Student Preparedness, Effort and Academic Performance in a Quantitative Business Course

P.J. Cybinski and J. Forster

No. 2009-06

Series Editor: Professor D.T. Nguyen

Copyright © 2009 by Griffith University. All rights reserved. No part of this paper may be reproduced in any form, or stored in a retrieval system, without prior permission of the authors.
Student Preparedness, Effort and Academic Performance in a Quantitative Business Course

P.J. Cybinski* and J. Forster
Griffith University

October 2009

ABSTRACT

Of the many factors influencing academic performance, the student’s personal inputs to learning are recognised as among the most critical. Some of these inputs are the focus of this study of performance in an introductory statistics course. The individual student’s inputs that are hypothesised to be central to academic performance are effort, ability and relevant prior training. Ability and training are necessarily fixed at the commencement of any course, with only effort potentially under the student’s control during the course. Effort is not directly observable and the use of self-reporting of personal actions is widely recognised as problematic. Consequently in this paper effort is measured by (voluntary) attendance, although it is recognised that attendance is only one part of a student’s engagement with the course content. Ability and prior training are jointly measured as a single score from a simple numeracy test administered at the start of the course. We found that individual students’ scores on this test, as well as their levels of attendance, were strongly related to academic success in the course. These results allow a discussion of the impact of student engagement, closely related to effort and specifically to attendance. Changes in universities and society over the past two decades have tended to reduce student engagement, and the longer-term consequences of changes designed to facilitate learning may be the opposite of those intended. Methodological problems involved in this and similar studies are discussed at greater length than is usual.

JEL classifications: A20, A29.

Keywords: Student attendance; student performance; business and management curriculum; introductory statistics course.

* Corresponding Author:
Dr P. Cybinski,
Dept of Accounting, Finance and Economics
Griffith Business School
Griffith University Nathan Campus
Nathan, Brisbane Q 4111
Australia
Email: P.Cybinski@Griffith.edu.au
1. Introduction: The Determination of Academic Performance

The relationship between a student’s academic performance and the inputs the students brings to a well-defined course of study is examined. The course of study is “well-defined” in being a quantitative subject where academic performance is examinable against objective criteria. An individual student’s inputs are preparedness and effort, and these are also open to objective measurement. The student’s preparedness is a combination of their mathematical ability and prior maths training and experience. Attention is also focussed on how attendance and preparedness combine to affect performance in a compulsory first year business statistics course. While education research has identified many factors that predict students’ tertiary academic performance, especially cognitive ability and personality variables, little has focused on attendance rates. (but see Woodfield et al, 2006; Lamdin, 1996; Romer, 1993).

The course is taken as part of a business degree at a large Australian public university. In this study the lecturer, the immediate teaching environment and course structures and processes are held constant. However, the external world faced by individual students potentially varies greatly. Here these external effects are necessarily treated as random, but are recognised as systematically affecting attendance in the interpretation of the study results.
2. Contemporary Academic Environments and Student Engagement

As opposed to their external environment, the teaching environment is constant across students, but it is changing over time. One example is that student-lecturer ratios have risen markedly as a result of funding cuts and increasing demand for tertiary education. This transforms the lecturer’s task to one of ‘facilitating learning’ rather than ‘teaching’. One response is that tertiary institutions design many of their courses in a flexible delivery mode, with first year courses especially having large student numbers with easy access to course materials but little access to the lecturer – except through lecture attendance.

At the same time students are now paying up to and beyond $8000 a year towards the cost of their tuition (for Australian business degrees\(^1\)). As a consequence, more students find paid work necessary to finance their studies (Chambers, 1992, de la Harpe et al, 1997). More students are engaged in more hours of paid employment every week to fund their studies: certainly more than were doing so a decade ago (McInnes et al, 2000). By 2002, 72.5% of Australian university students had paid employment during semester, for an average of 15 hours per week (McInnis et al, 2002). International students are often even more pressed, at the very least paying much higher fees. These international factors have been exacerbated since the study as many come from nations adversely affected by the global financial crisis, as well as suffering from the appreciation of the Australian dollar in mid 2009.

Life-long learning also means that an increasing proportion of students, even those studying full-time, are forced to subordinate study to family, job and mortgage. Many more are mature-aged, with only 27.2% aged under 20 (Australian Vice-Chancellors’ Committee, 2001, p.39). Overall, the Australian Vice Chancellors Committee (AVCC) (2007) found the number of students who claimed their paid work affected their studies had more than doubled, from 16 to 40 percent since 2000. So, while paid work has both positive and negative impacts on learning (Astin, 1993, McInnis, 1995, McInnis et al,
2000), many students are no longer able to fully participate (fully attend) in the educational opportunities provided at their learning institution. This has meant that educators are packaging their courses onto the web for students to access at any time, one intention being to help students with competing time demands.

