MATHS IS A STRONG PREDICTOR OF STEM ATTAINMENT IN FIRST YEAR UNIVERSITY

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ABSTRACT
Mathematics is often heralded as the foundation to Science, Technology, Engineering and Mathematics (STEM) education, yet we know relatively little about how student attainment in maths is related to attainment in science. Sadler and Tai's (2007) influential US study showed the importance of learning mathematics in high-school for subsequent learning in university science, while research in New Zealand does not support this assertion (NZ Government, 2010). Furthermore there have been no studies of how maths may predict science attainment within university study. To address this issue we investigated the role of mathematics in STEM courses in one elite university in Australia. Secondary data analysis employed linear multiple regression to examine the relationship between first semester mathematics and second semester science attainments, while accounting for prior learning and demographic variables. These analyses confirmed that prior learning in the examined science was the best predictor of later science attainment; but that mathematics is also a strong predictor of science across biology, engineering, molecular bioscience and physics. In biology and molecular bioscience, maths is a significant predictor of attainment over and beyond the first semester attainment in these sciences. The implications for degree structure and preparation for study within STEM degrees are discussed.

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INTRODUCTION
Maths has been widely cited as foundational to learning in the sciences. Sadler and Tai's (2007) influential study, *The two high-school pillars supporting college science,* established study in maths and the relevant science specialist subject as the most influential prior learning for attainment in biology, chemistry and physics, in universities and colleges across the US. However, other national studies have not supported this assertion (NZ Government, 2010) and questions remain as to the relationship between prior study in maths and later attainment in university maths. Studies in single institutions (see Nicholas, Poladian, Mack & Wilson, 2014, for example) have documented a positive relationship between high school maths and university science attainment. However, studies examining the relationship between maths and science across the high-school-university divide are further complicated by the shifts in teaching and learning that occur in that transition (Kajander & Lovric, 2005). Questions also remain as to whether this relationship may be explained simply on the basis that maths scores may act as a proxy for general ability; or whether some *transfer of learning* is also occurring between these subjects.

In this paper we make a contribution by examining the relationship between maths and science within first year university. Using secondary data, regression analyses are conducted to examine the relationship between first year maths service units of study (UOS) and attainment in second semester science UOS. These analyses include factors known to contribute to university attainment including: first semester attainment in science, university entrance rank, gender, age and socio-economic status.

The correlates of learning that are found between maths and science have been examined in terms of the *transfer* of mathematical learning and skills into science contexts (Roberts, Sharma, Britton, & New, 2007). However the relationship between maths and science attainment can also be explained by the underlying intelligence factors involved in these processes; these factors can be both general and specific (Nisbett, Aronson, Blair, Dickens, Flynn, Halpern, & Turkheimer, 2012). The *g factor* or *general ability* is an underlying foundation to diverse cognitive abilities and directly or indirectly affects all learning, including in mathematics and science. According to Cattell-Horn-Carroll theory, *g* is the strongest factor analytical construct in the hierarchical model of intelligence (see for example, Taub, Keith, Floyd & McGrew, 2008). Furthermore the *g factor* has been shown to be highly correlated with international assessments of educational attainment, such as PISA and TIMSS, and IQ tests

(Rindermann, 2007). Thus when examining two different educational attainments we would anticipate some correlation, reflecting the fact that both draw on the *g factor*.

The relationship between mathematics and general ability has been examined empirically. The *g factor* was correlated with 25 secondary school subjects in the UK; and Mathematics had the strongest association with *g* (r = 0.77), explaining approximately sixty percent of the variance in general ability (Deary, Strand, Smith & Fernandes, 2007). This suggests that among educational attainments maths is particularly linked to *g* and that this might also explain how maths would be a strong predictor of other educational attainments.

Complicating this picture of correlated educational attainments is the unique relationship between mathematics and science. These are highly cognate disciplines and thus the abilities underlying attainment in them may share additional factors. These may be factors contributing to *g,* or they may be specific intelligence factors which explain additional achievement variance beyond *g*. Taub and colleagues (2008) have demonstrated how cognitive ability factors, including *fluid reasoning, processing speed,* are associated with mathematical attainment. Because science and maths assessments may share requirements for *fluid reasoning, processing speed (*which contribute to *g*) and may also both draw on specific factors, like g_q (quantitative knowledge) we might expect higher levels of correlation between them than between other, less cognate disciplines.

