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Access to Higher Education in Victoria

Brendan Hough and Moshe Justman

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Brendan Houg[†] and Moshe Justman[‡]

**[†] Melbourne Institute of Applied Economic and Social Research,
The University of Melbourne**

**[‡] Melbourne Institute of Applied Economic and Social Research,
The University of Melbourne; and Department of Economics, Ben Gurion University**

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Melbourne Institute of Applied Economic and Social Research

The University of Melbourne

Victoria 3010 Australia

***Telephone* (03) 8344 2100**

***Fax* (03) 8344 2111**

***Email* melb-inst@unimelb.edu.au**

***WWW Address* <http://www.melbourneinstitute.com>**

Abstract

This paper examines the extent to which year-9 performance on the National Assessment Program—Language Arts and Numeracy (NAPLAN) predicts access to higher education as determined by subsequent achievement on year-12 Victoria Certificate of Education (VCE) exams. VCE performance is measured via three binary indicators: achieving an Australian tertiary admission rank (ATAR) above 50 ("ATAR50"), above 70 ("ATAR70"), and above 90 ("ATAR90"); and two continuous indicators: ATAR and the Tertiary Entrance Aggregate (TEA). We find that a four-way classification of year-9 NAPLAN results explains 35% of the variance in ATAR50, 37% in ATAR70 and 26% in ATAR90; and NAPLAN scores and basic demographic indicators explain 38% of the variance in ATAR and 42% of the variance in TEA values. Examining the joint effect of year-9 NAPLAN scores and socio-economic status in predicting VCE outcomes, we find that while both are significant, NAPLAN scores have a much stronger effect. At the school level, we find that predictions of success rates based on NAPLAN scores and basic demographic indicators explain over 82% of the variance in school achievement in each of the binary indicators.

JEL classification: I21, I24, I28

Keywords: Standardized tests, NAPLAN, ATAR, longitudinal analysis, predicting educational achievement, socio-economic gradient of achievement, school effects, Victoria, Australia

1. Introduction

This paper addresses the extent to which National Assessment Program—Language Arts and Numeracy (NAPLAN) scores accurately predict access to higher education as determined by performance on year-12 Victoria Certificate of Education (VCE) exams. Previous analyses have established the internal consistency of NAPLAN test scores in identifying students' core capabilities by demonstrating that early NAPLAN scores are reliable predictors of subsequent NAPLAN performance (Helal, 2012, Houg and Justman, 2013). NAPLAN scores in numeracy or reading in year 3, 5 or 7 explain over half the variation in NAPLAN scores in the same domain two years later; and scores in all five domains in the earlier year explain over 70% of the variance in reading and numeracy two years later (Houg and Justman, 2013, Table 4). In this paper we focus on how well NAPLAN scores predict students' year-12 VCE results—outcomes that shape further educational opportunities and life chances.

Specifically, we ask, how well does the performance of Victoria's year-9 students on NAPLAN tests administered in May 2008 predict their performance on year-12 VCE exams administered in October-November 2011.¹ VCE outcomes provide uneven indication of year-12 achievement. For the lower half students without an Australian tertiary admission rank (ATAR) we only have a binary indicator. Only for students in the upper half of the distribution do we have continuous indicators. This leads us to use a mixed set of outcome measures that includes both binary outcomes (ATAR50, ATAR70 and ATAR 90) and continuous measures (ATAR and TEA values).²

¹ Our initial population includes all year-9 students in Victoria. We are not able to identify students leaving Victoria between year-9 and year-12 or the small fraction of students who were either held back or pushed ahead and sat for their VCEs in a different year. We discuss this further in Section 2.

² We treat them separately, rather than simultaneously (e.g., through Tobit estimation) because of the difficulty of describing goodness of fit for a variable that takes both continuous and discrete values.

The three binary indicators and two continuous measures of success on these tests, which we use, together provide a comprehensive picture of student achievement across the full range of VCE outcomes. Our three binary indicators are:

- achieving an Australian tertiary admission rank (ATAR) above 50 (“ATAR50”);
- achieving an ATAR, above 70 (“ATAR70”); and
- achieving an ATAR above 90 (“ATAR90”);

and our two continuous indicators are:

- ATAR values; and
- Tertiary Entrance Aggregate (TEA) values.³

Previewing our results, we first apply a four-way classification of year-9 NAPLAN results and find that it explains 35% of the variance in ATAR50, 37% in ATAR70 and 26% in ATAR90. We then use a probit specification to regress each of the binary indicators on our basic set of regressors derived from individual NAPLAN scores and indicators for gender, language background other than English (LBOTE) and Aborigine and Torres Straits Islanders (ATSI). These regressions produce an individual predicted probability of success for each year-9 student with regard to each indicator. The Tjur statistic of goodness of fit for these equations is:⁴ 0.34 (ATAR50), 0.36 (ATAR70) and 0.31 (ATAR90); adding socio-economic variables to the right-hand side increased each of these statistics by about 0.02. We then regress ATAR and TEA values on the same basic set of regressors for students with ATAR values of at least 50, and find that they explain respectively 38% and 42% of the variance in each variable. Adding socio-economic indicators and school-level NAPLAN score averages in reading

³ The TEA is the basis for determining ATARs. It is calculated by adding a student's best four scaled scores plus 10% of that student's best Language Other Than English (LOTE) scaled score, within certain restrictions. For further details see <http://www.tisc.edu.au/static/guide/atar-about.tisc>

⁴ The Tjur statistic is the difference in the average predicted probability of success between those succeeding and those failing.

and numeracy improves the goodness of fit of both the probit and OLS regressions by about 5 percentage points.

