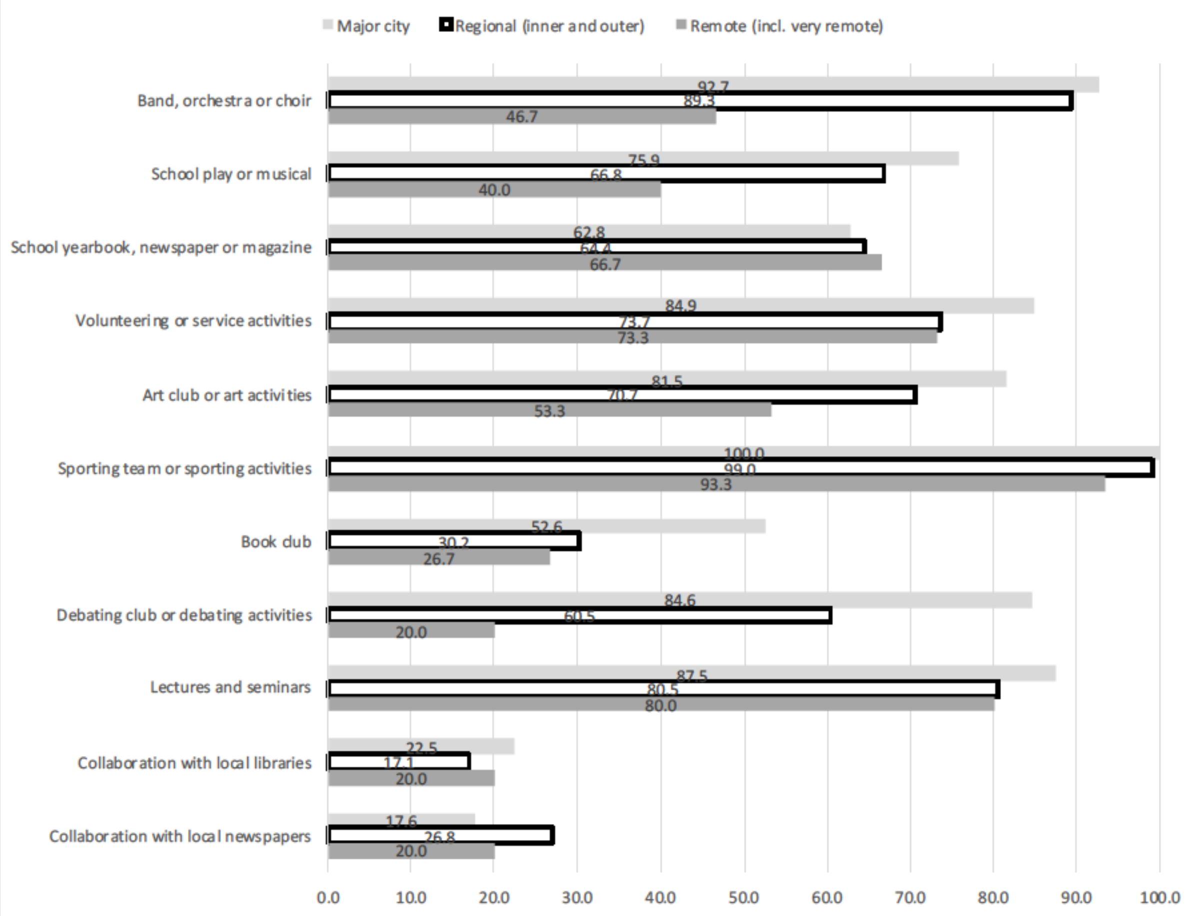
Source: PISA 2018.

Principals were asked which of a list of 11 activities the school offers for students in Year 10. The average number of activities was 7.63 in schools in major cities, 6.79 in regional areas, and 5.40 in remote areas. These differences were statistically significant.

There were seven types of activities for which there was a large negative difference between schools in regional areas and major cities, with the largest differences being for a book club (52.6 per cent compared to 30.2 per cent in major cities and regional areas respectively) and a debating club (84.6 per cent compared to 60.5 per cent). There was one activity for which there was a large positive difference between regional areas and major cities – collaboration with local newspapers (17.6 per cent in major cities compared to 26.8 per cent in regional areas)

There were nine types of activities for which there was a large negative difference between schools in remote areas and major cities, with the largest differences being for a debating club (84.6 per cent compared to 20.0 per cent in major cities and remote areas respectively), book club (52.6 per cent compared to 26.7 per cent) and Band, orchestra or choir (92.7 per cent compared to 46.7 per cent). There was one activity for which there was a small difference between remote areas and major cities – school yearbook, newspaper or magazine (62.8 per cent in major cities compared to 66.7 per cent in remote).

Figure 16 Student activities for major cities, regional, and remote areas, 2018



Source: PISA 2018.

7.4.5 Digital devices

Principals were asked to what extent they agree with a set of statements about their school's capacity to enhance learning and teaching using digital devices. Before answering the questions, they were asked to 'Please think of different kinds of digital devices such as for example desktop computers, portable laptops, tablet computers or interactive whiteboards.' For each of the 11 statements, principals were asked whether they strongly disagree; disagree; agree; or strongly disagree.

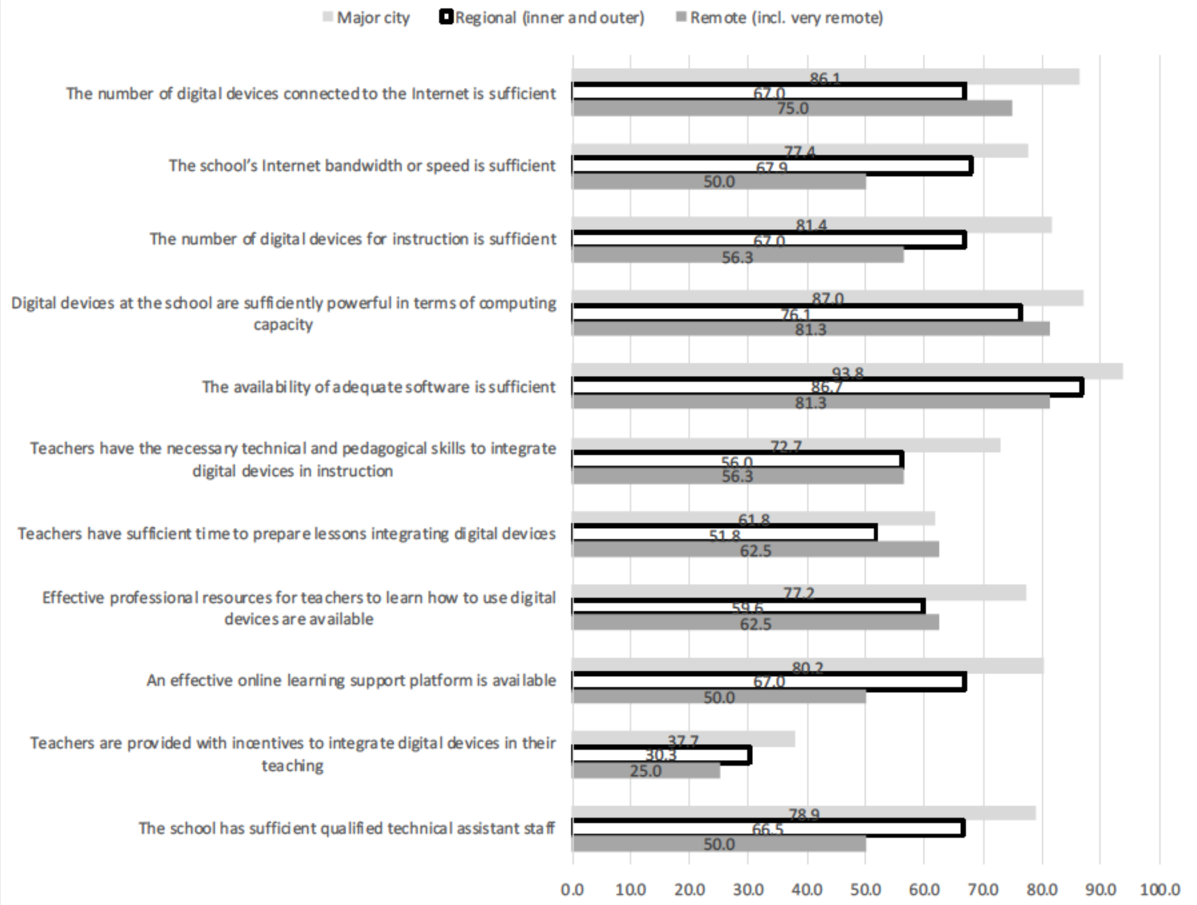
If values of 1 to 4 for the above response options are applied, then the average cumulative value was 32.9 in major cities; 30.1 in regional areas; and 27.7 in remote areas (theoretical range of 11 to 44, with higher values imply greater capacity). Combining those who agree and strongly agree, principals in major cities agree with an average of 8.3 statements, whereas those in regional areas agree with 7.0 statements and those in remote areas agree with 6.5 statements.

There are no statements about sufficiency of access to digital devices that principals in regional or remote areas are more likely to agree with than are principals in major cities (Figure 17). The only statement that teachers in remote schools are substantially more likely to agree with than are teachers in regional areas is that 'Teachers have sufficient time to prepare lessons integrating digital devices'.

Regional and remoteness funding loading

The statement about digital devices that principals in regional and remote areas are the least likely to agree with is that 'Teachers are provided with incentives to integrate digital devices in their teaching.' The two biggest relative gaps between regional areas and major cities is that 'The number of digital devices connected to the Internet is sufficient' and 'Effective professional resources for teachers to learn how to use digital devices are available.' The two biggest relative gaps between remote areas and major cities is that 'An effective online learning support platform is available' and 'The school has sufficient qualified technical assistant staff.'

Figure 17 Access to digital devices, major cities, regional, and remote areas, 2018



Source: PISA 2018.

7.5 Key findings

After carefully constructing a measure of student gain and taking into account baseline NAPLAN, students in all areas outside of major cities have been shown to have a lower level of adjusted gain in literacy and numeracy over a two-year period than those in major cities. The average gain for students over a two year period (across year levels and test domains) was 56.6. The average student in the most remote part of Australia has an adjusted gain that is 66.8 points lower than those in a major city.

Some, but not all of these differences are explained by other demographic and socio-educational characteristics. That is, despite the very high levels of income received by very remote schools, students in these areas fall further and further behind otherwise identical peers in a major city school over each two year period covered by NAPLAN.

School attendance is also correlated with levels of remoteness, with students outside of major cities being less likely to attend school on a given day, and less likely to attend a minimum threshold of days per year (set at 90 per cent). However, these differences are mainly explained by other characteristics of the school, with the exception of schools in very remote areas which have lower attendance than an otherwise similar school in the rest of the country.

After arguing that school outcomes beyond NAPLAN and attendance need to be considered, it is shown using data from PISA that principals in regional areas and remote areas in particular are more likely to say that there are constraints on student learning, more likely to say that there are hindrances, less likely to say that there is study help available, less likely to say that a range of activities occur, and less likely to say that they have the resources to give students appropriate access to digital devices. Once again, despite the very large differences in school income by location, students in regional and remote areas appear from the PISA data to have a far worse school experience.

8 The relationship between school income and student outcomes

Section 4 describes the variation in per-student income across locations. This showed that while average school incomes were substantially higher in more remote parts of the country, part of this was explained by other characteristics of the students in these areas. Furthermore, Section 6 showed that schools in very remote areas receive on average substantially less than their SRS allocation and that the gap between actual and SRS allocation is much larger on a per-student basis in very remote areas than in other areas of Australia.

Analysis of student outcomes (Section 8) reveals that despite the fact that per-student school income increases with remoteness, student outcomes are worse in regional, remote and very remote areas compared to major cities. Student outcomes are worst in very remote areas.