Utilising their cognitive abilities students learning maths may, because of the alignment with science, *transfer* some of their learning into science contexts (Roberts et al., 2007). Maths and science assessment tasks may ask similar questions and require students to use skills, knowledge and understanding that is shared by maths and science. Thus, theoretically *transfer* of learning provides additional rationale for association between maths and science assessments.

There is research evidence that educational interventions in school can impact upon intelligence (Nisbett et al., 2012). Schooling and the development of cognitive abilities are indissoluble; and both are also subject to variation by gender, socioeconomic status, social and environmental factors (McLoyd, 1998; Nisbett et al., 2012). These factors and prior learning (Martin, Wilson, Liem & Ginns, 2013) are therefore important considerations when examining any educational attainment. Consequently they are included in our analyses examining how attainment in mathematics UOS is associated with attainment in science UOS. The study is highly significant because of recent research highlighting declining participation particularly in maths, but also in science, among high school and university in Australia (Barrington, 2014; Kennedy, Lyons & Quinn, 2014; Wilson, Mack & Walsh 2013; Wilson & Mack, 2014) and because of academics' concern regarding students' readiness and progress in these subjects at university (IISME, 2014).

METHODOLOGY

This study, employing secondary data analysis, is a part of an ongoing research project examining the relationship between mathematics and science in an elite university in Australia (Nakakoji, Wilson & Poladian, 2014). The main characteristics of the students (N= 669) are high Australian Tertiary Admission Ranks (ATAR) and high socioeconomic background (see Nakakoji, Wilson & Poladian, 2013 for details). Anonymised data was accessed from university databases and included: students' demographics (age, gender, postcodes, international student status, ATAR) and academic attainment in 2012 first year mathematics plus additional results for either: physics, engineering, molecular bioscience and biology. International students were removed from analysis. Final science attainment subsamples consisted of students who studied both MATH1001 and relevant STEM UOS: physics (n=120), engineering (n=308), molecular bioscience (n=184) and biology (n=57). The wide range of assessments within STEM UOS in the university is outlined in Table 1. Final exams contributed the most to assessment marks, although the proportions varied considerably.

Table 1: Diverse assessment used in relevant STEM units of study

Subject	Semester 1 assessment	Semester 2 assessment
Maths	Assignment (5%), Quizzes (30%), Final Exam (65%)	Assignment (5%), Quizzes (30%), Final Exam (65%)
Biology	Reports (22%), Lab (10%), Tests (30%), Final Exam (38%)	Reports (17%), Lab (15%), Tests (30%), Final Exam (38%)
Bio-chemistry	Report (20%), Quizzes (15%), Case study (11%), Peer feedback (4%), Final Exam (50%)	Final exam (56.7%), Skills Test (12.7%), Assignments (26.6%)
Eng-ineering	Lab Exercise (10%), Lab Exam (15%), Major Project (25%), Final Exam (50%)	Assignment (10%), Quizzes (75%), Online Quizzes (15%)
Physics	Assignments (10%), Tutorials (2%), Laboratory Work (20%), Online Learning Modules (1%), Quizzes (1%), Laboratory Skills test (5%), Final Exam (61%)	6 assignments (9%), Tutorials (2%), Laboratory Work (10%), Laboratory Test (2%), Laboratory Project (14%), Final Exam (63%)

ANALYSIS

Linear multiple regression was used to model the relationship between demographic variables and first semester mathematics and science UOS and the second semester science UOS (outcome variables), see Figure 1. The analysis was conducted using SPSS and non-significant variables were removed from the *full models* one by one to leave a *final model* including only significant predictors of the outcome. In some cases, where maths was not significant predictor in the *final model*, an additional *math model* was produced to illustrate how maths could predict second semester science, if the first semester science attainment was not included. Pairwise analysis was used due to some missing values and residual analyses were conducted; including checking normality, linearity and homoscedasticity.