Next, we examine the interaction between NAPLAN scores and socio-economic status (SES) in predicting VCE outcomes. We order all students by standardized year-9 average NAPLAN scores, divide them into percentiles, define four levels of SES based on parental education and occupation (see Appendix B for a detailed definition), and for each binary indicator compare the success rate of each SES category as a function of NAPLAN scores, through summary tables and charts. The charts and the tables show that while both NAPLAN scores and socio-economic background have substantial influence, the effect of NAPLAN scores is much stronger. Thus, for example, a student in the bottom SES quartile with both NAPLAN scores in the bottom quintile has less than a 1% chance of achieving ATAR70; student in the top SES quartile with the same low NAPLAN scores has a 13.5% chance of success; a student in the bottom SES quartile with both NAPLAN scores in the top quintile has a 63.6% chance of achieving ATAR70; and a student in the top SES quartile with the same high NAPLAN scores has an 80.8% chance of success.

Finally, we consider how well NAPLAN scores predict *school-level* success rates for each of our three binary outcome variables. Restricting our analysis to 287 schools with at least 100 students in the year-9 cohort—comprising roughly three quarters of the full population—we regress actual school-level success rates on the average individual predictions of success for all students in the school. When individual prediction are based only on individual NAPLAN scores and basic demographic indicators we find that the predicted values explain over 82% of the variance in school success rates for each of the indicators, with estimated slopes all substantially greater than one. Thus our findings indicate that while there are positive school or classroom effects,⁵ they account for only a small

⁵ We cannot distinguish between direct peer effects and other classroom effects, such as schools with better students attracting better teachers (Manski, 1993). See also McVicar et al. (2013) for an analysis of peer effects from NAPLAN data.

fraction of school-level performance. When socio-economic indicators and school-level average NAPLAN scores are added to the individual prediction equations, the share of school-level variation explained increases to over 85% while the slopes fall significantly to values very near one, indicating that the school-level average scores largely capture the classroom effects.

Several papers have previously regressed tertiary entrance scores on Year 9 achievement in literacy and numeracy using Longitudinal Surveys of Australian Youth (LSAY). They have the disadvantage of (relatively) small sample size; they measure Year 9 achievement through tests specially designed for LSAY rather than standardized tests administered to the entire population; and year 12 outcomes, measured as Equivalent National Tertiary Entrance Ranks (ENTER) are self-reported. They have the advantage of covering all of Australia and, like the present paper, include both government and non-government schools.

The most comprehensive of these, Marks, McMillan and Hillman (2001) focuses on students achieving ENTER scores, regressing these scores on year 9 achievement in numeracy and reading, a variety of demographic and socio-economic factors, as well as affective factors, such as self-concept of ability and educational aspirations; and they examine the impact of individual schools on student performance. The fit they achieve, where comparable to our analysis, is less precise than ours—year 9 NAPLAN scores are substantially more accurate indicators of year 12 performance than the instruments used by LSAY to measure year 9 achievement.⁶ However, our qualitative conclusions are similar. They find as we do that the strongest influence on tertiary entrance performance is literacy and numeracy achievement in Year 9, with numeracy exercising a stronger influence; that socio-economic background affects year 12 outcomes over and above prior academic performance; that girls experience greater achievement growth between year 9 and 12 than boys; between school

⁶ The relevant regressions for comparison are those presented in Appendix Tables C4 and C5, which similarly restrict their attention to students with ATAR scores. Specifications vary, but their R-square values are generally half as large again as those reported by Marks, McMillan and Hillman (2001).

variation in year-12 outcomes after controlling for student characteristics is limited, accounting for 10-15% of total variation in outcomes. They also find that students in non-government schools achieve substantially better outcomes than students in government schools after controlling for student characteristics, a finding echoed in Marks (2004). In related work, Cardak and Ryan (2006) use the same LSAY data to ask why, controlling for year 9 achievement, individuals from poor backgrounds are under-represented at university. They find that it is not because they are credit-constrained but because they achieve lower ENTER scores compared to students with similar prior achievement from more affluent households. Again, this is consistent with our present findings that students with a high SES have better expected year 12 outcomes after controlling for year 9 academic performance.⁷

In what follows, Section 2 describes our data; Section 3 examines the accuracy of individual predictions; Section 4 characterizes the interaction between prior scores and socio-economic status; Section 5 considers school-level predictions; and Section 6 concludes.

2. The data

Our population comprises all 67,867 year 9 students aged 14 to 16 in Victoria in 2008, omitting 356 students of other ages in year-9. Data on these students includes year-9 NAPLAN scores in numeracy and reading, taken in May 2008, with indicators for missing scores; indicators for gender, language background other than English (LBOTE) and Aborigine and Torres Straits Islanders (ATSI); categorical variables describing mother's and father's education and occupation; and an indicator for whether the student attended a private or state school. Descriptive statistics are presented in Table 2.1.

⁷ In a related but different context, Benton and Lin (2011) examine the use of year 10 General Certificate of Secondary Education (GCSE) scores to predict school-leaving A and AS level outcomes, in Britain, to improve the setting of AS and A level grade boundaries for different testing authorities, so that they produce comparable grade distributions conditioned on GCSE scores.