This section brings together these two components of the analysis to examine the relationship between school income and student outcomes, and to estimate how much per-student school income would need to be increased for students living outside of major cities to achieve similar academic outcomes to students living in major cities.

Similar to the previous section, this section focuses on student growth in NAPLAN as the outcome of interest, but also consider broader student outcome measures, including school attendance. Ideally, the analysis presented in this paper would be based on a consistent dataset that has all outcomes of relevance for the student, the income of the school in which that student attends, as well as a full set of control variables that are correlated with student outcomes as well as school income. Unfortunately, such a dataset does not exist, or at the very least has not been made available for the analysis presented in this paper. However, by looking at the relationship between school income and student outcomes across a range of datasets, a reasonably consistent pattern emerges, and allows us to derive estimates of a potential school funding ratio to be applied across the remoteness distribution.

8.1 Modelling the relationship between per-student income and student outcomes using school-level data

In this sub-section of the paper, the relationship between school income and two sets of outcomes – growth in NAPLAN and student attendance – using school-level data is discussed. While this does not allow us to control for variation at the individual-level in terms of student outcomes and importantly determinants of those outcomes, it does have some of the richest dependent and independent variables available in this project.

The first important finding from the analysis is that even when controlling for a range of characteristics of the school (starting NAPLAN score, school size, location, socio-education and demographic characteristics) there is a positive and statistically significant relationship between per-student income of the school and improvement in literacy and numeracy. More precise estimates of the size of this association using student-level data are presented in subsequent sections. ss 47B(a), 47E(d)

There is also a positive association between per-student school income and school attendance, whether as measured by attendance rates (student-days attended as a percentage of the total number of possible student-days attended, Model 1) or attendance levels (per cent whose attendance rate is equal to or greater than 90 per cent, Model 2). The size of the association is slightly greater for attendance levels rather than attendance rates, but both are positive and statistically significant at the 1 per cent level of significance.

The final important finding from the school-level analysis of the association between outcomes and school income (Model 2) is that there is still a significant association between per-student income and growth in NAPLAN once average school attendance is controlled for. It is true that the size of the association declines between Model 1 and Model 2 when attendance is controlled for (ss 47B(a), 47E(d)). However, this simply reflects that one of the mechanisms for the relationship between income and growth in literacy/numeracy may be the effect income has on student attendance.

The importance of this data for subsequent sub-sections in this paper is fourfold. First, using detailed school level data there is a relationship between school income and student growth. Second, controlling for disability (albeit at the school level) which is not available on the student-level dataset does not change the measured relationship between school income and growth in literacy/numeracy. Third, there is a positive relationship between school income and school attendance (which is also not available on the student-level data). Finally, controlling for the relationship between school income and attendance does not change the relationship between school income and literacy/numeracy.

8.2 Modelling the relationship between per-student income and school experience

The literacy and numeracy outcomes available from ACARA, as well as school attendance, are core but not the only measure of a student's experience. A well-rounded school education also includes a breadth of activities, a school environment that is free from stress and anxiety, and a generally positive experience in terms of student-wellbeing and sense of belonging to the school.

Section 8.4 introduced a number of school-level measures reported by the school principal, showing for the most part that these measures were generally less positive in regional areas compared to major cities, and less positive still in remote areas. This section considers whether variation in school income can also explain some of the differences in these school experience measures.

In order to undertake this analysis, per-student income was linked to individual students on the PISA database, based on the school that they attended (in 2018). In total, there were 14,273 students on the PISA database, with 69.1 per cent attending a school in a major city, 29.4 per cent attending a school in a regional area, and 1.4 per cent attending a remote or very remote school. The vast majority of students were in Grade 10 (81.7 per cent) with a smaller proportion of students in Year 9 (11.1 per cent) or Year 11 (7.1 per cent).

In total 13,504 or 94.6 per cent of the sample were able to be linked to the ACARA database and therefore had an observed value for school income. Using sample weights, the mean per-student income for students in the sample was $18,352. This is only slightly higher than the mean per-student income for students in the individual-level ACARA database who undertook the Year 9 NAPLAN in 2018 ($17,752), though it does show that there may be a slight bias in the linked PISA sample towards high income schools.

8.2.1 Relationship between school income and school-level characteristics

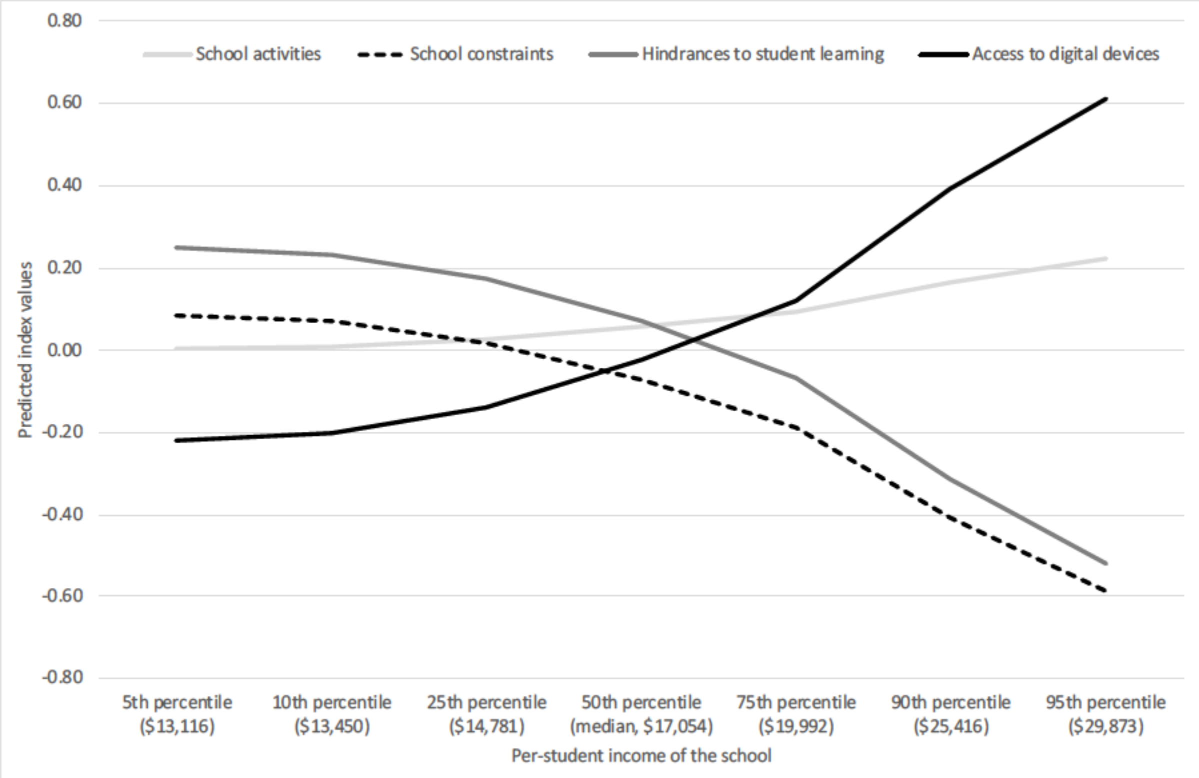
This section summarises the estimates of the relationship between school income and the ability of the school to provide different aspects of the learning environment as reported by school principals. The aspects of the learning environment considered are: school activities; school constraints; hindrances to student learning; and access to digital devices. The questions asked of school principals (see Section 8.4) on each of these aspects of the school environment are summarised into four additive indices:

- School activities (mean of 7.47, sample size of 12,472 students with available data)
- School constraints (mean of 12.79, sample size of 13,008)
- Hindrances to student learning (mean of 23.27, sample size of 12,998)
- Access to digital devices (mean of 32.09, sample size of 13,082).

For each of these measures of school performance three models are estimated. To keep the results comparable across the different indices, we scale these indices to have a mean of zero and a standard deviation of one across the sample. The first model for each of these scaled variables that we estimate includes per-student income as the only explanatory variable, and also includes the probability weights available on the dataset (using bootstrap standard errors with 80 replications). In the second model, we include two separate dummy variables for whether the school the student attending is in a regional or remote area, whereas the final model includes a range of other individual-level control variables (grade, gender, number of books in the household, whether or not a migrant, whether speaks a language other than English, index of home possessions, and index of household wealth).

Figure 18 summarises the relationship between school income and the principal-reported school outcomes through predicted values at fixed points across the income distribution. Keeping in mind that higher values of the school activities and access to digital devices indices and lower values of the school constraints and hindrances to student learning indices represent more positive outcomes, we can see that for all four variables higher values of per-student school income are associated with better outcomes. The strongest relationship is with access to digital devices (predicted variation of 0.83 times one standard deviation from the 5th to the 95th percentile of school income) whereas the weakest relationship is for school activities (0.22 times one standard deviation).

Figure 18 Variation in principal-reported school outcomes, by per-student income, 2018



Source: PISA 2018.

Note: Predictive models include controls for grade, gender, number of books in the household, whether or not a migrant, whether speaks a language other than English, index of home possessions, and index of household wealth. The latter two variables are fixed at their mean values.

8.2.2 Relationship between school income and individual-level wellbeing characteristics

The outcomes reported by the principal are important themselves, but are arguably more relevant for principals than for students. While variation in these characteristics is likely to filter down to the experience of students, it is important to also consider the more direct relationship between the income of the school in which a student attends (per student) and their own individual outcomes. In this section, we summarise results from an analysis of four student-level indices, designed to capture the students experiences and views of schooling.

The first dependent variable in the model is the index of sense of belonging (BELONG). This index variable was constructed by the OECD (2019) based on student responses to the following set of statements with possible response options of strongly disagree; disagree; agree; and strongly agree:

- I feel like an outsider (or left out of things) at school
- I make friends easily at school
- I feel like I belong at school
- I feel awkward and out of place in my school
- Other students seem to like me
- I feel lonely at school.

The index derived by the OECD is scaled to have a mean of zero, with positive values on this scale meaning that students reported a greater sense of belonging at school than did the average student across OECD countries.

The second dependent variable, self-efficacy or resilience, is based on the extent to which students agree ("strongly disagree", "disagree, "agree", "strongly agree") with the following statements about themselves:

- "I usually manage one way or another"
- "I feel proud that I have accomplished things"
- "I feel that I can handle many things at a time"
- "My belief in myself gets me through hard times"
- "When I'm in a difficult situation, I can usually find my way out of it".

Positive values in this index mean that the student reported higher self-efficacy than did the average student across OECD countries.

The third index, Exposure to bullying is based on the extent to which students have experienced ("never or almost never", "a few times a year", "a few times a month", "once a week or more") three experiences in school during the 12 months prior to the PISA test, including those that happen in social media,:

- "Other students left me out of things on purpose";
- "Other students made fun of me"; and
- "I was threatened by other students".

Positive values on this scale indicate that the student was more exposed to bullying at school than the average student in OECD countries.

The final index constructed by the OECD that we use captures the student's perceived value of school. Specifically, the index is based on the extent to which students agree ("strongly disagree", "disagree", "agree", "strongly agree") with the following school-related statements:

- "Trying hard at school will help me get a good job"
- "Trying hard at school will help me get into a good <college>"
- "Trying hard at school is important".