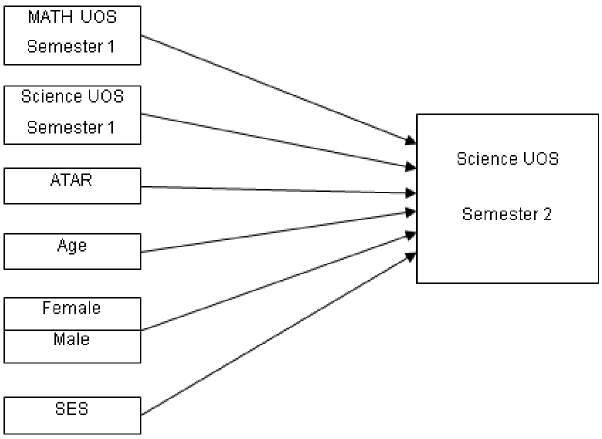

Figure 1: General model of the relationship between mathematics and science attainment with demographic variables

RESULTS AND DISCUSSION

Demographic and social-economic factors, such as age, gender, and SES, are important in educational attainment. As a part of exploratory data analysis, scatter plots of mathematics and science attainment were used to identify patterns and extremes/outliers. Before conducting analysis for the full model (see Figure 1), initially, only age, gender and SES were entered into the model in order to see the relationship with semester 2 science attainment without influence of prior attainment. The significant effects were: age for physics (R^2 = .070, n=120); gender for molecular bioscience (R^2 = .021, n=184); and SES for biology (R^2 = .071, n=57). However, there were no significant effects observed for engineering. SES effects observed in biology, shown in Figure 2, suggest a different linear relationship between maths and science attainment according to SES group. The R square effects are small but consistent with other educational research, where student characteristics (gender, Age, SES) contribute approximately 15% (Hattie, 2009).

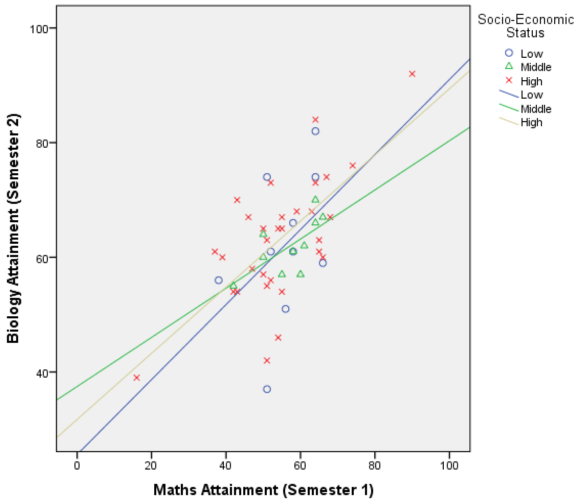

Figure 2: Scatter plot of mathematics and biology attainment by three SES groups

The regression models predicting semester 2 science attainments are summarised in Table 2. There were six major findings from the analysis. First, Semester 1 science UOS was the best predictor for attainment of the subsequent semester science UOS in the same discipline (biology, molecular bioscience, physics). This study showed this between university science UOS, but is consistent with the Sadler and Tai (2007) analysis of high-school and university science attainment. However, one exception to this is that engineering courses offered in the first semester were not predictive of second semester engineering. A possible reason for this, based on review of course outlines, is that first semester engineering UOS syllabi and assessment had very limited mathematical content, while the UOS in semester 2 there was much more mathematical content. Therefore, first semester mathematics is a strong predictor but first semester engineering is not.

An important second finding is that mathematics was also a significant predictor for attainment in the following semester science UOS across the disciplines. In molecular bioscience and biology mathematics provided an additional incremental explanation of variance, beyond that provided by first semester science (see Table 2 for R square change). In other words maths explains performance in these subjects over and beyond what is explained by pervious attainment in biology and molecular bioscience. In engineering maths is the only first semester predictor of second semester engineering. Furthermore, across the sciences, maths and student characteristics alone can explain substantial proportions of variance, ranging from 39 to 47, in science scores.