Table 2.1 Descriptive statistics, year-9, 2008, from NAPLAN data

<i>Demographics</i>		
Number of students		67,867
% male		51.3
% aged 14 / 15 / 16	20.2% / 74.4% / 5.4%	
% language background other than English		25.2
% Aborigine and Torres Straits Islanders		1.1
<i>NAPLAN scores</i>		
Mean Numeracy Score (standard deviation)		592.8 (69.8)
Mean Reading Score (standard deviation)		586.2 (67.4)
% missing numeracy score (%)		9.1
% missing reading score (%)		9.3
% missing both scores		6.7
<i>Parents' education</i>	<i>Mother</i>	<i>Father</i>
Not stated / unknown, %	13.7	28.2
9 years or less	7.4	5.7
10 years	10.2	7.0
11 years	11.3	6.4
12 years	10.5	7.6
Certificate I-IV	19.2	21.5
Diploma/ Advanced Diploma	11.3	8.3
Bachelor's degree or more	16.3	15.3
Total	100.0	100.0
<i>Parents' occupation</i>	<i>Mother</i>	<i>Father</i>
Senior manager or professional, %	11.4	12.5
Other business manager	15.8	17.9
Tradesmen / sales	18.2	17.4
Machine operator / hospitality worker	18.3	16.5
Has not worked in past 12 months	23.8	8.4
Not stated	12.4	27.3
Total	100.0	100.0
% in non-government schools		39.9

The Victorian Curriculum and Assessment Authority (VCAA) linked this data to VCE outcomes three and a half years later, in October-November 2011. Summary statistics on their achievements are presented in Table 2.2. Of the initial population, 25,129 (37.0%) do not appear in the year 12 data.⁸ We treat all of these as having dropping out of school before completing a VCE and achieving an ATAR. This slightly overstates the percentage of non-achievers as it includes students leaving Victoria

⁸ VCAA tabulations use an age-based methodology, computing completion rates as the ratio of 19-year olds with a VCE to the estimated population of 17 year-olds two years earlier. Our VCE completion rates are consistent with theirs, as we explain in detail in Appendix A.

between year-9 and year-12 (whom we cannot identify), many of whom are likely to have achieved an ATAR of 50 or more elsewhere. Based on Australian Bureau of Statistics (ABS) data on internal migration flows we estimate that the proportion of students leaving Victoria between years 9 and 12 (but remaining in Australia) is about 2.4% of the year-9 cohort (see Appendix A for data sources and details of our estimate). If their success rates are similar to the general population, we are understating the share of ATAR50 by 1.2 percentage points, the share of ATAR70 by 0.7 percentage points, and the share of ATAR90 by 0.2 percentage points.

Table 2.2: Year-12 VCE outcomes of the year-9 cohort	
Achieved an ATAR of 50 or more	45.5%
Achieved an ATAR of 70 or more	27.9%
Achieved an ATAR of 90 or more	9.1%
Mean ATAR for students with an ATAR $\geq$ 50	65.8
Mean Tertiary Entrance Aggregate scores for students with an ATAR $\geq$ 50	124.7

In addition, a small fraction of students were held back between year-9 and year-12, and may have completed their VCE after 2011.⁹ NAPLAN data from 2008 to 2011 indicates that on average roughly 0.8% of students in Victoria government schools repeat year-9 annually. The share of students repeating a year in private schools should be substantially lower, as should the fraction of repeaters in years 10 and 11, and the fraction of students with an ATAR of 50 or more among repeaters in this and subsequent years is likely to be lower than in the general population—all of which suggests that adding repeaters who achieve an ATAR in later years would increase our average indicators of success by less than a third of the adjustments indicated for migration flows.

⁹ Our focus is limited to students achieving an ATAR while in school. Those achieving qualifications that gain them to admission to tertiary education at a later age are beyond the scope of our data.

3. Predicting individual VCE achievement from NAPLAN scores

We begin by showing that even a rough four-way division of the student population by year-9 NAPLAN scores explains a significant share of the variance in our three binary measures of VCE achievement. The four categories of performance on NAPLAN we use are

- “strong”: the average of reading and numeracy scores is above the 80th percentile, or one is above the 90th percentile and the other is above the 50th percentile;
- “above average”: an average score above the median if both scores are present, but not “strong”, or one score missing and the other above the 60th percentile;
- “below average”: an average score below the median if both scores are present, or one score missing and the other between the 20th and 60th percentiles;
- “weak”: neither score above the 20th percentile (including students missing both scores).

Table 3.1 VCE success rates by NAPLAN category, and share of explained variance

	Success rates by category of NAPLAN scores					Total variance, $p(1-p)$	% variance between NAPLAN categories
	All (p)	Weak	Below average	Above average	Strong		
ATAR ≥ 50	45.5%	9.1%	32.7%	66.9%	86.1%	24.8%	32.6%
ATAR ≥ 70	27.9%	3.1%	10.5%	39.2%	75.2%	20.1%	33.7%
ATAR ≥ 90	9.1%	0.7%	0.8%	7.2%	37.9%	8.3%	22.4%
N	67,867	17,535	19,591	18,733	12,008		

The first column of Table 3.1 presents the overall success rates for each binary outcome variable and the next four columns present specific success rates for each of the four NAPLAN categories. The differences are marked. For example, students identified as “strong” by their year-9 NAPLAN scores have a better than 85% chance of achieving an ATAR of 50 or better, while those identified as weak by their year-9 performance have less than a 10% chance of achieving this level. Similarly, weak and

below-average students in year-9 have less than a 1% chance of achieving an ATAR in the top 10% while strong students have a 38% chance. Overall, as the right-most column of Table 3.1 shows, this four-way classification of year-9 NAPLAN results explains about a third of the variance in ATAR50 and ATAR70, and 22% of the variance in ATAR90.