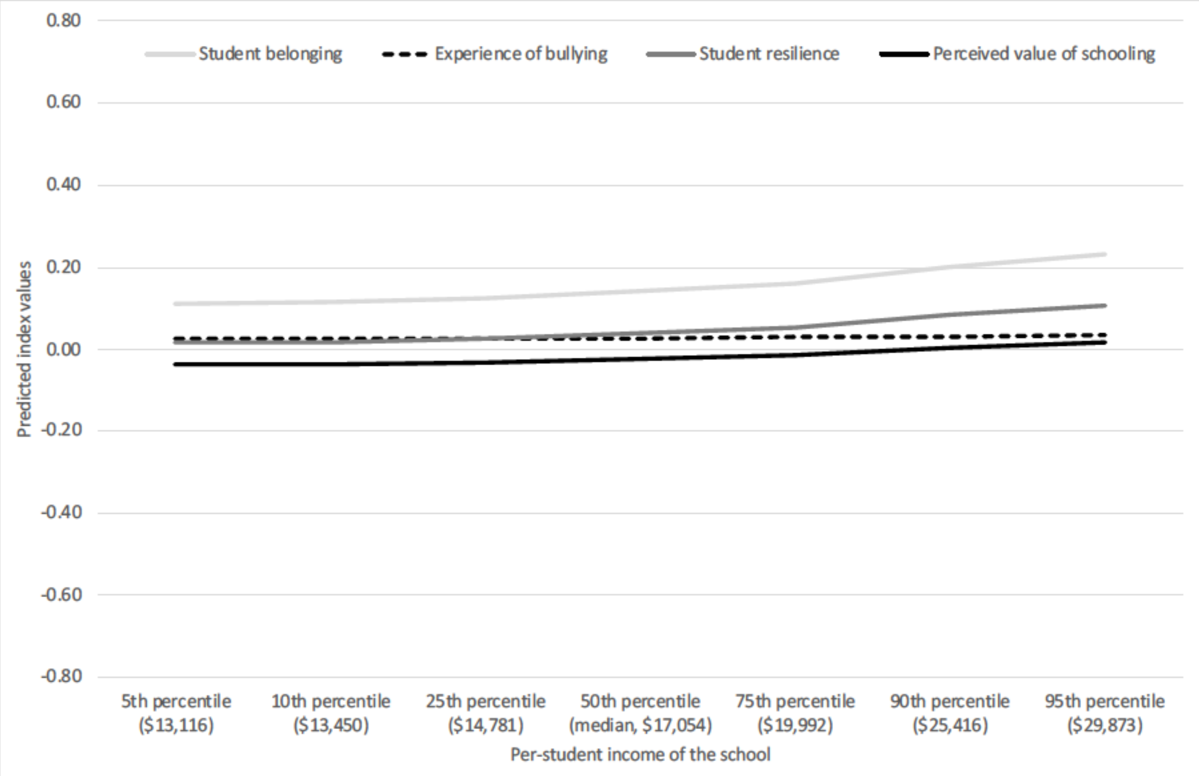
The index derived by the OECD is scaled to have a mean of zero, with positive values on this scale meaning that that the student valued schooling to a greater extent than the average student across OECD countries.

The four indices are re-scaled to have a mean of zero and a standard deviation of one across the Australian sample. Results are summarised in Figure 19.

For two of the student-level variables, student belonging and student resilience, there was a positive and statistically significant association with income when we control for a range of other characteristics. For a third, perceived value of schooling, the relationship is positive, but the p-value for the full model is 0.101. However, in the simpler model (that is, not controlling for other characteristics), the relationship is statistically significant at the 5 per cent level of significance.

Figure 19 summarises the size of the association between income and the student reports of the four school outcomes. The relationships are not anywhere near as strong as for the principal-reported outcomes, which is perhaps not surprising given principals must deal with budgets on a frequent basis and deliver on a range of school outcomes. Nonetheless, the figure does show that the per-student income of the school in which a student attends has a significant and positive association with key measures of wellbeing.

Figure 19 Variation in student-reported school outcomes, by per-student income, 2018



Source: PISA 2018.

Note: Predictive models include controls for grade, gender, number of books in the household, whether or not a migrant, whether speaks a language other than English, index of home possessions, and index of household wealth. The latter two variables are fixed at their mean values

8.3 The relationship between per-student income and student gain using individual-level data

The first section of results in this section showed using school-level data that there is a positive relationship between the income of the school in which a child attends and growth in NAPLAN between test years. One of the challenges of using school-level data to measure the relationship between income and student outcomes is that it does not capture the variation in student growth within a school, nor does it allow us to control for the relationship between student-level socio-educational and demographic characteristics.

To model the relationship between student income and adjusted student gain (as defined in the previous section), we make a number of adjustments and undertake a series of model specification tests.

First, to remove the effect of outliers, we restrict the analysis to schools with per-student income between $9,400 (above the first percentile) and $36,000 (below the 100th percentile). Next, we estimate the relationship separately for primary schools (Year 3 to 5 gain) and secondary schools (Year 7 to 9 gain), based on the assumption that the relationship between income and student outcomes is different in different sectors (as well as average income being different). We also control for the demographic and socio-educational factors that are associated with student growth and summarised in Figure 11 earlier.

We first estimate the relationship between income and student gain for government and non-government schools. However, we then use the sample of non-government schools as the more precise measure of the relationship between income and student gain. We do this for a number of reasons identified *a priori*, namely that:

- the government system more substantially redistributes income to schools inversely proportional to characteristics that are strongly associated with NAPLAN gain but not able to be captured in the model (reverse causality);
- there is less control over the use of school income in the government system for expenditure that is likely to improve student gain; and
- more of the expenditure that leads to student gain is made by the school system on behalf of government schools than non-government schools.

It should be noted that this does not mean that extra income received by government schools will not improve NAPLAN gain. Rather, it means that it is more difficult to estimate the relationship between income and NAPLAN gain for these schools and that the income of the school system as a whole is an additional determinant of student gain that is difficult to capture in the model.

When we analyse all schools together there is a positive relationship between adjusted student gain and income. However, as argued earlier, the sample of non-government schools provides a more robust measure of this relationship. ss 47B(a), 47E(d)

The income that a school receives clearly matters for student outcomes. There is a positive (albeit non-linear) relationship between income and outcomes using the observational data available for this paper, and the literature available that uses more precise causal estimates (summarised in the accompanying document) confirms that this effect is likely to be causal. ss 47B(a), 47E(d)

Regional and remoteness funding loading

ss 47B(a), 47E(d)

In line with literature which suggests that higher school income matters more for students from lower socioeconomic backgrounds we estimate the relationship between school income and outcomes for students from lower socio-economic backgrounds. We define students from lower socioeconomic background as students with parents who are both unemployed, or as students who have at least one parent who has not completed year 12.

We estimate this relationship for non-government schools for these two groups of students using the same specification as throughout Section 9.3. As discussed earlier, the sample of non-government schools provides a more robust measure of the relationship between income and adjusted student gain. ss 47B(a), 47E(d)

ss 47B(a), 47E(d)

8.4 Calculating a school-based value add

In this final section of results, we take a slightly different approach to understand the income required to achieve a similar school experience in regional and remote areas as major cities. Rather than looking at the income required to achieve the same per-student outcome across the areas (a hypothetical that uses school income to reduce all gaps between major cities and other locations), we look at the average difference in income for current schools in a regional and remote area compared to a major city that has the same level of school performance.

This is in many ways an extension and an enhancement of the methodology used in the original Gonski report, which looked at the average income differences across remoteness categories in 'top performing schools.' The limitation of that methodology though was that it (a) did not use a measure of student growth as the key metric (b) did not control for individual-level differences within schools that may have explained why schools appeared to be top performing when in fact it was simply because of the background characteristics of students and (c) most importantly it did not take into account the effect of location on whether a school was in that top decile to start with.

To construct a measure of school performance based on student gain we use a fixed effects regression and control for variation in student characteristics within a school. The fixed effect is a separate intercept for each school and captures all school level factors that impact student gain. We calculate a separate fixed effect for all government and non-government schools in the student-level dataset. ss 47B(a), 47E(d)

If we took the mean income of schools at the top of the distribution separately by remoteness category, we would find that for those schools at the top of the distribution there is a greater average income in very remote areas than there is in major cities.[24] ss 47B(a), 47E(d)

Comparing the two extremes of the remoteness distribution, 11.7 per cent of students in major city schools were attending a school in the top 10 per cent of the distribution of school performance (weighted). Only 5.8 per cent of students in very remote schools (weighted) or 721 students in total were in the top 10 per cent of schools. At the other end of the distribution, only 6.4 per cent of students in major city schools were in the bottom 10 per cent of schools, compared to 60.5 per cent of students in very remote schools.

To put this another way, in order for a very remote school to make it to the top of the distribution, it is likely that there is something very unique about the school, the school leadership, teachers, support workers, and students themselves. Some of this may be captured by income, but much of this difference is likely to be due to other characteristics not available in the model. ss 47B(a), 47E(d)

8.4.1 Equivalising school performance

One potential aim of the school funding model is to provide a loading to schools based on their location so that the predicted school-level performance (as captured by the fixed effect) with the same income loading as an otherwise identical school in a major city without the adjustment. In order to estimate what that loading would be, we follow a three-step process as described below. In essence though, we first estimate the relationship between school performance and income, we then estimate the gap in school performance between a school in a major city and every other point on the remoteness distribution, finally we convert that estimated gap into an income equivalent.

24 The mean income for schools in the top 10 per cent of the distribution, weighted by number of students and probability of being in the NAPLAN dataset is $16,403 for major cities, $16,021 for inner regional schools, $17,872 for outer regional schools, $23,053 for remote schools and $23,864 for very remote schools.

Step 1 Estimating the relationship between income and school performance

In order to estimate the relationship between school performance and income, we use data from non-government schools only, given the difficulties in estimating the relationship for government schools discussed earlier.[25] Because we control for demographic and socio-educational characteristics in the estimation of fixed effects, we do not include these as control variables in the model. Because this is a school-based measure, we analyse data at the school-level, but weight by the number of students who undertook a NAPLAN test in that school. Because the funding formula is currently applied to primary and secondary schools using the same ratio, but the starting value per student in secondary schools is higher, we convert income per student to a multiple of the mean for that sector. ss 47B(a), 47E(d)

Finally, because we do not control for remoteness in the estimation of fixed effects, we control for it in the model using a very flexible specification (linear, squared, cubic, and quartic term). To control for the non-linear relationship between income and school performance, we use a linear and squared term in the model. The estimated model for school *j* is:

ss 47B(a), 47E(d)

Holding constant remoteness at a value of zero, the estimated relationship between school income and school performance is given below.

ss 47B(a), 47E(d)

ss 47B(a), 47E(d)

Step 2 Estimating the gap in school performance by ARIA

To estimate the difference in school performance between a school in a major city and a school at every other point on the ARIA distribution, we estimate the same equation as above, but use the full sample of schools (weighted again by number of students) rather than just non-government schools. This allows us to estimate the average difference in school performance for a school across the government, Catholic, and independent sectors for every point on the remoteness distribution, for a school with a fixed level of income.

The estimated model for school *j* is given below. ss 47B(a), 47E(d)

ss 47B(a), 47E(d)

ss 47B(a), 47E(d)

Step 3 Converting the school performance gap to income equivalents

The final step in the process is to convert the observed gaps presented in Figure 22 into income equivalents using the relationship summarised in Figure 21. We do this by identifying the value for income (by solving the quadratic Equation 1) which leads to a predicted increase in school performance equivalent to the gap in school performance between a school with each ARIA value of 1.1 to 15 (in 0.1 increments) and the average school performance between 0 and 1 (inclusive) with increments of 0.1, estimated from Equation 2. We set the starting value of income equal to the mean for those schools in an ARIA+ category of zero. We then divide this estimated increased income by the baseline income to obtain the ratio of income to major city income to have the same average school performance.

ss 47B(a), 47E(d)

Regional and remoteness funding loading

ss 47B(a), 47E(d)

Regional and remoteness funding loading

ss 47B(a), 47E(d)

ss 47B(a), 47E(d)

Regional and remoteness funding loading

ss 47B(a), 47E(d)

8.4.3 Average school performance

The results presented in the previous sub-section represent the best estimate of the additional income required in each remoteness category for there to be the same level of school performance in a regional and remote school as one in a major city, where school performance is measured by a school-level fixed effect, or the extent to which growth in NAPLAN in that school is above or below the national average. On the one hand, this would not lead to convergence in literacy and numeracy across regional and remote areas, but rather the same gap in Year 5 as there was in Year 3, and the same gap in Year 9 as there was in Year 7. ss 47B(a),

ss 47B(a), 47E(d)

On the other hand, the estimated ratios are assuming that schools themselves are responsible for all of this equivalisation, and that there is no additional policy support from school systems themselves, the social security system, or more targeted interventions from outside of the school system. Furthermore, it does not allow for any improvement in the way in which income or more importantly resources are allocated and used across schools in regional and remote areas. It may be that such interventions are more cost effective, and the increase in income presented in Figure 23 is unsustainable.