Third, a different pattern was evident for physics. Mathematics was not a significant predictor of second semester physics when first semester physics was included in the model. This might be because the physics assessment contained more mathematical content, so mathematical attainment could provide no additional explanation of the second semester performance, which is also highly dependent on mathematical knowledge and skills. It can also be noted that age had a negative impact on physics. School physics is very predictive of university physics (Sadler & Tai, 2007) and school maths is also highly predictive of university physics (Nicholas, Poladian, Mack & Wilson, 2014) therefore continuity of study may be an especially important factor in physics attainment.

Fourth, overall it is clear that in general prior attainment, in maths, science or ATAR, is highly predictive of university science. Some of this may be due to the assessment tapping relevant general and specific factors in intelligence. We know, for example, that maths attainment is the most predictive school attainment upon *g* factor intelligence (Dreary et al., 2007). University ranking (ATAR), which is based on attainment across a range of diverse subjects which students choose, is significant in two models – physics and molecular bioscience. Both these subjects draw upon a range of intelligence factors and skills. In supplementary analyses we found that ATAR alone explained between 14.7 and 28 per cent of the variance in the first semester science UOS. If we use maths to predict semester 2 physics, ATAR also makes a substantial contribution but this is only the case if we do not include (or control for) semester 1 physics. In molecular bioscience all three attainments (ATAR and first semester maths and molecular bioscience) make unique contributions and together predict over 50 per cent of the variance in second semester molecular bioscience.

Table 2: Summary of regression models, excluding international students. MATH1001 and normal semester 1 science UOS as predictors of semester 2 science UOS.

Outcome – Semester 2 UOS	Model	Effect & Covariates	Coefficient	Standard error	Standardised Beta
PHYS1003 Physics 1 (Technological) Sem 2 (n=120)	Full R^2 = .727	**PHYS1001 Sem 1**	**.733*** **	**.096**	**.665*** **
		MATH1001 Sem 1	.120	.103	.109
		ATAR#	.262	.204	.105
		Age	**- 1.049** **	**.369**	**- .186** **
		Gender	.465	2.067	.014
		SES	.019	.012	.103
	Final R^2 = .696	**PHYS1001 Sem 1**	**.876*** **	**.072**	**.794*** **
		Age	**- 1.098** **	**.371**	**- .194** **
	Math (without Sem 1 science) R^2 = .470	**MATH1001 Sem 1**	**.486*** **	**.106**	**.439*** **
		ATAR#	**.669** **	**.235**	**.269** **
		Age	**- 1.094***	**.435**	**- .194***
ENGG1802 Engineering Mechanics Sem 2 (n=308)	Full R^2 = .450	ENGG1801 Sem 1	- .053	.085	- .045
		MATH1001 Sem 1	**.731*** **	**.108**	**.614*** **
		ATAR#	.222	.240	.083
		Age	.588	.444	.097
		Gender	- 1.735	2.493	- .050
		SES	- .011	.014	- .056
	Final R^2 = .429	**MATH1001 Sem 1**	**.779*** **	**.053**	**.655*** **
MBLG1001 Molecular Biology and Genetics Sem 2 (n=184)	Full R^2 = .524	**BIOL1003 Sem 1**	**.472*** **	**.105**	**.395*** **
		MATH1001 Sem 1	**.266***	**.113**	**.238***
		ATAR#	**.626** **	**.233**	**.249** **
		Age	.718	.430	.126
		Gender	- 2.400	2.430	- .074
		SES	- .009	.014	- .047
	Final R^2 = .502	**BIOL1003 Sem 1**	**.469*** **	**.103**	**.393*** **
		ATAR#	**.651** **	**.232**	**.259** **
		MATH1001 Sem 1	**.246* (ΔR^2 = 2.7%)**	**.110**	**.220***
	Math (without Sem 1 science) R^2 = .389	**MATH1001 Sem 1**	**.433*** **	**.090**	**.387*** **
		ATAR#	**.783*** **	**.203**	**.312*** **
BIOL1002 Living Systems Sem 2 (n=57)	Full R^2 = .868	**BIOL1001 Sem 1**	**.836*** **	**.098**	**.760*** **
		MATH1001 Sem 1	**.340** **	**.106**	**.300** **
		ATAR#	- .184	.233	- .072
		Age	.734	.415	.127
		Gender	- .933	2.325	- .028
		SES	.020	.014	.106
	Final R^2 = .842	**BIOL1001 Sem 1**	**.863*** **	**.091**	**.784*** **
		MATH1001 Sem 1	**.254* (ΔR^2 = 3.8%)**	**.093**	**.224***
	Math (without Sem 1 science) R^2 = .463	**MATH1001 Sem 1**	**.709*** **	**.120**	**.626*** **
		SES	**.053** **	**.020**	**.287** **