But, whatever the motivation for web-based content, an unintended result may be to give students a false sense of control over that content, so that they perceive attendance as less critical. This also creates a methodological difficulty for studies of attendance. Previously attendance was largely a matter of choice on the part of the student. Now attendance rates are also partly a measure of constraints upon choice. Assessing the significance of these differences depends upon answering the question, ‘does attendance matter?’ It can also be surmised that attendance of one student affects other students in a variety of ways (we can term these effects “externalities of attendance”). One such externality is that it creates congestion and is therefore negative. Another is that students benefit from contact with each other, and learn from each other. And yet a third is that attendance by one student reinforces the attendance of other students. Attendance, both in aggregate and for the individual student, is the outcome and a potential measure of a complex set of factors.

The previous discussion points to the crucial importance of attendance. It is vital to consider the implications of (what appears to be) a trend for students to be disengaged from campus life. Falling student attendance rates over time and across courses and institutions may herald both state and private funding moving towards “more efficient” and less labour intensive forms of teaching, bolstered by arguments that students are voting with their feet. At the same time it is easy to envisage accreditation bodies and quality assurance regimes requiring the use of attendance measures, pulling institutions in opposite directions. Funding bodies may also begin to require such measures. Consequently, attendance rates may become increasingly crucial in such system level debates, while citing the impacts of attendance upon student performance.
Despite these considerations, relatively few researchers have placed emphasis on class attendance rates as indicators of either application or motivation (Woodfield et al., 2006). The role of application in relation to academic performance research has long been presumed significant, and conscientiousness has been called ‘a powerful predictor of academic performance’ (Furnham et al., 2002, p.62 Busato et al., 1999) but measuring these concepts has proved difficult. Certainly in secondary schools in the U.S.A student attendance positively correlates with standardised achievement tests (Lamdin, 1996, Borland, 1998, Roby, 2004). It is the same for U.S.A. universities (Hovell et al., 1979, Park and Kerr, 1990, Romer, 1993, Marburger, 2001, Donathon, 2003), the U.K. (Woodfield et al., 2006) and Australia (Massingham and Herrington, 2006).

3. Performance, Preparedness and Attendance: A Simple Model

Preparedness and Academic Performance

Preparedness may be less problematic than attendance and the importance of mathematical skills to student performance in quantitative disciplines is widely recognised. Johnson and Kuennen (2006) found that a math-quiz score was significantly related to performance in an introductory statistics course (as was student GPA and gender) and was robust across course formats and instructors. Others have used the maths score component of a tertiary entrance test such as the Scholastic Aptitude Test (SAT) or American College Test (ACT), and others have used possibly less well related measures: the number of mathematics credits, or having taken a calculus course (Cohn, 1972, Ely and Hittle, 1990, Anderson et al., 1994, Ballard and Johnson, 2004).

Bringing both preparedness and attendance together, along with differential interactions between the two measures and gender, the model to be tested is below:
\[ P = b_0 + b_1 A + b_2 S + b_3 G + b_{13} I_{GA} + b_{23} I_{GS} \]

where:

\[ P = \text{Academic Performance, with } 0\% < P < 100\% \]

\[ A = \text{Attendance} \]

\[ S = \text{Pre-Test Score} \]

\[ G = \text{Gender} \]

\[ I_{GA} = \text{Interaction of Attendance and Gender} \]

\[ I_{GS} = \text{Interaction of Gender and Pre-Test Score.} \]

This linear model treats the impacts of each variable as additive in their impact and the interactions between gender and attendance and preparedness variables as multiplicative.

4. Characteristics of the Course, the Students and Behaviour

Because of the sampling problems involved in many studies of student performance the data are described in some detail, as are the descriptive statistics derived from those data.

A basic numeracy pre-test was distributed to all first year, B.Com. degree students attending the first lecture of the compulsory ‘Business Statistics’ course. Course information, enrolment numbers and response numbers are contained in Table 1. The final data set contained 231 student records (57% of the initial enrolments and 66% of students completing the course). This ‘respondent group’ all sat the pre-test, completed the course and provided verifiable student ID² at the pre-test. This allowed matching of examination results, tutorial attendance figures and pre-test scores.