An alternative approach would be to identify the current difference in income between a school in each remoteness classification (compared to a major city) where the schools have the same level of performance. This is similar to the approach taken in the original Gonski review, but importantly does not take into account the effect remoteness has on where schools are on the performance distribution.

To measure the average difference in income at each point on the school performance distribution, we estimate a model with per-student school income as the dependent variable, school-level fixed effects as the main independent variable as well as a very flexible specification for remoteness and student characteristics. This model is based on non-government schools only, given the difficulties in capturing the effect of income on school performance in government schools. The model presented in the previous sub-section was closer to a standard regression model where we were trying to measure the causal relationship between school income and student outcomes (albeit with observational data). The model estimated in this sub-section is more descriptive and allows us to estimate the average difference in income between a school in a regional/remote area compared to a major city with the same level of school performance and student characteristics

ss 47B(a), 47E(d)

ss 47B(a), 47E(d)

8.5 Key findings

Using school-level data, there is a positive relationship between school income and adjusted growth in NAPLAN, as well as a positive relationship between income and student attendance. There is also a positive relationship between school income and broader measures of school experience and wellbeing, and in particular whether the school principal reported that there were adequate access to digital devices and lack of hindrances to student learning. While the relationship between school income and student-level wellbeing measures were weaker, we were able to show that as per-student income went up students had a greater sense of school belonging, a greater level of resilience, and a higher perceived value of schooling.

Using detailed individual-level data linked to the per-student income of the school in which the child attends, there is a positive relationship between income of the school and student outcomes, controlling for other characteristics of students.

ss 47B(a), 47E(d)

9 Summary and concluding comments

Income from the Commonwealth and state and territory governments is allocated to schools using a complicated formula. For government and Catholic schools and independent school systems the funding is allocated first to the system and then by each system to its individual schools. For non-systemic schools the funding is allocated directly to schools. The SRS provides for a base funding amount for each student with a set of student-level loadings (for disability, Aboriginal and Torres Strait Islander status, socioeconomic status, and English language ability) and school-level loadings (for location and school size) is applied. The paper provides estimates of the adequacy and the operation of the school location and size loading.

The key conclusions from the analysis reported in this paper are:

- While schools in remote and very remote areas receive higher income per student than schools in major cities, the amount of government income they receive is less than the SRS allocation, particularly for schools with an ARIA +score of about 8 or greater (that is schools towards the more remote end of remote areas and all very remote areas).

ss 47B(a), 47E(d)

ss 47B(a), 47E(d)

While school size does not appear to have a large effect on student outcomes (at least for the outcomes measured in NAPLAN), other aspects of schools and school students are important aspects of education and found to be significant in the models. In particular, these include school sector, jurisdiction, Aboriginal and Torres Strait Islander status, sex, and socioeconomic status (disability status was not available in the student dataset). While these factors were beyond the scope of this paper, they do interact with school location and need to be considered ss 47B(a), 47E(d)

Appendix A – Literature review, model and expenditure analysis

Review of school cost functions and estimation methods

The school cost function is an econometric model which estimates the amount a school must spend to achieve a given student performance level for specified input prices, student demographics and school characteristics. The challenge in estimating school cost functions is that unlike spending, education costs cannot be directly observed. We follow a conceptual model widely used in the literature (e.g., Duncombe and Yinger 1997, 2011; Baker 2009; Zhao 2020) which models spending as a function of education outcomes, labour input prices (teacher salaries), student needs, and a set of observable school characteristics. For this study, school characteristics will include geographic remoteness as well as other factors that are of policy interest or which are expected to be related to the costs of education and which differ between regional and remote schools and those in metropolitan areas. In general, we expect per-student costs to increase with higher performance outcomes, higher teacher salaries and student needs, as well as in rural areas due to a higher need for resources.

The cost function estimation is a robust statistical approach that is based on actual data and has several advantages over other methodologies such as production functions or professional judgement. It has been described by leading scholars in this field as “the best currently available method for estimating the cost of reaching any given performance target”, “logically compelling”, “complete” and “a particularly flexible and low-cost way to forecast what each school district must spend to meet the standards in a state’s accountability system” (Duncombe and Yinger 2011). This approach has the flexibility to estimate how the costs of achieving specific education outcome levels vary across schools and students, while it can also calculate alternative cost indices for policy analysis and evaluate schools with respect to multiple outcomes. Another advantage relative to some other methodologies is that the cost function approach does not require profit maximising and instead, it relies on minimising costs which is more applicable in the context of non-profit and public institutions such as schools (Gronberg et al. 2004). Cost functions can be used for various types of empirical analyses, such as program evaluation, policy analysis and for forecasting the spending required to meet performance targets (Duncombe and Yinger 2011). For example, the estimates from a cost function can provide some guidance on the base amount (foundation) and the loadings (weights) to be used in formula funding of schools

Measure of costs and spending (outcome variable)

Education costs are defined as the amount a school (or school authority) must spend to achieve a given student performance outcome while using the best available technology for teaching and school management (Duncombe and Yinger 2011). However, we can only observe spending, and one concern is that schools could be inefficient in their spending. Therefore, spending is modelled as a function of the school’s costs as well as its efficiency in delivering education outcomes.

Spending is usually measured as the current operating spending (expenditure) per student. In the context of cost functions, current spending usually excludes capital outlays, debt services, transportation and food expenditures because these expenditures add noise to the analysis due to a different mechanism in how they affect student performance (e.g., Gronberg et al. 2004; Duncombe and Yinger 2011; Zhao 2020). For example, the “current operating cost” that Duncombe and Yinger (2011) use for school districts in Missouri includes instructional and support spending but excludes items such as total capital outlay, food service sales, state food service aid, federal food service aid, and receipts from other districts. In Australia, school funding data is provided by the Australian Curriculum Assessment and Reporting Authority and reported via the MySchool website (Chakraborty and Harper 2017). The measure of per-student spending is often expressed as a logarithm in cost function regressions (e.g., Duncombe and Yinger 2011; Zhao 2020).

Measure of education outcomes (explanatory variable)

Education outcomes are included to be able to evaluate how spending varies across schools as student and school characteristics change but holding education outcomes (student performance) constant. Measures of education outcomes are usually standardised test results (e.g., NAPLAN scores), but alternative measures are sometimes included in the literature, such as dropout rates (Duncombe and Yinger 1997), high school graduation rates and the percentage of high school graduates pursuing higher education (Zhao 2020). In the U.S. context, the test scores are calculated as the weighted average of the percentage of students who are at or above the proficiency level across year levels in each district, using the number of tested students in each year level as a weight (Duncombe and Yinger 1997, 2011; Zhao 2020). When there are multiple test scores (e.g., reading, writing, mathematics), the scores are often aggregated to an index based on the simple mean of the individual scores or they are included individually (to avoid multicollinearity). The student performance measure is also usually expressed in logarithmic form (Duncombe and Yinger 2011). A limitation of these measures is that they do not cover all education outcomes that a school provides, as due to data constraints, there are usually no measures of other types of education outcomes such as foreign languages or social skills.

A major concern when measuring education outcomes is that this variable can be endogenous. First, because of potential reverse causality (spending can affect student performance and vice versa), but also because of omitted variables as student performance and spending are jointly determined and influenced by school district decisions which may not be captured in the regression (Costrell et al. 2008; Baker 2009; Duncombe and Yinger 2011). In that case, estimated coefficients may be biased.[26] One way to address endogeneity is to use two-stage least squares regressions (using instrumental variables). This is the standard approach in the literature, although it can be difficult to find a valid instrument that explains student performance but is not related to spending. Instruments that have been used in early studies

26 In the case of omitted variables, Costrell et al. (2008) argue that the relationship between spending and performance will be biased upward, because there is a variation in districts in their degree of education orientation which may not be fully captured by the observable variables (e.g., more spending at district level due to the gathering of “like-minded citizens”, which results in higher performing children). In practice, most studies control for this by including relevant variables in the cost factor regressions (as discussed in Section 2.6).

include median family income and tax share as estimated from a separate demand equation (Duncombe and Yinger 1997), whereas more recent studies employ characteristics of schools that are in the same district or in another district but within the same labour market area (see, for example, Baker 2009; Duncombe and Yinger 2011; Baker et al. 2018; Zhao 2020).[27] The idea is that schools in the same district share labour markets and create other pressure on student outcomes in a given school, while characteristics of these districts should not affect the given district's spending in any other way (Duncombe and Yinger 2011).

Another approach to address endogeneity is through a panel data structure and by expressing student outcomes as a value-added measure. This means that test scores are expressed as a change (growth) in scores between two time periods for the same cohort of students. The advantage of this approach is that it controls for the skills and knowledge a student already possesses and the home environment, and therefore it is a better representation of the contribution of the current school (Gronberg et al. 2004). It is also important to control for the starting level of student achievement as a certain level could make it more or less difficult to achieve growth in test scores, and therefore measures of the lagged level score (matched to the base period) needs to be added to the cost function (e.g., Gronberg et al. 2004).[28] The value-added approach is not used very often, mainly due to data constraints. Zhao (2020) also argues that value-added measures cannot be applied to one-time events such as high school graduation and college entrance. Another potential concern is the volatility of test score measures, especially for small school districts (Kane and Staigner 2002). Gronberg et al. (2004) address this issue by using three-year averages of their value-added output measures to reduce the noise and uninformative volatility in these output measures.

Measure of input prices (explanatory variable)

Inputs are mainly labour costs such as salaries of teachers, principals and administrative staff, but also instructional equipment, computers and other supplies. However, instructional equipment and resources may be excluded from cost function estimations if there is little variation in their costs across districts or schools (Gronberg et al. 2004; Duncombe and Yinger 2011). In practice, teachers' salaries are therefore usually used as the only input price in cost functions. To make teacher salaries comparable across districts, Duncombe and Yinger (2011) come up with a salary measure to control for the differences in average education and experience across districts. First, they regress the natural logarithm of teacher salaries on the natural logarithm of total experience and a dummy variable for teachers with a graduate degree, and then they use this to estimate average salaries for teachers in each district with the state-wide average experience and the state-wide average percentage of teachers with a graduate degree (Duncombe and Yinger 2011). Another concern is that teacher salaries can be endogenous because both teacher salaries and school spending are influenced by school district decisions and this can again be addressed by including instrumental variables. For example, Duncombe and Yinger (2011) treat the salary variable as endogenous and use private

27 However, the selection of these instrumental variables relies on statistical tests and often varies across studies (Zhao 2020).

28 This is also related to the underlying model, such as models that are derived from standard Cobb-Douglas value-added production functions in which student performance depends on the starting point (base period) plus current year inputs. This lagged logarithm of level scores has a predicted negative sign (Duncombe and Yinger 2011).

sector salaries and student enrolments in another district within the same labour market area as instruments. Alternatively, actual teacher salaries can be replaced by a proxy such as the Education Comparable Wage Index (ECWI) in the U.S., which computes the salaries of college graduates who are not teachers for each labour market area, making it therefore exogenous to the spending of school districts (see Zhao 2020).

Measure of student needs (explanatory variable)

Higher student needs require higher costs to achieve any given level of student performance. For example, more resources are required to teach students who have special needs (e.g., disability or limited English proficiency) as they may require smaller class sizes and specialised teachers and supplies to achieve the same performance level as a student without special needs. Also, students from a lower socio-economic background may receive less time and resources from their families and again, schools with a higher proportion of low-income students need to spend more to reach performance targets (Zhao 2020).