Next we estimate a probit regression for each of our outcome variables, regressing each on six NAPLAN score variables (standardized year-9 numeracy and reading scores, the same scores squared, and indicators for missing scores in each domain), indicators for gender, for language background other than English (LBOTE), and for Aborigine and Torres Straits Islanders (ATSI), and interactive terms between gender and LBOTE and between gender and ATSI. Detailed regression results are presented in Appendix C, Tables C1-C3. All the coefficients are highly significant. We derive from these equations for each student a predicted probability of success for each outcome, which we use to calculate the Tjur statistic of goodness of fit. The Tjur statistic is the difference between the average predicted probability of success for those actually succeeding and the average predicted probability of success for those not succeeding, a value of 1 indicating perfect prediction and a value of 0 indicating no predictive power. The first column of Table 3.2 presents the Tjur statistic for each binary outcome variable; values range between .321 and .386.

Table 3.2 Tjur statistic of goodness of fit of probit regressions

	NAPLAN scores, gender, LBOTE, ATSI	Adding parents' education and occupation categories	Adding also NAPLAN school means
ATAR $\geq$ 50	0.375	0.401	0.409
ATAR $\geq$ 70	0.386	0.411	0.422
ATAR $\geq$ 90	0.321	0.341	0.357

We then re-estimate the probit equations, first adding socio-economic variables describing parents' education and occupation (definitions are provided in Appendix B) and then adding school-level

average standardized NAPLAN reading and numeracy scores. Tjur statistics for these regressions are presented in the next two columns of Table 3.2. Adding both sets of variables increases the Tjur statistic by about .035 over the Tjur values for the basic equation, an increase of about 10%.

To further characterize the goodness of fit of the basic probit equation for each outcome variable we order the entire student population by predicted probability of success and divide the population into 20 ventiles of equal size. Within each ventile j , we calculate p_j , the average predicted success rate, and s_j , the actual success rate in the quintile. These are presented graphically in Figures 3.1-3.3, with solid circles indicating actual values and hollow circles indicating predicted values. All three graphs show a close fit between actual and predicted values. When actual ventile success rates are regressed on predicted rates the *R-squared* values are all greater than 0.99, with intercepts not significantly different from 0 and slopes not significantly different from 1 (at a 95% confidence interval).

To complete our analysis of goodness-of-fit at the individual level, we estimate OLS regressions of ATAR and TEA values on our basic set of NAPLAN score variables and demographic indicators, for students with an ATAR of 50 or more. These regressions explain respectively 38% and 42% of the variance in ATAR and TEA. Adding student-level socio-economic covariates and school-level NAPLAN score averages in reading and numeracy increases it by another 5.5 percentage points. Detailed results are presented in Appendix C, Tables C4 and C5.

Figure 3.1 Actual and predicted ATAR50 success rates, by ventiles

Hollow and solid circles indicate predicted and actual success rates, respectively

Figure 3.2 Actual and predicted ATAR70 success rates, by ventiles

Hollow and solid circles indicate predicted and actual success rates, respectively

Figure 3.3 Actual and predicted ATAR90 success rates, by ventiles

Hollow and solid circles indicate predicted and actual success rates, respectively

4. The effect of socio-economic background

In this section we examine the interaction between NAPLAN scores and socio-economic status (SES) in determining VCE outcomes. Table 4.1 presents frequencies and success rates for the three binary indicators by NAPLAN achievement category and four SES categories corresponding roughly to quartiles (see Appendix B for detailed definitions). In each of the bottom three panels, moving down a column shows the effect of SES background holding prior academic achievement fixed; moving across a row shows the effect of prior academic achievement holding SES background fixed. Thus, for example, looking at the first column of success rates in the ATAR50 panel, students who are academically weak in year-9 (as defined in Section 3, above) and come from the lowest SES category, have only a 4.2% chance of achieving an ATAR of 50 or better while students with the same, weak level of prior academic achievement in the highest SES category have a 27.2% success rate, a difference of 23 percentage points. Next, looking at the fourth row of success rates in the same panel, comparing students in SES category 4, the highest category, across different levels of prior

academic achievement, we find that students with the weakest prior achievement have a success rate of 27.2% while those with the highest level of prior achievement have a success rate of 79.1%, a difference of 52 percentage points. We find similar patterns for ATAR70 and ATAR90. Table 4.1 shows that both prior NAPLAN scores and socio-economic background have substantial predictive power in regard to ATAR achievement, but that prior NAPLAN scores have a stronger effect.

This is presented graphically in Figures 4.1-4.4. Figures 4.1-4.3 present success rates as a function of the student's average standardized NAPLAN scores in numeracy and reading, by SES level. To construct these graphs, we first ordered all students by their year-9 average standardized NAPLAN scores in numeracy and reading,¹⁰ and then divided them into percentiles. Then, for each binary indicator, we charted the success rate of each SES category within each NAPLAN percentile, using the LOESS procedure to smooth the graphs. Figure 4.4 demonstrates this from a different viewpoint, showing how for a student of given ability the probability of success varies with socio-economic status.

¹⁰ If either the numeracy or reading score was missing, we reduced the other score by 20%. The 6.7% of students with both scores missing are not included in these figures.