Table 1 here

Measures:
a) Physical Engagement in the Course

Attendance data were used as a proxy measure for engagement in the course. In a study of determinants of degree outcomes of 700 U.K. undergraduates by Woodfield et al. (2006), attendance data were from end-of-term tutorial reports rather than from lectures. In the present course there were 17 tutorials and 17 computing laboratories, all held in tandem, and within a few hours of the two-hour lecture on the same day. Attendance was not compulsory but tutors can record individual tutorial attendance. If a student attends the tutorial, they have usually (but not always) attended the lecture. The computing labs are an additional resource, with self-paced material for students who want to work together on the weekly computing exercises. This work can also be done at home or at any time the computing labs are empty, so attendance data were not collected.

The weekly attendances at the tutorials (from week 2 to 13 of the 13 week semester) and the week 1 attendance at the lecture are shown (Figure 1). These are attendances recorded by the tutors and not self-reported (as opposed to many studies). These data relate to individually identifiable students and have the advantages of being complete, and not restricted to survey respondents. As a first year course, week one attendance is generally lower than week two as some students, especially overseas students, have not yet arrived, have not yet enrolled or are confused about where to be. There were no classes in week 7 when the midsemester exam was held.

Figure 1 shows that attendance drops off in the first few weeks until about half are attending each week. For the respondent group, median attendance was close to 8 out of the 11 tutorials, but due to a slightly negatively skewed distribution the attendance mean was 7.6 tutorials or 69.2% of the available sessions. Neither lecture nor tutorial attendance is compulsory for the course nor was any mark given for participation—a possible cause of bias in past studies that may have been overlooked or not reported. Conversely Massingham and Herrington (2006) reported an 80% average attendance at
tutorials but noted that students were required to attend 75% of tutorials or risk failing the subject. Other researchers report the following: - Rodgers and Rodgers (2003): 62% at lectures, 73% at tutorials; Rodgers (2001): 68% at lectures, 80% at tutorials; and Romer (1993) reports that ‘attendance counts … indicate usually about one-third of students are not in class’. [p.167]

**Figure 1 here**

b) Pre-test Score

The maths pre-test (see Appendix) was given before the course began and consisted of 10 questions in 20 minutes. Held without prior warning (to avoid deliberate non-attendance) it measured student basic numeracy, knowledge of mathematical concepts and calculative ability without the use of a calculator. The results indicated that significant numbers of students would have difficulty in performing statistical calculations and in interpreting statistical results. **Figure 2** is a histogram of the respondents’ results on the pre-test.

**Figure 2 here**

Previous participation in quantitative courses, especially subjects taken in high school, is a measure expected to correlate with the pre-test score. As there is no high school maths prerequisite for enrolling in the business degree, there was a huge range of numeracy in the class. A question relating to maths experience was included with the pre-test. The measure, with 6 levels of maths experience is a subjective one. It is difficult for students to gauge reliably the level of their experience. The question, therefore, prompts the student’s decision by giving examples of courses they may have studied, with descriptors of content. This question had a high “no response” rate.

d) Academic Performance/Achievement Overall Score

At the end of the course student performance was measured as the sum of the three individual assessment item scores comprising a mid-semester exam (25), a computing
exam (25) and a final exam (50). These are three closed-book exams taken during and at the end of the course.

e) Gender

There is little research relating to different attendance rates for female and male undergraduates though Woodfield et al, 2006, found a difference.

5. Preliminary Data Analysis

Initial bivariate analyses were used to explore the relationships between a number of variables of interest. In the presentation of these preliminary findings, a “boxplot” is a summary of the distribution showing the range of the data, the upper and lower quartiles and the median value. When placed side-by-side these provide a simple visual comparison of any major differences.

(i) Gender Effect

*Gender and Performance Overall*

Table 2 shows the mean final course marks (total_100). Although females score slightly better, this not statistically significant at p>0.05.

*Table 2 here.*

*Gender and Pre-test Performance*

Table 3 shows the mean and median pre-test marks (Pre-test_18) for males and females. As was the case for overall performance, any gender difference is not statistically significant (p>0.05).

*Table 3 here.*

*Gender and Attendance*
Table 4 shows the mean and median attendance figures (AttendTotal_11) for males and females with the more illustrative box-plots in Figure 3. They indicate that females engaged more with the course than males and the difference in their means is significant (p=0.02), especially as the male distribution is highly skewed toward low attendances (see Figure 3) with the mean much lower than the median. This is consistent with the differential rates of attendance by males and females found in Woodfield et al (2006). Because of these differences an interaction term ‘gender by attendance’ is included in the multivariate analysis.

Table 4 here.

Figure 3 here.