Cost functions include various measures of student need such as socio-economic variables (e.g., median household income, proportion of adults with a college education, subsidised lunch students, single-parent households), race or ethnic background, students with special needs (some studies differentiate between low level versus high level disabilities) and limited English proficiency (Duncombe and Yinger 1997, 2011; Gronberg et al. 2004). These variables are usually expressed as percentages and can be either on individual student and family level when data is available, or more often, on a school or district level. Interaction terms and quadratic specifications are sometimes employed, such as an interaction between poverty and race (Duncombe and Yinger 2011). It is also possible to construct an index based on these factors, especially when these measures are highly correlated or when there is low variation in one of these variables across schools.

In the Australian context, Chakraborty and Harper (2017) use an Index of Community Socio-Educational Advantage (ICSEA) which is constructed by ACARA. This index is a proxy for the average level of educational advantage of the students in a given school and this measure is intended to be comparable across all schools in Australia. The ICSEA index is derived from variables included in the Australian Bureau of Statistics (ABS) census data, such as remoteness and the percentage of Indigenous student enrolment, as well as socio-educational variables which are obtained from enrolment records for each student and include parental occupation, school education and non-school education (ACARA 2020).

Measures of school characteristics – size and remoteness (explanatory variable)

School size is another important variable that affects costs (spending) per student because of economies of scale, that is schools with very low numbers of students have higher fixed costs per student and are therefore more expensive to operate, although very large schools may also be expensive due to inefficiencies. School size is usually measured as the average of enrolment estimates at two points in time across a school year and it can be expressed in logarithmic form (e.g., Gronberg et al. 2004; Duncombe and Yinger 1997, 2011). A squared term of enrolments is added to account for the nonlinear relationship between school size and per-student spending (e.g., Duncombe and Yinger 1997, 2011; Zhao 2020). Alternatively, dummy variables can be included to capture different categories of school size. Using data on districts in the U.S., Zhao (2020) uses 500 and 2000 as the cut-off values for small, medium and large school districts in view of economies of scale. While Zhao (2020) prefers the dummy variable approach because it is easier to understand and implement for policy makers, Duncombe and Yinger (2011) argue that the forecasting accuracy is slightly worse compared to modelling the quadratic relationship for school size.

In terms of geographic location and remoteness, several studies have included a variable of geographic isolation, capital city or rural districts in their cost functions which are intended to capture the differences in non-teacher input prices when there are less suppliers and higher shipping costs (Gronberg et al. 2004). Duncombe and Yinger (2011) argue that costs of providing education can also differ across districts due to variations in teacher salaries, as teachers receive higher compensation for higher cost of living, fewer amenities in the area and more difficult working conditions. This is relevant for regional and remote schools in Australia and discussed in more detail in Section 3. Meanwhile, in the U.S., Gronberg et al. (2004) identify a rural effect as there are higher costs for rural districts relative to urban districts in terms of mean and maximum values as well as higher standard deviation. Zhao (2020) also finds that school districts have to spend more if they are in a regional school district (holding everything else constant).

Measures of school efficiency (explanatory variable)

As mentioned earlier, we cannot observe costs and need to include measures of spending instead, which may exceed costs. The difference between costs and spending is defined as school inefficiency (Duncombe and Yinger 2011). There are different sources of inefficiency in the context of school cost functions. First of all, not all school outputs are measured and included in the cost function. A school may devote resources to other costly outputs that are not measured, such as non-tested subject areas (foreign languages, music, art and athletic programs, but also social skills and wellbeing programs) and may appear as inefficient when measured in terms of test scores in mathematics or literacy (assuming those additional programs have little impact on test scores) (Duncombe and Yinger 2011). Alternatively, inefficiency could arise due to “waste”, when schools do not employ the best available technology and the most effective teachers and fail to minimise costs in providing education outputs (Duncombe and Yinger 2011). It is therefore important to control for school efficiency in cost functions to avoid biased coefficient estimates due to omitted variables bias. By definition, efficiency is unobserved and therefore we can only control for it indirectly. There are three main methods that are used in the literature to control for efficiency in cost regressions.[29]

First, a number of studies include district fixed effects which control for district characteristics that do not vary over time, but this requires panel data, and the main limitation is that other time-invariant variables (such as the remoteness of the school) cannot be estimated (Duncombe and Yinger 2011). Geographic-level fixed effects can also be defined on labour market areas to control for time-invariant differences across the areas in terms of the labour

[29] For more detailed explanations of the concept of “efficiency” and a discussion of the advantages and disadvantages of each of the three methods refer to Duncombe and Yinger (2011).

pool, available technologies in teaching and school management, and the competitiveness of the education market (Zhao 2020).

Second, there are studies that employ statistical methods, such as a stochastic frontiers analysis or a data envelopment analysis to estimate efficiency. The stochastic frontiers analysis divides the error term in the regression into a component due to school inefficiency and another component due to random factors for each district (Gronberg et al. 2004; Gronberg, Jansen and Taylor 2011). The data envelopment analysis estimates a cost frontier based on the lowest observed spending for obtaining any given student performance and then estimates each district's deviation from this spending as an index of inefficiency which is then used as a control in a cost function (Duncombe and Yinger 1997; 2011). However, Duncombe and Yinger (2011) argue that the DEA may lead to underestimated coefficients of cost variables.

Third, the most common approach in recent studies is to control for efficiency in a cost function regression by identifying observable school-district characteristics that can be conceptually linked to efficiency. Zhao (2020) argues that it is important to establish the conceptual link even when these cannot be directly tested and includes three broad measures of efficiency: (1) voters' incentive to monitor the school district's spending which is expected to have a positive effect on efficiency, (2) the competitiveness of the education market which makes it more likely to employ the most effective teachers and the best available technology for teaching and to run its schools efficiently, and (3) parents' demand for education on untested subjects.

Zhao (2020) uses the following proxies for voters' incentives to monitor school spending: higher local revenue capacity (less likely to monitor), higher tax price (more likely to monitor),[30] the percentage of registered Republican voters which is a proxy for fiscally conservative voters (more likely to monitor), as well as the percentage of the elderly in the school district. Other potential variables that are mentioned in that paper are the education background, the percentage of population aged 5 to 17 and homeownership status. Further, to proxy for competitiveness Zhao (2020) includes dummy variables for school districts bordering on other states, because schools in border districts compete not only with other school districts within the state (e.g., for students, teachers, and school managers), but also with school districts in the adjacent state, and a border district may also be exposed to different labour pools and different teaching and management technologies used in the neighbouring state (Zhao 2020). Finally, to proxy for parents' demand for education on untested subjects Zhao (2020) adds their educational attainment level (the percentage of adults with a Bachelor degree or higher).

Other studies usually include related variables. Duncombe and Yinger (2011) use fiscal capacity measures (property wealth, income, a state aid/income ratio) and expect a positive relationship with spending because of a greater inefficiency or more demand for a broader array of educational services. They also include other monitoring variables that are either associated with lower spending (the share of senior citizens in the population, the share of owner occupied housing, and the share of school taxes paid by the typical voter), or associated with higher spending (the share of adults who are college educated) (Duncombe and Yinger

[30] Zhao (2020) argues that voters are more likely to monitor a school district when they pay higher taxes towards the school district's total revenue, as opposed to other revenues that come from federal and state sources and the percentage of the property tax base that comes from businesses and non-residents.

2011). Imazeki (2008) include the Herfindahl index for the number of districts in the labour market as a proxy for local competition.

Other methodological considerations

One of the methodological considerations is the selection of an appropriate functional form for the regression.[31] Cost function regressions are often estimated in logarithmic form for the dependent variable and some independent variables (Duncombe and Yinger 2011). In fact, most education cost studies use a simple multiplicative cost function (as based on the Cobb-Douglas function which is multiplicative in form), although this imposes limits on both factor substitution and economies of scale (Duncombe and Yinger 2011). Another approach is to use flexible cost functions, such as the translog cost function which does not impose significant restrictions on production technology. However, this approach adds many variables to the cost model, such as squared terms for each input price and outcome, and it adds interaction terms between all factor prices, and outcomes (Duncombe and Yinger 2011). For instance, Gronberg et al. 2004) use a translog cost model with more than 100 variables due to the number of interaction terms between outcomes, teacher salaries, and non-school factors.

Spending and cost variables are adjusted for inflation if the analysis is done over more than one time period (e.g., Zhao 2020). Regressions are estimated with robust standard errors clustered at the school or district level to allow for correlations within districts (Baker 2009; Duncombe and Yinger 2011; Zhao 2020). There is also a possibility of non-linear relationships between spending and some of the explanatory variables (e.g., low-income students) which can be tested by including additional square terms (Zhao 2020). Interactions, such as between the poverty rate and population density and race are also potential additional variables to include (Zhao 2020). In some cases, factors are aggregated as an index if there is multicollinearity between explanatory variables, such as special education students, poverty and single-parent households (Zhao 2020).

A cost index can be computed from the various cost factors, and this index is frequently used to estimate the amount each school district needs to spend compared to a district with average characteristics to provide its students an opportunity to reach the same performance level (Duncombe and Yinger 1997, 2011; Zhao 2020). Alternatively, Gronberg et al. (2004) report marginal effects on spending per student from a change in one of the individual explanatory variables (at the mean of the values of the other explanatory variables). Further analysis that has been done in the literature is the performance evaluation of cost functions, such as the test-retest reliability across different time periods and the predictive validity for policy evaluation (Duncombe and Yinger 2011), and additional measures can be computed such as cost-adjusted spending, spending-to-cost ratio and spending gap (Zhao 2020).

Further considerations include high quality data (Gronberg et al. 2004) and being aware about the limitations of historical data when making inferences, preferably ensuring that there are no significant changes in the relevant structures and institutions between the historical sample period and the period of interest for the policy makers (Gronberg et al. 2004).

[31] This functional form reflects underlying assumptions about the technology of production, such as "the degree of substitution between inputs, economies of scale, and the interaction between school and non-school factors" (Duncombe and Yinger 2011).

Effect of geographic remoteness and school size on school costs

Lamb et al. (2014) present raw and adjusted NAPLAN scores for schools in Victoria by their level of remoteness. Even after adjusting the scores for socio-economic status they find a gap in student performance between major cities and all other areas (including regional, rural and remote areas). An educational disadvantage has been identified in rural areas in Australia going back to at least 1975, and the Commonwealth School Commission partially attributes this to a "high teacher turnover, a lack of specialist services, a restricted range of curriculum options and a high proportion of young inexperienced teachers" (Stokes et al. 1999). Similar gaps between urban and rural education are reported in other countries. For instance, Cartwright and Allen (2002) find gaps in education between rural and urban areas in Canada and relate this to characteristics in rural areas such as lower educational aspirations of students due to limited employment opportunities that require tertiary qualifications and due to a lack of role models as there are relatively fewer adults with higher educational qualifications. Likewise, Heinesen (2005) also reports that the smaller size of a school district has a negative effect on educational attainment after compulsory school in Denmark. School lockdowns during the COVID-19 pandemic are likely to exacerbate the existing inequalities while also providing new opportunities for access to education through online resources and learning platforms.

The experience of schooling in regional and remote Australia can vary substantially within and between states and territories, geographic areas, the degree of remoteness, school sectors, and many other factors. It is also important to be precise about defining rural and remote areas (see, for example, Thier et al. 2020).