Table 4.1 Frequencies and success rates by NAPLAN and SES categories

SES categories	Categories of NAPLAN scores				
	Weak	Below average	Above average	Strong	Total
	Frequencies				
1	7,619	5,618	3,439	1,246	17,922
2	4,543	5,539	4,339	1,756	16,177
3	3,699	5,221	5,431	3,409	17,760
4	1,674	3,213	5,524	5,597	16,008
Total	17,535	19,591	18,733	12,008	67,867
ATAR 50 success rates					
1	4.2	21.0	50.8	79.1	23.6
2	7.8	28.5	60.6	83.6	37.3
3	12.6	37.7	69.7	86.2	51.6
4	27.2	52.6	79.0	88.4	71.6
Total	9.1	32.7	66.9	86.1	45.5
ATAR 70 success rates					
1	0.9	5.7	23.8	63.6	11.1
2	2.0	6.8	31.0	65.7	18.3
3	4.3	13.1	41.1	75.2	31.8
4	13.5	20.8	53.3	80.8	52.2
Total	3.1	10.5	39.2	75.2	27.9
ATAR 90 success rates					
1	0.1	0.4	3.0	23.4	2.4
2	0.3	0.3	3.5	25.5	3.9
3	0.9	0.9	7.4	35.3	9.5
4	4.1	2.1	12.7	46.6	21.5
Total	0.7	0.8	7.2	37.9	9.1

Figure 4.1 ATAR50 Success Rates by NAPLAN Percentile and SES

Figure 4.2 ATAR70 Success Rates by NAPLAN Percentile and SES

Figure 4.3 ATAR90 Success Rates by NAPLAN Percentile and SES

Figure 4.4 Probability of success of weak and strong students, by SES category

5. School-level indicators

Finally, we consider the ability of NAPLAN scores to predict school-level success rates for each of our outcome variables, focusing our attention on 287 schools with at least 100 students in their year-9 cohort, which account for about three quarters of the entire student population. For each school, we calculate the average individual prediction of success for all students in the school—from the first set of probit equations, without socio-economic variables or school averages—as a predictor of the school’s success rate; and regress schools’ actual success rates on these predicted values. The results of the three regressions are summarized in Table 5.1 and presented graphically in Figures 5.1-5.3. We find that the predicted values explain over 82% of the variance in school success rates for each of these indicators; and the estimated slopes are all significantly greater than one, indicating significant positive classroom effects. (We cannot distinguish between direct peer effects and other classroom effects that arise, e.g., schools with better students attracting better teachers.)

Table 5.1 School-level regressions of actual on predicted success rates, basic regressor set*

	Intercept (standard error)	Slope (standard error)	R ²
ATAR50	-.249 (.02)	1.489 (.03)	0.856
ATAR70	-.131 (.01)	1.412 (.03)	0.850
ATAR90	-.038 (.004)	1.365 (.04)	0.828

*Individual predictions of success based on individual NAPLAN scores and demographic variables

We then recalculated the school level predicted success rates from the probit regressions using the full set of regressors, including students’ socio-economic covariates and school-level NAPLAN averages as well as individual NAPLAN scores, and re-estimated the school-level regressions. The results are presented in Table 5.2. The share of variance explained increases slightly and now exceeds 85% for all three indicators. We also find a sharp fall in the slope estimates, which are now

all close to one: including school level NAPLAN averages in the prediction equations largely controls for classroom effects.

Table 5.2 School-level regression of actual on predicted success rates, extended regressor set*

	Intercept (standard error)	Slope (standard error)	R ²
ATAR50	-.057 (0.01)	1.139 (.02)	0.879
ATAR70	.029 (.01)	1.122 (.02)	0.870
ATAR90	-.007 (.00)	1.094 (.03)	0.842

*Individual predictions based on individual NAPLAN scores and demographic variables, parents' education and occupation categories and school-level NAPLAN score averages

Figure 5.1 Actual *versus* predicted school rates of ATAR50 success, with regression line

Figure 5.2 Actual *versus* predicted school rates of ATAR70 success, with regression line

Figure 5.3 Actual *versus* predicted school rates of ATAR90 success, with regression line

The large share of the variance in school-level VCE outcomes explained by NAPLAN scores highlights the large extent to which the average performance of a secondary school is shaped by the prior achievements of its students. Large divergences from predicted outcomes at the school level are not common, but where they occur deserve further attention. Large positive divergences may well indicate that something very good is happening in the school, while large negative divergences may indicate a need for intervention.

6. Summary

Year-9 performance on NAPLAN numeracy and reading tests predicts subsequent access to higher education as determined by achievement on year-12 Victoria Certificate of Education (VCE) exams and reflected in a set of five indicators that capture the full range of VCE achievement. We find that regressing ATAR values on NAPLAN scores and basic demographic indicators explains roughly 40% of the variance in ATAR values. Probit regressions that predict success in achieving an ATAR of at least 50, 70 or 90, from NAPLAN scores and basic demographic variables, achieve Tjur values between .321-.386; adding parents' education and occupation categories and school-level average NAPLAN scores raises the Tjur values by about .035. Socio-economic status has further explanatory power at both the individual and school level, but NAPLAN scores have much the stronger effect in predicting access to higher education. For example, the probability that a student in the bottom quintile of year-9 NAPLAN scores and classified in the lowest socio-economic quartile achieves a minimal ATAR of 50 or better is 4%; for an academically similar students in the top socio-economic quartile it is 27%; for a student in the top quintile of year-9 NAPLAN scores classified in the weakest socio-economic quartile it is 79%; and for a student in the top quintile of year-9 NAPLAN scores and in the top socio-economic quartile it is 88%. Finally, at the school level, we find that predictions based on individual NAPLAN scores and basic demographic indicators explain over 82% of the variance in school success rates. When parents' education and occupation categories and school average NAPLAN scores are added over 85% of the variance in school success rates is explained.