(ii) Numeracy/Maths Experience Effect

Academic Performance vs. Pre-test score

The positive relationship between academic performance and preparedness is seen in Table 5. A statistically significant difference emerged, but only between the lowest 20th percentile of pre-test scores and the other two groups (Scheffe’s Multiple comparison test: p_{low-med}=0.02; p_{low-high}=0.05).

Table 5 here.

Academic Performance vs. Maths Experience

Table 6 shows a similarly positive relationship between the years of high school maths studied and the level of maths reached. Overall performance is significantly related to the maths experience score using all six ordinal levels for maths experience (Spearman’s r = +0.16 p<0.02).

---

1 Boxplots provide a quick, visual summary of any number of groups as they summarize distributions with a five-number summary: the median, the 25th and 75th percentiles (the upper and lower quartiles), and the minimum and maximum observed values that are not statistically outlying. Outliers and extreme values are shown separately.
Preliminary models using the six levels for maths experience showed little significance for some of the levels, so these were combined to form a dummy variable with just two levels: ‘pre-calculus experience’ and ‘calculus to grade 11 level or higher’. Further analysis involving the maths experience variable employed this dummy.

In Figure 4, where maths experience is split into just two levels, the medians are roughly equal but the distributions vary greatly. The distribution for those with little high school maths experience is highly skewed towards very low overall performance scores, so their mean is significantly lower. The Mann Whitney U Test gave an asymptotic one-tail Z score with p=0.032. In other words those students with little high school maths perform significantly lower.

Table 6 and Figure 4 here.

Pre-test Performance vs. Maths Experience

As the pre-test score would be related to high school maths experience, it was not surprising that the sample correlation coefficient between the variables indicated likely problems of multicollinearity (Spearman’s r = +0.25 p=.0003) if both variables were included in any model estimation. Consequently, the variable fitting better with overall performance (pre-test performance score) was included in the regression model. The pre-test had more relevance to preparedness since some students were many years out of high school.

Table 7 and Figure 5 show the relationship between the two indicators of numeric ability, Pre-test Performance vs. Maths Experience. Again the distribution of those with little high school maths experience is highly skewed towards lower pre-test scores, their mean score being significantly lower (the Mann Whitney U Test gave an asymptotic one-tail Z score with p=0.027).

Table 7 and Figure 5 here

(iii) Physical Engagement Effect
Table 8 and Figure 6 show the relationship between attendance and academic performance. The existence of a relationship is compelling, although a significant difference is shown only between the group with highest attendance and the other two groups.

Table 8 and Figure 6 here

Those students who engaged (attended) the most with the course on campus do significantly better. (Scheffe’s Multiple comparison test P high-low < .0001; P high-med=.004) and the relationship looks decidedly linear. But are these students merely those that have higher numeracy skills on the pre-test, or is attendance a reason for performing better academically.

6. Testing the Model and Results

To model the determinants of academic performance, ordinary least squares (OLS) regressions were estimated, as in other studies in the field (Marburger, 2001, Woodfield et al, 2006). In doing so it is recognized that the dependent variable is not strictly continuous but ranged between 0 and 100. Other studies have rather used discrete grade outcomes as the dependent variable with a logit, multinomial or probit model estimation (Spector and Mazzeo, 1980, Park and Kerr, 1990, Johnson and Kuennen, 2006). Multivariate analysis in the form of stepwise multiple regression techniques can be used to see if variables of interest are still significant to the relationship with academic performance once other variables have already been considered. Parametric rather than nonparametric methods were applied although some of the distributions illustrated with box plots in the previous section (viz. attendance by gender, and both pre-test and overall performance by high school maths experience) were not symmetrical, so certainly not normally distributed - but skewed. It was assumed that the methods would be robust against any non-normality violation of the errors arising from these
explanatory variables. To check this assumption, regression diagnostics were carried out on the residual error distribution, which showed no significant deviation from normality for the final model. The Kolmogorov-Smirnov statistic with a Lilliefors significance level for testing showed a nonsignificant lack-of-fit (p=0.22) to a normal distribution and the Shapiro-Wilk test agreed (p=0.6).

*Multiple Regressions*

General linear models were estimated, categorizing variables that did not show a linear relationship with academic performance, whereas covariates were used rather than factors (i.e. dummy variables) for continuous variables to prevent loss of information - but only if the response variable exhibited a linear relationship with the variable in question. For example, High school maths experience as an ordinal variable showed a nonlinear relationship with performance – so a dummy variable was created ‘pre-calculus’ and ‘calculus’ that gave a better fit in the preliminary regressions.