School size

It generally costs more to operate small schools because fixed costs are spread over fewer students and this results in diseconomies of scale. Schools in rural and remote areas tend to be smaller in size compared to urban areas (Lamb et al. 2014; Ross 2015). While there can be some advantages of smaller class sizes and more individual attention, smaller school size can present a number of disadvantages in terms of school costs: "smaller schools tend to have fewer resources, are often less able to employ specialist staff or offer specialist subjects or programs, have to use composite multigrade classes, provide fewer opportunities for professional development, have more difficulty recruiting and retaining teachers, provide less support for special needs students and offer fewer options for courses" (Lamb et al. 2014). In terms of program breadth, there is often a lack of subject choice, especially in secondary schools, with students being more critical than were their parents and teachers (Stokes et al. 1999; Lamb et al. 2014). Similar findings hold in other countries such as the United States, where rural schools (especially remote, small and poor rural schools) are less likely to offer Advanced Placement coursework due to a lack of sufficiently prepared students, teaching constraints and logistical challenges (Gagnon and Mattingly 2016).

Further, small schools tend to have a more expensive teacher profile as principals are more likely to be teaching and there is overall a higher proportion of Principal Class and Leading Teachers relative to all teachers (Lamb et al. 2014). At smaller schools the per-student cost to employ staff is greater relative to larger schools (Borrey 2018).

Haepp and Lyu (2018) examine the impact of merging schools in rural areas of China which was initiated by the national government to generate economies of scale and to improve school quality. They find that this policy had indeed helped in reducing the rural-urban education gap and there were positive effects on education due to resource pooling and higher teacher quality, but at the same time there were adverse effects in terms of school completion rates due to higher costs (travel or boarding), especially for girls, with evidence of increasing gender inequality and intergenerational transmission of education inequality (Haepp and Lyu 2018).

Labour input prices – School staffing, salaries, challenges and incentives for teachers

A major challenge that is emphasised throughout the literature is the attracting and retaining of qualified teaching staff in rural and remote areas, including relief teachers and specialist teachers, such as music and physical education staff (e.g., Stokes et al. 1999; Ross 2015). Jenkins et al. (2011) describe many benefits of teaching in an Australian rural setting. But at the same time, there are additional challenges that teaching in a rural setting presents which often results in teacher shortages (OECD 2013). Teachers may feel socially, culturally and professionally isolated, have fewer opportunities for professional exchange and development, less resources, technology and specialist teaching staff to support the curriculum (Jenkins et al. 2011; Lamb et al. 2014). This is made more complicated due to large distances that teachers need to travel to attend training, but also due to limited availability of relief teachers to replace staff while they are away (Borrey 2018). Teachers may not always have support to teach students from different cultural, socio-economic and language backgrounds, including disadvantaged students, those with special needs or challenging behaviour (Jenkins et al. 2011; Borrey 2018). The complexities of multi-age and multi-grade classroom present another challenge, especially when the mainstream curriculum is not adapted to such circumstances. Professional networking and mentoring is particularly difficult due to the high turnover of staff and large distances (Jenkins et al. 2011; Borrey 2018). Further challenges and disadvantages for teachers in rural, and especially in remote areas, include the high cost of relocation and generally a higher cost of living, and limited quality housing options (Ross 2015; Borrey, 2018). In some cases, the Education Department subsidises the cost of relocation or provides housing, especially in areas where housing is expensive and difficult to find (Stokes et al., 1999).

To address these additional challenges of teaching in regional and remote areas, there are often incentives put in place for teachers, such as higher salaries and entitlements to extra leave. These tend to work in the short-term but teachers rarely stay for long (Borrey 2018). Other suggestions that have been put forward to improve the situation of teachers in rural areas include a better preparation as part of their education degrees, such as including components relevant to teaching in rural context into the curriculum or including a practicum in rural communities; incentives such as an attractive pay scale, including for mid-career and senior teachers to act as mentors; and supporting local graduates who are more likely to stay in rural communities (Ross 2015; Borrey 2018). In terms of professional learning, leadership skills are often identified as a common area of need, while Stokes et al. (1999) also emphasise the importance of teachers being aware of basic issues in Indigenous education as there can be a lack of relevance of the curriculum for some Indigenous students, different learning styles, language and cultural barriers. Overall, Jenkins et al. (2011) conclude that additional resources are required to provide teachers in rural and remote areas with similar opportunities to access professional learning as teachers in urban areas and this would attract additional costs such as more travel time, more resources (e.g., relief teachers) and finances to cover costs.

Funds and costs of other resources

Lamb et al. (2014) argue that schools in remote areas are more constrained in their ability to raise local funds from their school communities to supplement government income. Educational resources can also be more expensive, as it takes more time, effort and expense to create and transport educational resources to schools in rural areas (Borrey 2018). Curriculum enrichment is more costly and complicated due to large distances, such as excursions to museums, cultural experiences, art galleries, business links, interschool sport and big libraries (Stokes et al. 1999). Some schools provide a bus (shared with other schools) that allows schools to provide enrichment (this could be, for instance, swimming lessons at the nearest pool 100 km away) (Stokes et al. 1999). Extreme climate conditions may require higher costs of air-conditioning in some areas (Stokes et al., 1999). The provision of bus routes for long distances and vehicles for other purposes, such as excursions, are another additional expense that rural schools incur (Stokes et al. 1999). Finally, costs of distance education (full-time or individual subjects) also incur additional costs, such as home tutors or supervisors, expenses for resources and camps (Stokes et al. 1999).

Student needs

The Coleman Report (1966) found that socio-economic characteristics of students explained the largest proportion of differences in education achievement in the United States. This is similar in Australia, where the Index of Community Socio-Educational Advantage (ICSEA) has been shown to explain about 62 per cent of the variance in NAPLAN test performance of primary schools and 56 per cent for secondary schools (Chakraborty and Harper 2017). Azano et al. (2014) describe that students often have limited resources outside of school due to their lower socio-economic backgrounds, such that parents often lacked resources to support their children with basic supplies, academic support or enrichment opportunities. While poverty and lower socio-economic backgrounds of students pose challenges in all schools, it amplifies the challenges that already exist in rural areas, especially given the lower access to support and resources and the large distances.

Students in rural and remote areas may face additional challenges and have fewer opportunities for involvement in cultural activities and social interaction due to the impact of location (Lamb et al. 2014). Students and their parents incur large costs and additional time for travel to school, extra-curricular activities, excursions, camps, sporting teams, specialised teaching staff and other curriculum enrichment – in some cases families even need to set up two houses (one closer to the school) or boarding (Stokes et al. 1999). Internet can be limited and costly, there may be a lack of mobile coverage (or it is very expensive), difficult climatic conditions, a higher cost of freight and a lack of services (Federal Council of the Isolated Children's Parents' Association of Australia, 2019).

Rural and remote schools often experience shortages of highly qualified special education teachers for students with disabilities (Brownell et al. 2005; Hodge and Krumm 2009). This is in part due to the small size of many rural and remote schools and their remote locations, but also a lack of resources (McLaughlin et al. 2005). Teachers at rural and remote schools may not be specifically trained in disability issues and it can be difficult to access support services such as speech therapists through the schools or the community (Stokes et al. 1999). As a result, special learning needs incur extra costs for travel to see specialists, such as a speech language pathologist (Federal Council of the Isolated Children's Parents' Association of Australia (ICPA) 2019, 2019). Staff shortages often mean that mainstream teachers need to cater for students with disabilities without having the opportunities to receive adequate training or support and mentoring from colleagues.

Gifted and talented students can come from all ethnic, socio-economic and geographic locations and can also concurrently underachieve or have learning disabilities (Walsh and Jolly 2018; Davis et al. 2020). Such students need support and access to appropriate learning opportunities to realise their potential (Davis et al. 2020). If gifted students do not receive instruction by teachers with the necessary skills to address their educational needs, they can become disengaged and present challenging behaviours.

However, identifying gifted students from different ethnic and socio-economic backgrounds (e.g., Indigenous students) can be more challenging for inexperienced teachers due to language barriers and low access to educational resources and intellectual stimulation at home. In particular, there is no requirement for Australian teachers to have training in gifted education as part of their qualifications, so teachers may lack understanding of gifted education (Walsh and Jolly 2018). Lewis and Boswell (2020) confirm that it can be difficult to identify gifted students in a rural context as gifted characteristics will be influenced by rural culture that may not appear on standard behavioural checklists and may be masked by poverty (Lewis and Boswell 2020). Davis et al. (2020) also emphasise the additional challenges that gifted black students from rural areas in the U.S. face due to the interaction of race, poverty and remoteness.

Teachers of gifted students can face additional challenges in rural areas due to limited funding, fewer resources and specialists, as well as due to social stigma, while students also lack intellectual peers (Duff 2020). Specialised teachers are likely to be serving multiple schools and may spend a lot of time travelling between schools which means that they are exhausted and they only see students at each school once a week (Azano et al. 2014; Lewis and Boswell 2020). Related to a high turnover of staff, there is often a lack of appropriately qualified teachers to offer extension programs, or extra-curricular and enrichment opportunities in general, including programs that are suitable for gifted students, which leads to boredom and frustration for these students (Stokes et al. 1999).

Education production functions

Overview of education production functions

Education production function estimation is another commonly used approach in the literature and it focuses on the impact of various inputs on student performance. In other words, education production functions estimate the underlying determination of skills and link inputs[32] related to the teaching and learning environment to outputs which are related to student achievement and are often measured in terms of test scores (Deutsch et al. 2013). According to Hanushek (2020), there is generally only weak evidence that simply increasing school funding and teacher salaries will lead to improved student performance, however this could be because it is more important *how* money is spent rather than *how much* is spent. Hanushek (2020) also refers to literature on teacher effectiveness which shows that differences in teacher quality can have a significant impact on student outcomes. This

[32] These inputs include family background (socio-demographic characteristics such as parental education, income, and family size); (2) peer inputs (usually aggregates of student socio-demographic characteristics or achievement for a school or classroom); (3) school inputs, such as teacher background (education level, experience, sex, race, etc.), school organization (class sizes, classroom resources, facilities, administrative expenditures), and district or community factors (average expenditure levels) (Hanushek 2020).

literature measures teacher quality (effectiveness) or "value-added of teacher" by looking at differences in growth rates of student achievement across teachers. the variation in student outcomes from a good to a bad teacher can be as much as a full year of knowledge per academic year (Hanushek 1992). This could mean that the differences among teachers are not closely correlated with commonly measured teacher characteristics such as teacher salaries, credentials and teacher training (Hanushek 2020).

Jackson et al. (2016) offer another explanation for the lack of evidence of positive relationship between school spending and student outcomes. They argue this could be due to the focus on test scores as the main outcome, even though they do not capture all of the positive effects on learning and subsequent life outcomes. They address this limitation by looking at the effect of school spending on long-run outcomes such as educational attainment and labour market success (earnings), and they use panel data and state finance reforms in the U.S. to study the causal effect of school spending on outcomes. They show that schools used these additional school funds to reduce student-to-teacher ratios, to have longer school years, and to increase teacher salaries. Increased school spending improved student outcomes and helped reduce the intergenerational transmission of poverty. Low-income families benefitted the most from these reforms, with large improvements in educational attainment, wages, family income, and reductions in adult poverty. Their results imply that a 25 per cent increase in per-student spending throughout one's school years could eliminate the average attainment gaps between children from low-income and higher-income families.[33] Lafortune et al. (2018) use a similar event study framework and confirm that schools used these additional funds to increase instructional spending, reduce class size, and spent it on capital outlays. Most importantly, they show that these reforms had a positive effect on student achievement in low-income districts and on students' eventual earnings. Their findings imply that a $1 increase in funding to low-income school districts raises students' eventual earnings by more than $1 in present value.[34]

A more recent meta-analysis (which pools findings from a range of studies) provided very strong evidence that a school's income directly affects school outcomes. Jackson and Mackevicius (2021) find that across all "credibly causal" studies 'a $1000 increase in per-pupil public school spending (for four years) increases test scores by 0.044 standard deviations, high-school graduation by 2.1 percentage points, and college-going by 3.9 percentage points'.[35] To reinforce the point, the authors stated up front that 'Speaking first to the "does money matter? " question, we show that 94 percent of all included studies find a positive overall effect of increased school spending (irrespective of significance). If positive and negative impacts were equally likely (as is the case if school spending did not matter), the likelihood of observing this many positive estimates or more is less that one in 4.3 million.'