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Appendix A: Completion rates

A2. Internal migration flows and students repeating year-9

Total annual departures from Victoria amounted to just over 60,000 (Australian Bureau of Statistics, 2009, *Migration Australia*, cat. no. 3412.0, viewed 6 November 2013,

<http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3412.02009-10?OpenDocument>). In

Australia as a whole, just under 4% of internal migrants were between the ages of 15-19 (Australian Bureau of Statistics, 2009, *Migration Australia*, cat. no. 3412.0, viewed 6 November 2013,

<http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3412.02009-10?OpenDocument>).

Assuming this applies also to Victoria and distributes evenly among the five years, this implies just under 500 departures per cohort each year, or 1500 departures between year-9 and year-12—about 2.4% of the initial cohort of 62,098.

5.3 INTERSTATE MIGRATION FLOWS—2009–10(a)

DEPARTURES FROM:									
	NSW	Vic.	Qld	SA	WA	Tas.	NT	ACT	Total arrivals(b)
Arrivals to:									
NSW	.	20 088	35 355	4 989	7 525	2 118	2 969	9 938	82 982
Vic.	22 686	.	17 594	6 544	8 109	3 185	2 451	2 527	63 096
Qld	42 044	18 605	.	5 823	8 295	3 193	5 208	3 237	86 405
SA	4 628	5 552	4 548	.	2 458	634	2 257	624	20 701
WA	8 297	8 422	8 696	2 849	.	1 443	2 605	879	33 191
Tas.	2 405	2 731	3 341	691	1 660	.	419	260	11 507
NT	3 320	2 783	4 482	2 007	2 284	315	.	471	15 662
ACT	10 142	2 360	2 813	762	898	297	595	.	17 867
Total departures(b)	93 522	60 541	76 829	23 665	31 229	11 185	16 504	17 936	331 411
Net	-10 540	2 555	9 576	-2 964	1 962	322	-842	-69	.

Source: Australian Bureau of Statistics, 2009, *Migration Australia*, cat. no. 3412.0, viewed 6 November 2013, <http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3412.02009-10?OpenDocument>

5.8 INTERSTATE MOVERS FOR QUEENSLAND AND AUSTRALIA, Age and sex(a)—2009–10(b)

Source: Australian Bureau of Statistics, 2009, *Migration Australia*, cat. no. 3412.0, viewed 6 November 2013, <http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3412.02009-10?OpenDocument>

Table A2. Students repeating year-9 in Victoria government schools

Year	Number of students in cohort	Students repeating year-9	Share
2009	40,794	335	0.82%
2010	39,962	309	0.77%
2011	39,848	373	0.94%
2012	39,486	344	0.87%
total	160,090	1,361	0.85%

Source: Victoria DEECD NAPLAN data, authors' tabulation

A2: Reconciling our completion rates with those reported by VCAA

VCAA computes completion rates as the ratio of 19-year olds with a VCE to the estimated population of 17 year-olds two years earlier, where our base figure is the population of students enrolled in a Victorian school in Year 9 in 2008 (aged 14-16), and we consider only VCE completion in 2011. For the closest corresponding cohort to ours, those reaching 19 years of age in 2012, VCAA's completion rate is 68.7%, compared to our rate of 63%, a difference of 5.7 percentage points. We attribute most of the difference to students completing their VCE more than four years after attending Year 9: DEECD found that 2,500 students due to complete in 2011 were still participating in a senior secondary program in 2012. In addition, we estimate that about 1,000 students emigrated from Victoria between year-9 and age 17 (see above). Together, these come to about 5.2% of our base population of just under 68,000.

Appendix B. Definitions of socio-economic variables

We define five categories of parental education from separate indicators of parents' education:

1. Least educated: neither parent above grade 10
2. Partial HS-school: at least one parent grade 11 or certificate
3. Both missing: both not stated or unknown
4. Full HS: at least one parent grade 12 or diploma
5. Higher education: at least one parent with bachelor degree or more

Similarly, we define a single, joint indicator of parental occupation, with five exclusive categories, from data on father's and mother's occupation types, classified as: senior manager or professional; other business manager; tradesman or sales; machine operator or hospitality worker; unemployed; and not stated or unknown. We combine them into a single parental indicator as follows:

1. "Both unemployed or father's occupation unknown": Both parents are unemployed, or the father's occupation is unknown and the mother is not a manager or professional. When only the father's occupation is unknown we interpret this as generally indicating an absent father.
2. "One parent not working": The father is unemployed and the mother is not a manager or professional, or the mother is unemployed or has unknown occupation and the father is employed but not as a manager or professional.
3. "Both employed": Father and mother both working but neither is a manager or professional
4. "Both unknown": Father's and mother's occupation category unknown; we interpret this as generally indicating that they are self-employed and do not fall comfortably in any category.
5. "Manager": Father or mother is a manager or professional

The precise definition of each category is set out in Table B1:

Table B1. Definition of occupation types

	<i>Father's occupation</i>					
<i>Mother's occupation</i>	Senior manager or professional	Other business manager	Trade or sales	Machine operator or hospitality	Unemployed	Not stated or unknown
Senior manager or professional	5	5	5	5	5	5
Other business manager	5	3	3	3	2	1
Trade or sales	5	3	3	3	2	1
Machine operator or hospitality	5	3	3	3	2	1
Unemployed	5	2	2	2	1	1
Not stated or unknown	5	2	2	2	2	4