Multiple regression models were tested for overall course performance with the four explanatory variables listed below; firstly without any interaction effects and secondly, with interaction effects included in the model:

1) Attendance (*linearly related to performance – a covariate*)

2) Gender (*dummy*)

3) Pre-test score (*reasonably linear related to performance – a covariate*)

4) High school maths experience (*dummy – ‘pre-calculus’ and ‘calculus’*)

Firstly, a stepwise regression model *without* interaction effects was estimated to see which of the two highly correlated variables representing maths ability (variables 3 and 4 above) gave the best fit with the academic performance measure. The following results were obtained in a stepwise fashion:

- Attendance was first to enter the model p <=.001
• Pre-test score was next to enter the model p=.002

• High school maths experience was next to enter the model p=.008

• Gender was not significant p>.075

The high school maths experience variable was therefore dropped in subsequent regressions.

Next, a stepwise regression model including the two-way interaction effects with gender was estimated as follows on the full sample of 231 respondents.

\[
\text{Performance (\%) = } b_0 + b_1 \text{Attendance}_{11} + b_2 \text{Pre-Test score}_{18} + b_3 \text{Gender} + \\
+ b_{13} \text{Gender x Attendance}_{11} + b_{23} \text{Gender x Pre-Test score}_{18}
\]

Neither the main effect for gender nor the interaction terms with gender showed any significance with respect to performance (p>0.05) after the main effects were fitted, although gender and attendance were shown in Section 5 to be significantly correlated (see Table 4 and Figure 3).

So the final model for academic performance from Table 9 is written as: -

\[
\text{Performance (\%) = 35.628 + 1.855 Attendance}_{11} + 0.859 \text{Pre-Test score}_{18}
\]

\[F_{2,228}=20.246, \ p<0.0001\text{ and both coefficient parameters in the model are highly significant at } p<0.0001\]

Table 9 here

Interpreting these results, it was found that mean student performance overall is increased by nearly 2% for each tutorial attended and by nearly 1% for every extra point scored out of 18 on the basic numeracy test. The existence of differential attendance rates between male and female students, noted by Woodfield et al (2006) in the UK, was also tested and supported. However, it was found that this had no statistically significant impact on overall performance in the course.
7. Methodological Issues

Section 2 indicates that despite the simplicity of the model, methodological issues such as respondent bias are especially important in the interpretation of the model. Too often these issues are overlooked by researchers. One example flows directly from the discussion of section 2 where it was noted that non-attendance was no longer just a matter of student choice, but partly dependent upon the difficulty and/or impossibility of attendance for some students. Those who sat the pre-test may not be a representative sample of the students. And the statistical impact of non-attendance may be very different for those who can attend but choose not to, and those that are constrained to miss the first lecture by circumstance. This does not invalidate the results obtained but means that they have to be treated circumspectly both in terms of statistical analysis and in terms of interpretation.

For these reasons we have to address the problem of selectivity bias in our sample. The sample is 231 individuals for whom we have complete survey and performance information, a subset of the 408 students in the course. In other words, those who took the pre-test may be systematically different from those who did not (Chan et al, 1997, Douglas and Sulock, 1995).

Consequently, performance outcomes were compared for the pre-test respondent group versus the non-respondent group for all who sat the final exam i.e. completed the course. The average final marks for the two subgroups and total group are presented in Table 10.

Table 10 here.

Respondents performed better on average than the non-respondents. The students who sat the pre-test and completed the course scored higher marks in the course overall than those who missed the first lecture (57% vs. 51.3%; p< 0.05). Among the possible reasons for this is that the first lecture content is critical above all others. Alternatively,
those missing the first lecture included some hoping for entry to other courses and were not able to enrol in the course they preferred. It could be for reasons as prosaic as the convenience of the day and time of the lecture. Two educationally important hypotheses are that there was:

(a) Increased motivation in the course by attendees at the first lecture over non-attendees.

(b) Differential performance by males and females and a non-representative gender distribution in the respondent group, since a greater proportion of females (129/189 or 68.3%) attended the first lecture than males (102/155 or 65.8%)\textsuperscript{5}.

*Hypothesis (a) - Motivation*

A comparison of the two groups, respondents and non-respondents (that completed the course), using physical engagement gauged by their attendance throughout the course as an indicator of motivation is given in Table 11 in order to test the Motivation Hypothesis (a). The mean attendances for the two subgroups are presented in Table 11, with the Box Plot in Figure 7.