*Sig. at p<.05, **Sig. at p<.01, ***Sig. at p<0.01
[#] ATAR Australian Tertiary Admission Rank

A fifth point to consider is that all of the models explain fairly large proportions of the variance in science attainment; from 43 to 87 per cent. These figures are large when compared to predicting university attainments from high school attainment. Sadler & Tai's models range from 31 to 35 per cent and the NZ government (2010) concluded that secondary attainment was not a strong predictor of university attainment. There are several factors which may explain this. First, clearly modes of assessment within university are more aligned that those across school and university contexts. Second, our sample is more homogenous than the large national samples: they are a high ability cohort. It may also be significant that the assessment for ATAR is 50% external and highly standardised; and the outcome first semester attainment scores for science are comprised of a wide range of assessments (see Table 1).

A sixth and final finding is that demographic variables, such as age, gender and SES, were not explicitly significant when previous attainment was included in the models. This is because the influence of demographical and socio-economic factors was already implicit in the prior attainment variables. Only age proved to be a significant demographic factor explaining physics performance beyond that predicted by first semester physics. However in initial data exploration the impact of socio-economic status and gender were evident in the educational attainments and we included an example to illustrate this (see Figure 2) so as not to forget these important considerations in education.

LIMITATIONS
This study was limited by the following points. A major limitation could be that this study focused on one elite institution, which leads to poor sample representativeness and limited generalisability beyond elite university contexts. The study also looked at only 2012 data, so longitudinal trends were not observed. Furthermore, we relied on only the largest cohort UOS for the analysis, this sometimes caused a bias in attainment as some smaller cohort units offered concurrently focus on highly able students, or those with less preparation. Our disciplinary focus was also limited and did not, for example, explore chemistry, medicine and psychology. Finally, due to missing data, pairwise analysis was conducted.

CONCLUSION
Our study has found that among first year university students first semester maths is a highly significant predictor of attainment in second semester science. Maths is a predictor of second semester molecular bioscience and biology, even when controlling for first semester science. However, when first semester physics is included, maths does not make a substantial further contribution to second semester physics. This may be because the two subjects are so similar in their assessment of mathematical skills, knowledge and understanding and *g,* that maths is not able to make any additional explanation of the variance in physics scores. Maths alone however explains 47% of the variance in physics attainment.

These findings have several implications. Firstly, the high levels of variance explained highlight the strong relationship between maths and science attainment. For example 84% of the variance in second semester biology can be explained by first semester biology and maths scores. Somewhat surprisingly maths most strongly predicts biology (a science subject with limited mathematical content in first year); where it uniquely explains an additional 3.8% of the variance in scores. This strong relationship may be due to the substantial *g* factor within maths (Dreary et al., 2007), but also could be due to shared specific factors (like *fluid reasoning*) and/or additional *transfer* of learning from first semester maths to second semester STEM courses. Additional research is needed to explore these possibilities. Regardless, it is evident that maths skills, knowledge and understandings are predictive of success in science and engineering; maths should therefore be a central consideration in these degrees' structures.

A second, corollary point is that if maths attainments, inclusive of the *g* and specific factors discussed, are highly predictive of science achievement, educational institutions and authorities should examine the nature of these more closely. Furthermore, universities may need to consider strategies to optimise the maths preparedness of cohorts entering science degrees. Making a strong start with appropriate prior learning and success in first year are critical to successful degree progression (Martin et al., 2013).This is currently an issue for Australian universities where university prerequisites have all but disappeared and numbers studying intermediate and advanced maths at school are dwindling (Barrington, 2014; 2013; Wilson & Mack, 2013) This study makes a small contribution, emphasising the strength of maths as a predictor in university attainment, but there is still much more needs to be done to secure the place of maths within Australian education and to provide additional insight into the role that maths plays in both developing and reflecting general cognitive abilities.

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