[33] More precisely, they find that for low-income children, "a 10% increase in per pupil spending each year for all 12 years of public school is associated with 0.46 additional years of completed education, 9.6% higher earnings, and a 6.1 percentage point reduction in the annual incidence of adult poverty".

[34] "Ten years after a reform, relative achievement of students in low-income districts has risen by roughly 0.1 standard deviation, approximately one-fifth of the baseline gap between high- and low-income districts. The implied impact is between 0.12 and 0.24 standard deviations per $1,000 per pupil in annual spending. This is at least twice the impact per dollar that is implied by the Tennessee Project STAR class size experiment." (Lafortune et al. 2018).

[35] This is equal to an Australian amount of $1,286 based on the exchange rate on 2 March 2021.

Such studies have not been publicly available in Australia, because the data to undertake them has not been made available previously (or the results have not been released). It is tempting to dismiss the findings and assume the positive results are particular to different points on the income distribution. However, the most plausible assumption is that returns are highest at the bottom part of the school-income distribution, with Australia in recent history having on average lower levels of spending on elementary and secondary education than the US (around 20 per cent lower in 2016)[36] Perhaps more importantly though, there do not appear to be diminishing returns in the studies available, with Jackson and Mackevicius (2021) stating that 'Some have argued that while school spending may have mattered when baseline spending levels were low, the marginal impacts may be smaller at current spending levels … Precision-weighted models reveal that the marginal impacts are remarkably stable for a wide range of baseline per-pupil spending levels'

Methods for estimating education production functions and school efficiency

Models that estimate education production functions need to take into account that the educational process is cumulative, which implies that inputs applied in the past will affect students' current levels of achievement (Hanushek 2020). Therefore, estimates will be biased if models only use current input measures. Hanushek (2020) proposes to use the "value-added" form in estimation (i.e., growth in achievement across grades) which incorporates initial achievement levels of students and captures some of the prior inputs of schools and families. Another methodological consideration relates to schools operating within a policy environment that is largely determined by higher levels of government which are responsible for establishing the curriculum, providing funding, governing labour laws, and determining rules for the certification and hiring of teachers (Hanushek 2020). The solution is to analyse schools within a state with the same basic policy environment or to control for the different states in a regression. Another recommendation that Hanushek (2020) makes with regards to estimating causal relationships is the use of regression discontinuity or panel data approaches (e.g., administrative data) which track students over time and permit controlling for a wide range of influences on achievement through the introduction of fixed effects for schools, individuals and time.

Deutsch et al. (2013) examine the determinants of cognitive ability. Their study reviews and extends methods for modelling the efficiency in the production of education and applies this to PISA data in five Latin American countries. They discuss limitations of commonly used datasets and standard regression models, as well as the advantages and disadvantages of alternative approaches such as multilevel modelling, data envelopment analysis, corrected ordinary least squares and the stochastic frontier approach. They focus on estimating efficiency at an individual level (instead of a school level) which they estimate in four steps:

First, they conduct a data reduction procedure to obtain the inputs from the maximum amount of available information from PISA. They do this by this sorting the variables into five categories and then they aggregate the variables used for each of the categories via correspondence analysis (a data reduction technique which is better adapted than principal components analysis when the variables are of a qualitative nature).[37]

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36 https://nces.ed.gov/programs/coe/indicator_cmd.asp

37 The first category is the education means available at home, the second two categories are the inputs of the school, which may be divided into two categories, the pedagogical characteristics of school and the

Second, they apply corrected ordinary least squared (COLS) to determine the individual efficiency of each student from the residuals. This method adjusts the (negatively biased) OLS estimator of the intercept parameter by the value of the greatest negative residual, so that the new residuals become non-negative. Negative residuals would have been a problem because residuals are a measure of efficiency, and individual efficiency (i.e., cognitive abilities) should not lead to a reduction in individual performance. Further, they introduce the average performance (mean scores) by school in reading, mathematics and science in order to control for the peer effect (i.e., a student's performance is likely correlated with that of other students at the same school, which would result in biased efficiency scores).

Third, they look at the determinants of individual efficiency, using a Feasible Generalized Least Squares regression to estimate a school random effect model with the efficiency score for individual students (from step two) as dependent variable and a set of explanatory variables (again obtained via correspondence analysis),[38] a school-specific disturbance term and another disturbance term that depends on both the individual and the school. There is again a potential issue of a peer effect and they employ a random effect models to take into account these unobserved effects.

Fourth, they implement a Shapley decomposition procedure to derive the relative importance of the various explanatory variables in explaining individual efficiency (i.e., which of these factors contribute most to the R-square of the regression). Overall, they find that the source of efficiency varies across countries, with a mix of individual characteristics, parents' characteristics, and school characteristics playing an important role.

A model of school performance

Based on the review of the existing literature outlined above, it is possible to construct a simplified model of school performance. In this model, without loss of generality, there are two regions remote, and non-remote, with the level of school performance as defined by average outcomes for a given school (P_j) defined as follows:

$$P_j = \alpha_0 + \alpha_1 Y_j + \alpha_2 X_j + \alpha_3 R_j + \mu_j$$

where:

- α_0 is a constant term reflecting the school performance when all other variables are equal to zero;
- Y_j is the per-student income for a given school (j);
- α_1 is the returns on that income;
- X_j is a vector of other observed school inputs, including family background;
- α_2 is the vector of returns on those inputs;
- R_j is a binary variable with a value of 1 if the school is in a remote area and 0 if it is in a

physical and human capital available at school, and the last two categories refer to the time inputs of students, which can be classified into two categories, time devoted to informal learning or to formal learning.

38 The set of explanatory variables that could affect the efficiency of inputs use in producing the output: gender of the student, the human capital of parents, the material wealth of parents, information on school governance, the location of the school, the importance of learning efforts in the eyes of the students and the self-rated ability of the student

non-remote area;

- α_3 is the average reduction in performance for a school in a remote area; and
- μ_j is the unexplained component of school performance, which is independently and identically distributed with a mean of zero across all schools and, for simplicity, for remote and non-remote schools separately.

This model can be extended to have multiply categories of remoteness, with R_j then a categorical or continuous variable. It is also possible to extend the model (as is done in the paper) to include non-linear effects of income, or interactions between income and school inputs. The average values of school performance is then:

- $\overline{P_j} = \alpha_0 + \alpha_1\overline{Y_j} + \alpha_2\overline{X_j} + \alpha_3$ for remote schools, where $j = 1\ to\ n_1$, for remote schools; and
- $\overline{P_j} = \alpha_0 + \alpha_1\overline{Y_j} + \alpha_2\overline{X_j}$ for non-remote schools, where $j = (n_1 + 1\ ) to\ N$.

Assume (based on the literature) that $\alpha_1 > 0$ (that is, there are positive returns to income) and $\alpha_3 < 0$ (performance is lower in remote schools for a given income and other inputs). However, α_2 can be positive or negative, depending on the particular input.

For a given value of $X_j = X$ (that is, holding constant other inputs) and setting the error term to their mean value $\left(\mu_j = 0\right)$ then performance in a remote school $(j = 1)$ is equal to performance in a non-remote school $(j = 2)$ if

$$\alpha_0 + \alpha_1 Y_{j1} + \alpha_2 X \quad + \alpha_3 = \alpha_0 + \alpha_1 Y_{j2} + \alpha_2 X$$

or

$$Y_{j1} = Y_{j2} - \frac{\alpha_3}{\alpha_1}$$

Alternatively, performance is equal if $\frac{Y_{j1}}{Y_{j2}} = 1 - \frac{\alpha_3}{\alpha_1 Y_{j2}}$ or $Y_{j1} - Y_{j2} = -\frac{\alpha_3}{\alpha_1}$, which we refer to D_1or the income boost required to have the same level of performance in remote compared to non-remote areas, or the additional cost associated with remoteness is greater as the performance gap increases, or the return on income decreases.

To achieve the same level of performance, the other alternative is to boost other inputs into education. That is, with the same level of income, performance in a remote and non-remote school is equal if $\frac{X_{j1}}{X_{j2}} = 1 - \frac{\alpha_3}{\alpha_2 X_{j2}}$

To achieve the same level of performance, it is more efficient to provide additional income to the school rather than improve inputs directly if

$$\frac{X_{j1}}{X_{j2}} < \frac{Y_{j1}}{Y_{j2}}$$

or

$$1 - \frac{\alpha_3}{\alpha_2 X_{j2}} < 1 - \frac{\alpha_3}{\alpha_1 Y_{j2}}$$

or

$$\alpha_1 < \frac{\alpha_2 X_{j2}}{Y_{j2}}$$

If X and Y are observed, and μ_j is identically and independently distributed, then a regression model will give an unbiased estimated of the parameters $(\alpha_0, \alpha_1, \alpha_2, and\ \alpha_3)$ of the model.

One approach that has been used to estimate the income required to have the same level of school performance P in a regional and remote area is to identify a particular point on the performance distribution (or a range on the distribution) and compare the average income for a school in a remote area with the average income of a school in a non-remote area. Under certain assumptions this difference will be equal to D_1 above. Specifically, if we fix P then

$$\alpha_1 Y_{j1} = P - \alpha_0 - \alpha_2 X_{j1} - \alpha_3 - \mu_{j1}$$

and

$$\alpha_1 Y_{j2} = P - \alpha_0 - \alpha_2 X_{j2} - \alpha_3 - \mu_{j2}$$

and

$$Y_{j1} - Y_{j2} = \frac{P - \alpha_0 - \alpha_2 X_{j1} - \alpha_3 - \mu_{j1}}{\alpha_1} - \frac{P - \alpha_0 - \alpha_2 X_{j2} - \alpha_3 - \mu_{j2}}{\alpha_1}$$

$$Y_{j1} - Y_{j2} = \frac{\alpha_2 X_{j2} - \alpha_2 X_{j1} + \mu_{j2} - \mu_{j1} - \alpha_3}{\alpha_1} - \frac{P - \alpha_0 - \alpha_2 X_{j2} - \alpha_3 - \mu_{j2}}{\alpha_1} = D_2$$

If school inputs and the unobserved component of performance at that point on the distribution equal each other for remote and non-remote schools, then $D_2 = D_1$and the differences between a remote and a non-remote school can be taken as the income required to have equal school performance. However, this is highly unlikely to be the case *a priori*. It is possible to fix $X_{j2} = X_{j1}$ in the measure of school performance (assuming other inputs are observed), but it is not possible to fix the unobserved components to be equal. Therefore $\mu_{j2} \approx \mu_{j1}$and $D_2 = D_1 \left(\frac{\mu_{j2} - \mu_{j1}}{\alpha_1}\right)$

So, if $\mu_{j2} > \mu_{j1}$ then $D_2 > D_1$ or the increase in income required to achieve equivalent outcomes is overstated. However, if $\mu_{j2} < \mu_{j1}$ then $D_2 < D_1$ and the increase in income required to achieve equivalent outcomes is understated. Furthermore, the smaller the returns to income (α_1) the more this difference will be over/under stated. If the performance level is fixed at the very top of the distribution, then remote schools will be further away from their mean values (that is, there are fewer remote schools at the top of the distribution than the bottom. Therefore, the unexplained component of school performance at the top of the distribution for remote schools is greater than the unexplained component for non-remote schools, which means the difference in income at those points on the distribution are likely to significantly understate the income required to achieve similar outcomes.