**Table 11 and Figure 7 here.**

Hypothesis (a) is statistically supported (Mann Whitney U Test, p<.00001). As hypothesized, the respondents were more likely than non-respondents to attend classes i.e. a relationship exists between respondent status and performance. So further multivariate analysis performed upon only the respondent sample will apply tests that have reduced power due to the missing data as well as reduced generalisation to the population of students at large.

There are two major alternatives that cannot be distinguished at this stage. One is that attendance at the first lecture motivated a higher attendance rate while the other is that the probabilities of attendance for the first lecture reflect the probabilities of overall attendance.
Hypothesis (b) - Gender Distribution

The mean final exam scores for the respondent and non-respondent groups by gender are presented in Table 12. Females in both groups performed slightly better in the final exam but not significantly so (p>.05).

Table 12 here.

Hypothesis (b) is therefore not supported. Around 6% difference in final mean performance between the respondents and non-respondents was found for both gender groups.

Pre-test Outcomes as a Prediction of Course Retention

Is a test of basic numeracy skills useful in targeting which students are most likely drop out of a course? The pre-test scores were compared for those who did not complete the course and for those who did (see Table 13).

Table 13 here.

Of those students who sat the pre-test, those completing the course indeed scored higher on the pre-test than those who dropped out (means 8.4 vs. 6.1; p<0.05). While this is not surprising it supports the case for additional early remedial tutorials in basic numeracy for students who score below a given score on the pre-test. The results presented here can be used in fixing such a score.

8. Discussion and Conclusions

This study focuses on the determinants of success in an introductory business statistics course using data from 231 student respondents taking the course in September-December 2005. The most important determinant of student performance was found to be physical engagement in the course as measured by class attendance. Numerical ability-cum-prior training as measured by a pre-test of basic math skills, as well as high school maths experience, were also important variables The results also support the
existence of differential attendance rates between male and female students. But gender was not an important determinant of success once differential attendance was accounted for. This may be one of the study’s most important conclusions.

The results support the view of other studies that attendance rates do matter in terms of academic outcomes (Romer, 1993, Lamdin, 1996; Rau and Durand, 2000, Farsides and Woodfield, 2003, Woodfield et al, 2006, Massingham and Herrington, 2006). The focus of this study was on student performance in just one course. Romer (1993) suggest that making attendance mandatory may deserve serious consideration. Oxford University has done this by introducing legally binding contracts requiring students to attend lectures (Richards and Halpin, 2006), although the reason may be to protect itself from litigious students.

It is not controversial that quantitative skills are important to success in introductory statistics as well as for other quantitatively based courses. However, it is informative that mastering the very basic mathematics skills tested at the outset of the course, and found wanting in many of the students, was an important indicator of student success. This is despite the fact that many of the skills assessed in the course (i.e. analysing data using descriptive and inferential statistics) were not necessarily of a basic numeracy skills nature.

The finding that the pre-test score and high school maths experience are both important covariates for academic performance has implications for curriculum development, course content, and especially, course prerequisites. This has particular relevance to the recommendations of the Strategic Review of Mathematical Sciences Report (Rubinstein and Hughes, Dec.2006):

Recommendation 5: Encourage greater numbers of high school students to study intermediate and advanced maths and 5c. Reward students for taking intermediate and advanced mathematics at high school by including scaling or bonus mechanisms when computing the Equivalent National Tertiary Entrance Rank (ENTER) or other tertiary entrance scores. [p.11]
Since prior maths experience has been shown to be important for future academic success in so many areas of study, the greater need for university departments to not only offer remedial maths courses or holiday (summer) maths but to also identify and target those requiring them is highlighted.

The methodological limitations of this study (and by implication almost all other studies in this area) are nevertheless considerable limiting the meaning of the statistical tests and the generalizability of the conclusions. These as discussed in Section 7

There is also the issue of completeness of the model tested. Other variables may contribute significantly to the model and further improve its ability to explain academic performance. Intervening variables relevant to attendance might be hours in paid employment, family responsibilities or certain personality or cognitive factors.

References


<www.amstat.org/publications/jse/v13n2/johnson.html>

<www.amstat.org/publications/jse/v13n2/johnson.html>


8. Notes

1. The cost of Higher Education in Australian universities is partially offset by HECS, the Higher Education Contribution Scheme, introduced by the Australian Parliament in 1989. These fees are paid up front or through the taxation system afterwards.

2. Only four students gave no i.d. number and we suspect a few also gave incorrect ones in that they did not match any i.d. on the final enrolment lists, but we cannot be sure of this as these may also have belonged to students who dropped out of the course in the first three weeks of the semester before enrolments were finalised.