Finally, we define four levels of family socio-economic status (SES) based on these five categories of parental education and five categories of parental occupation, as follows:

- (1) (lowest) Both education and occupation categories are in the lower range
- (2) Both education and occupation are mid to low range and equivalents
- (3) Both education and occupation are mid-range or one is high and one is low
- (4) (highest) Both high range categories or one high and one mid-range

We set out the precise definition in Table B2:

Table B2. Definition of family SES levels

	<i>Family occupation</i>				
<i>Family education</i>	<i>Lowest</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>Highest</i>
<i>Lowest</i>	1	1	2	2	2
<i>2</i>	1	1	2	2	3
<i>3</i>	1	1	3	3	4
<i>4</i>	1	2	3	3	4
<i>Highest</i>	2	3	4	4	4

Table B3. Cross Tabulation of Occupation and Education

Occupation	Education Categories					Total
	less	partial hs	both missing	full hs	one par bachelor	
father missing	3,893	4,337	982	2,768	850	12,830
one not working	1,481	3,919	542	3,130	1,053	10,125
working	1,547	9,816	851	8,209	3,508	23,931
both missing	193	581	6,169	816	657	8,416
manager	60	662	238	2,011	9,594	12,565
Total	7,174	19,315	8,782	16,934	15,662	67,867

Appendix C. Detailed regression results

Table C1. Probit regressions of ATAR50 (average marginal effects; standard errors in parentheses)

	Individual NAPLAN score and basic demographics	with parents' education and occupation	and with school-average NAPLAN scores
Std. NAPLAN Numeracy	0.190 (0.002)	0.169 (0.002)	0.152 (0.002)
Std. NAPLAN Reading	0.132 (0.002)	0.115 (0.002)	0.109 (0.002)
Std. Numeracy squared	-0.040 (0.001)	-0.039 (0.001)	-0.041 (0.001)
Std. Reading squared	-0.027 (0.001)	-0.027 (0.001)	-0.027 (0.001)
Numeracy missing	-0.150 (0.007)	-0.138 (0.007)	-0.135 (0.007)
Reading missing	-0.143 (0.008)	-0.126 (0.007)	-0.119 (0.007)
Male	-0.138 (0.003)	-0.136 (0.003)	-0.132 (0.003)
LBOTE	0.058 (0.005)	0.057 (0.005)	0.060 (0.005)
LBOTE & male	0.031 (0.007)	0.030 (0.007)	0.032 (0.007)
ATSI	-0.216 (0.029)	-0.175 (0.029)	-0.160 (0.028)
ATSI & male	-0.004 (0.044)	0.002 (0.043)	0.001 (0.043)
Partial secondary		0.045 (0.006)	0.036 (0.006)
Both missing		0.067 (0.008)	0.054 (0.008)
Full secondary		0.117 (0.006)	0.097 (0.006)
Higher education		0.169 (0.007)	0.131 (0.007)
One not working		0.038 (0.005)	0.037 (0.005)
Employed		0.077 (0.005)	0.063 (0.005)
Both missing		0.103 (0.007)	0.057 (0.007)
Manager		0.102 (0.006)	0.073 (0.006)
Mean Std. Score			0.130 (0.004)
N	67,867	67,867	67,867

Table C2. Probit regressions of ATAR70 (average marginal effects; standard errors in parentheses)

	Individual NAPLAN score and basic demographics	with parents' education and occupation	and with school-average NAPLAN scores
Std. NAPLAN Numeracy	0.183 (0.002)	0.166 (0.002)	0.151 (0.002)
Std. NAPLAN Reading	0.122 (0.002)	0.107 (0.002)	0.102 (0.002)
Std. Numeracy squared	-0.026 (0.001)	-0.025 (0.001)	-0.027 (0.001)
Std. Reading squared	-0.018 (0.001)	-0.018 (0.001)	-0.018 (0.001)
Numeracy missing	-0.069 (0.007)	-0.063 (0.007)	-0.063 (0.007)
Reading missing	-0.062 (0.007)	-0.049 (0.007)	-0.042 (0.007)
Male	-0.107 (0.003)	-0.105 (0.003)	-0.101 (0.003)
LBOTE	0.046 (0.004)	0.044 (0.004)	0.046 (0.004)
LBOTE & male	0.020 (0.006)	0.020 (0.006)	0.022 (0.006)
ATSI	-0.138 (0.030)	-0.105 (0.030)	-0.091 (0.029)
ATSI & male	-0.005 (0.046)	0.004 (0.045)	0.006 (0.045)
Partial secondary		0.021 (0.006)	0.012 (0.006)
Both missing		0.058 (0.008)	0.044 (0.008)
Full secondary		0.083 (0.006)	0.062 (0.006)
Higher education		0.135 (0.007)	0.099 (0.007)
One not working		0.027 (0.005)	0.025 (0.005)
Employed		0.047 (0.004)	0.035 (0.004)
Both missing		0.091 (0.006)	0.046 (0.006)
Manager		0.070 (0.005)	0.043 (0.005)
Mean Std. Score			0.115 (0.003)
N	67,867	67,867	67,867

Table C3. Probit regressions of ATAR90 (average marginal effects; standard errors in parentheses)