School expenditure by remoteness – Western Australia, South Australia and Tasmania

The existing literature has identified several reasons as to why school costs tend to be higher in more remote areas. A summary of the existing literature is provided earlier in Appendix A, with the key points being:

- The costs of employing teachers on average increases with the school remoteness. This is a result of challenges in attracting and retaining teachers in rural and remote areas and the use of higher salaries and entitlements such as extra leave, housing allowances and relocation subsidies;

- Educational resources can be more expensive in more remote areas due to the time, effort and expense of transporting educational resource to more remote areas;
- Higher costs of curriculum enrichment such as excursions to museums and inter school sport due to higher travel costs from more remote areas;
- Challenges and high costs associated with getting access to highly qualified specialised teachers and special education teachers for students with special needs (e.g., speech pathologists); and
- High costs of attending training and further qualifications for teachers in remote areas which includes travel costs and higher costs of sourcing relief teachers

As part of the review of the Regional and Remote SRS loading the NSRB requested data from state and territory governments on school income and expenditure. Data was provided for Western Australia, Tasmania, South Australia and the Northern Territory. The data provided by the Northern Territory was in a different and less detailed format to the data provided by the other jurisdictions and not able to be used in this analysis.

The expenditure data is used to analyse the additional per-student expenditure as remoteness increases. The relationship between remoteness and five categories of expenditure is also analysed. The categories of expenditure are: (i) teachers and school leaders; (ii) other salaries; (iii) utilities; (iv) property maintenance; and (v) other expenditure.[39]

Cost per student

The first set of analysis is based on a regression model that estimates the average relationship between school expenditure and geographic remoteness as measured by ARIA+ with a set of control variables that are intended to control for other factors that influence expenditure and which may also vary with remoteness and if not taken into account in the regression may confound the estimated impact of remoteness. The control variables included in the regression model are the number of primary students and secondary students separately (including a squared term to capture economies and diseconomies of scale), number of students with a disability, and a dummy variable for whether the school is in South Australia or Tasmania, with the base case being a school in Western Australia (the choice of base case does not impact on the estimation of the relationship between remoteness and expenditure per student). The model then includes a variable for the number of primary students interacted with the school's remoteness classification and the number of secondary students interacted with the school's remoteness classification. The specification of the model allows the effect of remoteness to vary between primary and secondary students, but assumes that the additional cost of a primary school student is the same in a combined school and a primary-only school (and similarly for secondary school students).

The estimated associations between remoteness and each category of expenditure are provided in Figure A1. ss 47B(a), 47E(d)

39 Other expenditure includes professional development, transport and travel, ICT resources, purchases; administration, communication camps and excursions.

ss 47B(a), 47E(d)

While the data from Western Australia, South Australia and Tasmania provides some information on how expenditure varies by remoteness, the precise numbers should be treated with some caution for the following reasons. Firstly, the results are for government schools only. Secondly, data is only available on three jurisdictions, and none of the three largest jurisdictions in Australia. Third, there are some differences in how expenditure is treated across the jurisdictions for which data is available, resulting in a need to collapse some expenditure categories that are of particular relevance (for example school teachers compared to school leaders). These results also reflect differences in expenditure, rather than differences in costs, with expenditure combining costs per unit and decisions made on the number of units to purchase.

A final point to note when interpreting these results is that the model does not control for other characteristics other than disability that may impact expenditure, including Indigenous status, socioeconomic status, or English language ability. ss 47B(a), 47E(d)

[40] ss 47B(a), 47E(d) While in principle the expenditure categories should be modelled using a system of equations, because the impact of an increase in remoteness on total expenditure derived by summing the individuals components is close to that obtained when total expenditure is modelled this suggests that the interactions are minimal.

Regional and remoteness funding loading

ss 47B(a), 47E(d)

Average additional expenditure by remoteness category

The analysis presented in the previous sub-section assumes a linear relationship between remoteness and expenditure, does not take into account the variation in total expenditure across the different categories, and assumes a separate relationship between remoteness and expenditure for primary and secondary students. The data provided for this project does not allow for a detailed non-linear model of the type used for the income and outcomes analysis, as there are very few schools in many of the points on the remoteness distribution. For example, there are only two secondary schools in very remote areas in our analysis, and only seven secondary schools in remote areas.

Regional and remoteness funding loading

In order to more closely replicate the SRS funding formula, in this sub-section of results a model is estimated that gives a prediction of the additional funding relative to a major city in that expenditure category for each of the four other remoteness categories in the SRS formulae. The steps involved in estimating the model are as follows:

1. Convert the expenditure in each category into expenditure per student;
2. Divide the expenditure in each category by the average expenditure across the sample, with averages calculated separately for primary and secondary schools;
3. Estimate a model with expenditure per student relative to the mean as the dependent variable, and the following sets of explanatory variables:
    a. A dummy variable for whether the school is a secondary school (combined schools are excluded from the analysis, and the omitted category is a primary school);
    b. A dummy variable each for whether the school is in South Australia or Tasmania (the omitted category is in Western Australia);
    c. The number of students with a disability in the school (the base case has zero students with a disability);
    d. A dummy variable each for whether the school is a very small school; small school; or medium school (the omitted category is a large school);
    e. A dummy variable each for whether the school is in an inner regional area; an outer regional area; a remote area; or a very remote area.
4. Divide the estimated (relative) expenditure in each of the four remoteness categories for a school with the base case/omitted characteristics by the estimated (relative) expenditure for an otherwise equivalent school in a major city.

ss 47B(a), 47E(d)

Regional and remoteness funding loading

ss 47B(a), 47E(d)

Regional and remoteness funding loading

ss 47B(a), 47E(d)

Appendix B – Additional tables

Table B1 Number of schools, by State/Territory, Sector and Remoteness

	Major City	Inner regional	Outer regional	Remote	Very Remote	Total
New South Wales						
Government	1,398	347	347	37	14	2,143
Catholic	397	82	62	8	3	552
Independent	328	53	18		2	401
Victoria						
Government	1,101	259	169	6		1,535
Catholic	396	67	32	1		496
Independent	186	15	15			216
Queensland						
Government	619	174	304	73	67	1,237
Catholic	180	39	63	14	10	306
Independent	154	23	33	2	1	213
South Australia						
Government	308	24	131	25	23	511
Catholic	78		15	3		96
Independent	93	2	11	1	1	108
Western Australia						
Government	537	18	106	70	60	791
Catholic	114	1	21	9	11	156
Independent	117	4	14	4	10	149
Tasmania						
Government		101	82	6	3	192
Catholic		25	12	1		38
Independent		24	8			32
Northern Territory						
Government			44	27	80	151
Catholic			10	6	2	18
Independent			8	6	6	20
Australian Capital Territory						
Government	87	1				88
Catholic	29					29
Independent	18					18
Australia						
Government	4,050	924	1,183	244	247	6,648
Catholic	1,194	214	215	42	26	1,691
Independent	896	121	107	13	20	1,157

Table B2 Number of students, by State/Territory, Sector and Remoteness

	Major City	Inner regional	Outer regional	Remote	Very Remote	Total
New South Wales						
Government	663,237	87,773	45,570	2,951	778	800,309
Catholic	179,397	27,411	9,385	738	153	217,084
Independent	188,162	16,269	2,811		31	207,273
Victoria						
Government	556,311	41,293	27,279	475		625,358
Catholic	183,350	19,098	6,307	39		208,793
Independent	136,929	5,473	2,196			144,597
Queensland						
Government	407,118	52,016	83,555	7,364	7,241	557,293
Catholic	102,378	16,472	27,023	1,971	732	148,577
Independent	104,077	8,903	9,607	202	104	122,893
South Australia						
Government	139,846	2,566	25,108	5,066	2,178	174,764
Catholic	36,016		4,738	981		41,735
Independent	49,144	550	2,342	496	126	52,658
Western Australia						
Government	237,312	4,121	22,604	13,991	6,027	284,056
Catholic	57,279	136	5,506	2,059	572	65,552
Independent	67,309	591	3,570	394	444	72,308
Tasmania						
Government		38,551	17,368	441	272	56,632
Catholic		12,002	2,820	96		14,918
Independent		8,302	1,301			9,602
Northern Territory						
Government			17,097	4,990	7,614	29,702
Catholic			2,785	1,383	634	4,802
Independent			3,677	1,686	500	5,863
Australian Capital Territory						
Government	43,594	27				43,621
Catholic	14,014					14,014
Independent	13,990					13,990
Australia						
Government	2,047,419	226,346	238,582	35,279	24,110	2,571,736
Catholic	572,433	75,119	58,564	7,267	2,091	715,475
Independent	559,611	40,088	25,503	2,778	1,205	629,185

Table B3 Factors associated with per-student school income (log transformed in $,000's), 2018

Explanatory variables	Coefficient	Significance
Inner regional school	ss 47B(a), 47E(d)	
Outer regional school		
Remote school		
Very remote school		
Victoria		
Queensland		
South Australia		
Western Australia		
Tasmania		
Northern Territory		
Australian Capital Territory		
Catholic school		
Independent school		
Medium-sized school		
Small School		
Very Small School		
Combined school		
Secondary school		
Special school		
Per cent of students in bottom SEA quartile		
Per cent of students in lower-middle SEA quartile		
Per cent of students in upper-middle SEA quartile		
Per cent of students who are Indigenous		
Per cent of students who speak a language other than English		
Per cent of students with a disability		
Constant		
Number of observations		
Adjusted R-Squared		

Source: ACARA school-level data.

Notes: Linear Regression Model. The base case school is in a Major City in NSW; and is a large, government primary school. Coefficients that are statistically significant at the 1 per cent level of significance are labelled ***; those significant at the 5 per cent level of significance are labelled **, and those significant at the 10 per cent level of significance are labelled *.

Table B4 Factors associated with per-student school income (log transformed in $,000's), by income source, 2018

	Comm. income		State/Terr. income		Fees/Charges		Other income	
Explanatory variables	Coeff.	Signif.	Coeff.	Signif.	Coeff.	Signif.	Coeff.	Signif.
Inner regional school	ss 47B(a), 47E(d)							
Outer regional school								
Remote school								
Very remote school								
Victoria								
Queensland								
South Australia								
Western Australia								
Tasmania								
Northern Territory								
Australian Capital Territory								
Catholic school								
Independent school								
Medium-sized school								
Small School								
Very Small School								
Combined school								
Secondary school								
Special school								
Per cent of students in bottom SEA quartile								
Per cent of students in lower-middle SEA quartile								
Per cent of students in upper-middle SEA quartile								
Per cent of students who are Indigenous								
Per cent of students who speak a language other than English								
Per cent of students with a disability								
Constant								
Number of observations								
Adjusted R-Squared								

Source: ACARA school-level data.

Notes: Linear Regression Model. The base case school is in a Major City in NSW; and is a large, government primary school. Coefficients that are statistically significant at the 1 per cent level of significance are labelled ***; those significant at the 5 per cent level of significance are labelled **, and those significant at the 10 per cent level of significance are labelled *.

Table B5 Average per student gap between total income received from government sources and SRS, by remoteness, school sector and State/Territory

	Government	Catholic	Independent
	Major city		
Australian Capital Territory	ss 47B(a), 47E(d)		
New South Wales			
Northern Territory			
Queensland			
South Australia			
Tasmania			
Victoria			
Western Australia			
	Inner regional		
Australian Capital Territory	ss 47B(a), 47E(d)		
New South Wales			
Northern Territory			
Queensland			
South Australia			
Tasmania			
Victoria			
Western Australia			
	Outer regional		
Australian Capital Territory	ss 47B(a), 47E(d)		
New South Wales			
Northern Territory			
Queensland			
South Australia			
Tasmania			
Victoria			
Western Australia			
	Remote		
Australian Capital Territory	ss 47B(a), 47E(d)		
New South Wales			
Northern Territory			
Queensland			
South Australia			
Tasmania			
Victoria			
Western Australia			
	Very remote		
Australian Capital Territory	ss 47B(a), 47E(d)		
New South Wales			
Northern Territory			
Queensland			
South Australia			
Tasmania			
Victoria			
Western Australia			

Source: ACARA school-level data.

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