3. Large sample theory (and the Central Limit Theorem) can apply here for using more powerful (with smaller p-values) parametric rather than nonparametric tests for differences between means. Nevertheless, the Mann Whitney U Test (often called the Wilkoxon rank sum test) for differences in medians is reported because of the obviously skewed distributions and gave an asymptotic Z score that is also significant.

4. Not 67% as predicted by the Empirical Rule, since the distribution is not normally distributed.

5. Eight students are missing from this analysis as they had no gender recorded.
Appendix

Pre-test: Basic Numeracy Skills Test (no calculators allowed – except your brain)

Note for overseas/interstate students to assess the equivalence of their high school subjects:
Maths C (earlier called Maths II) is a pre-engineering degree matriculation maths subject that includes geometry, vectors and forces.
Maths B (called Maths I in earlier years), taken for two years prior to matriculation, includes the calculus and is a prerequisite requirement for most science-based university courses.

Highest Maths Level Attained
Maths C (II - Advanced Math) Grade 12 usually with Maths B (I) Gr 12 6
Other (other states) eg NSW 3rd level Maths 6
Maths C (II - Advanced Math) Grade 11 with Maths B (I) Gr 12 5
Maths B (I) Grade 12 4
Maths B (I) Grade 11 3
Advanced Maths Grade 10 3
Junior or Grade 10 Maths 2
Maths in Society, (Maths A) Grades 10/11/12 2
Ordinary Maths, Citizenship Maths Grades 10/11/12 2
Grade 9 Maths 1
Grade 8 or lower Grade Maths or "no answer" 0

Student ID _______________    Total Mark              /18

1. Convert the following to percentages:
   (i) 1
   (ii) 5/8

2. Convert the following to fractions (expressed in their lowest terms)
   (i) 22.5%
   (ii) 66\(\frac{2}{3}\)%

3. Convert the following to decimals with four decimal places
   (i) 31.59%
   (ii) 16\(\frac{2}{3}\)%

4. Find the value of \(\left(4^2 \times 3^{-1} \times 2^1\right) ÷ \left(4 \times 2^2\right)\)

5. Find the value of \(\left(\frac{1}{5} + \frac{3}{4}\right) \times \left(2 + \frac{1}{3}\right)\)

6. Find (i) \((64)^{1/3}\)
   (ii) \((27)^{-1/3}\)

7. Express the ratio 2 \(\frac{1}{2}:3\ \frac{1}{2}\) in its lowest terms.

8. Write down for the graph of the equation of the line 3x – 2y = 24
   (i) the y-intercept
   (ii) the slope of the line

9. Solve for x: (i) 4x – 2 = 8 – x
    (ii) 6 – 2(x – 1) = 0

10. If values of x are 5, 2, 1, 1, 2, 3, 4 find the following:
    (i) \(\sum x\)
    (ii) \(\sum x^2\)
    (iii) \(\left(\sum x\right)^2\)

The pre-test was developed, based on the principal author’s long experience teaching remedial mathematics.
Figure 2: Pre-test Score Results

![Histogram showing pre-test score results with mean = 8.4, standard deviation = 4.699, and N = 231.](image)
TABLES AND FIGURES

Table 1
A Summary of Student Characteristics and Course Information

<table>
<thead>
<tr>
<th>Description</th>
<th>Number/Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of students officially enrolled at day 1</td>
<td>408</td>
</tr>
<tr>
<td>Number of students who sat the pre-test (attended the first lecture)</td>
<td>277 (69%)*</td>
</tr>
<tr>
<td>Number of students who completed the course</td>
<td>352 (86%)</td>
</tr>
<tr>
<td>Number of students who sat the pre-test with i.d. provided and who completed the course (The Respondent Group)</td>
<td>231 (57%) (or 66% of those completing the course)</td>
</tr>
<tr>
<td>Average number of students attending tutorials each week</td>
<td>241.3</td>
</tr>
<tr>
<td>Attendance Related Learning Resources</td>
<td></td>
</tr>
<tr>
<td>• 2 hr Lecture x 12 weeks</td>
<td></td>
</tr>
<tr>
<td>• 1 hr Tutorial x 11 weeks</td>
<td></td>
</tr>
<tr>
<td>• 1 hr Computing Laboratory x 11 weeks</td>
<td></td>
</tr>
<tr>
<td>Non-Attendance Related Learning Resources</td>
<td></td>
</tr>
<tr>
<td>• Textbook</td>
<td></td>
</tr>
<tr>
<td>• Self-paced Computer workbook</td>
<td></td>
</tr>
<tr>
<td>• Blackboard Notes on the Web - all lecture material prior to the lecture and tutorial solutions after the tutorial.</td>
<td></td>
</tr>
<tr>
<td>Assessment</td>
<td></td>
</tr>
<tr>
<td>• Mid-semester closed-book exam (25%)</td>
<td></td>
</tr>
<tr>
<td>• End-of-semester closed-book Computing exam (25%)</td>
<td></td>
</tr>
<tr>
<td>• Final closed-book exam (50%)</td>
<td></td>
</tr>
</tbody>
</table>

*percentages shown in brackets of the number of students officially enrolled at day 1.