	Individual NAPLAN score and basic demographics	with parents' education and occupation	and with school-average NAPLAN scores
Std. NAPLAN Numeracy	0.089 (0.002)	0.081 (0.002)	0.073 (0.002)
Std. NAPLAN Reading	0.060 (0.002)	0.053 (0.002)	0.050 (0.002)
Std. Numeracy squared	-0.006 (0.001)	-0.005 (0.001)	-0.007 (0.001)
Std. Reading squared	-0.006 (0.001)	-0.005 (0.001)	-0.005 (0.001)
Numeracy missing	0.012 (0.006)	0.012 (0.006)	0.010 (0.005)
Reading missing	-0.000 (0.006)	0.005 (0.006)	0.009 (0.006)
Male	-0.042 (0.002)	-0.041 (0.002)	-0.040 (0.002)
LBOTE	0.015 (0.003)	0.015 (0.003)	0.013 (0.003)
LBOTE & male	0.019 (0.004)	0.018 (0.004)	0.018 (0.004)
ATSI	-0.100 (0.029)	-0.081 (0.028)	-0.075 (0.028)
Partial secondary		-0.005 (0.005)	-0.008 (0.005)
Both missing		0.023 (0.006)	0.017 (0.006)
Full secondary		0.022 (0.005)	0.012 (0.005)
Higher education		0.056 (0.005)	0.037 (0.005)
One not working		0.015 (0.004)	0.014 (0.004)
Employed		0.015 (0.004)	0.010 (0.004)
Both missing		0.042 (0.004)	0.020 (0.004)
Manager		0.028 (0.004)	0.016 (0.004)
Mean Std. Score			0.052 (0.002)
N	67,867	67,867	67,867

Table C4. OLS regressions of ATAR (standard errors in parentheses)

	Basic regressor set	With socio-economic variables	And with mean school scores
Std. Numeracy	7.321 (0.126)	6.933 (0.123)	6.456 (0.122)
Std. Reading	4.432 (0.120)	4.136 (0.117)	4.033 (0.115)
Std. Numeracy squared	-0.158 (0.053)	-0.143 (0.052)	-0.336 (0.052)
Std. Reading squared	0.017 (0.060)	-0.052 (0.058)	-0.083 (0.057)
Numeracy missing	2.329 (0.415)	1.860 (0.405)	1.443 (0.398)
Reading missing	2.067 (0.419)	2.069 (0.408)	2.102 (0.402)
Male	-3.713 (0.154)	-3.950 (0.150)	-3.968 (0.148)
LBOTE	1.859 (0.196)	1.958 (0.194)	1.923 (0.191)
LBOTE & male	0.728 (0.283)	0.810 (0.276)	0.876 (0.271)
ATSI	-4.060 (1.836)	-3.263 (1.789)	-2.593 (1.758)
ATSI & male	0.764 (2.928)	1.467 (2.851)	0.869 (2.803)
Partial secondary		-0.528 (0.338)	-0.892 (0.332)
Both missing		1.911 (0.396)	1.371 (0.389)
Full secondary		1.522 (0.330)	0.684 (0.326)
Higher education		4.660 (0.343)	3.200 (0.340)
One not working		0.487 (0.268)	0.476 (0.263)
Employed		0.759 (0.227)	0.245 (0.223)
Both missing		3.828 (0.308)	1.894 (0.308)
Manager		2.128 (0.257)	1.050 (0.255)
Mean Std. score			4.940 (0.150)
Constant	70.372 (0.111)	67.134 (0.343)	68.371 (0.339)
R^2	0.380	0.412	0.432
N	30,874	30,874	30,874

Table C5. OLS Regressions of Tertiary Entrance Aggregates (standard errors in parentheses)

	Basic regressor set	With socio-economic variables	And with mean school scores
Std. Numeracy	11.273 (0.210)	10.612 (0.205)	9.762 (0.202)
Std. Reading	6.936 (0.200)	6.446 (0.196)	6.259 (0.192)
Std. Numeracy squared	0.902 (0.089)	0.929 (0.087)	0.586 (0.085)
Std. Reading squared	0.649 (0.100)	0.529 (0.097)	0.478 (0.095)
Numeracy missing	4.823 (0.690)	4.033 (0.672)	3.289 (0.659)
Reading missing	3.564 (0.697)	3.586 (0.678)	3.649 (0.665)
Male	-6.168 (0.257)	-6.575 (0.250)	-6.604 (0.245)
LBOTE	3.106 (0.327)	3.246 (0.323)	3.190 (0.317)
LBOTE & male	1.465 (0.472)	1.603 (0.460)	1.708 (0.451)
ATSI	-5.826 (3.090)	-4.370 (3.007)	-3.156 (2.948)
ATSI & male	-0.891 (4.886)	0.208 (4.754)	-0.878 (4.661)
Partial secondary		-0.972 (0.567)	-1.633 (0.556)
Both missing		2.668 (0.662)	1.703 (0.649)
Full secondary		2.092 (0.555)	0.590 (0.545)
Higher education		7.579 (0.575)	4.970 (0.568)
One not working		0.842 (0.447)	0.832 (0.438)
Employed		1.158 (0.378)	0.245 (0.372)
Both missing		6.703 (0.512)	3.263 (0.511)
Manager		3.623 (0.429)	1.711 (0.424)
Mean Std. score			8.783 (0.249)
Constant	128.142 (0.184)	122.992 (0.576)	125.195 (0.568)
R^2	0.416	0.447	0.469
N	30,688	30,688	30,688