Figure 1
Weekly Attendances at each Semester Week

Note: There were no formal lectures or tutes in Week 7 when the midsemester exam was held
### Table 2
**Overall Performance by Gender**

<table>
<thead>
<tr>
<th>Gender</th>
<th>Performance</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>total_100</td>
<td>Male Mean 55.90</td>
<td>1.74</td>
</tr>
<tr>
<td>N=231</td>
<td>Female Mean 57.81</td>
<td>1.50</td>
</tr>
</tbody>
</table>

### Table 3
**Pre-Test Performance by Gender**

<table>
<thead>
<tr>
<th>Gender</th>
<th>Attendance</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-test_18</td>
<td>Male Mean 8.6</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>95% CI for Mean</td>
<td>7.7</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>8.0</td>
</tr>
<tr>
<td></td>
<td>Female Mean 8.2</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>95% CI for Mean</td>
<td>7.4</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>8.0</td>
</tr>
</tbody>
</table>

### Table 4
**Attendance by Gender**

<table>
<thead>
<tr>
<th>Gender</th>
<th>Attendance</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>AttendTotal_11</td>
<td>Male Mean 7.1</td>
<td>0.3</td>
</tr>
<tr>
<td>N=102</td>
<td>95% CI for Mean</td>
<td>6.5</td>
</tr>
<tr>
<td></td>
<td>Lower Bound</td>
<td>7.7</td>
</tr>
<tr>
<td></td>
<td>Upper Bound</td>
<td>Median</td>
</tr>
<tr>
<td>Female</td>
<td>Mean 8.0</td>
<td>0.2</td>
</tr>
<tr>
<td>N=129</td>
<td>95% CI for Mean</td>
<td>7.6</td>
</tr>
<tr>
<td></td>
<td>Lower Bound</td>
<td>8.5</td>
</tr>
<tr>
<td></td>
<td>Upper Bound</td>
<td>Median</td>
</tr>
</tbody>
</table>
Figure 3
Box Plot Summary of the Gender Distributions for Attendance

Table 5
Overall Performance and Pre-test score

<table>
<thead>
<tr>
<th>Pretestfactor</th>
<th>Performance</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>lowest third percentile</td>
<td>Mean 50.31</td>
<td>2.61</td>
</tr>
<tr>
<td></td>
<td>95% CI (45.0,55.6)</td>
<td></td>
</tr>
<tr>
<td>middle two-thirds</td>
<td>Mean 58.32</td>
<td>1.42</td>
</tr>
<tr>
<td></td>
<td>95% CI (55.5,61.1)</td>
<td></td>
</tr>
<tr>
<td>upper third percentile</td>
<td>Mean 58.89</td>
<td>2.50</td>
</tr>
<tr>
<td></td>
<td>95% CI (53.8,63.9)</td>
<td></td>
</tr>
</tbody>
</table>

Table 6
Academic Performance and High School Maths Experience

<table>
<thead>
<tr>
<th>High School Maths Experience</th>
<th>Performance</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low level maths only- no calculus</td>
<td>Mean 51.33</td>
<td>3.01</td>
</tr>
<tr>
<td></td>
<td>95% CI (45.25, 57.40)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Median 56.54</td>
<td></td>
</tr>
<tr>
<td>Some calculus yr 11 or higher</td>
<td>Mean 58.50</td>
<td>1.34</td>
</tr>
<tr>
<td></td>
<td>95% CI (55.86, 61.14)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Median 57.35</td>
<td></td>
</tr>
</tbody>
</table>
**Figure 4**
Box Plot Summary of the Two-Factor Maths Experience Distributions for Overall Performance

**Table 7**
Pre-test Performance and High School Maths Experience

<table>
<thead>
<tr>
<th>High School Maths Experience</th>
<th>Pre-test</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-test_18 Low level maths only - no calculus</td>
<td>Mean</td>
<td>6.90</td>
</tr>
<tr>
<td>95% CI</td>
<td>Lower Bound</td>
<td>5.58</td>
</tr>
<tr>
<td>Median</td>
<td>Upper Bound</td>
<td>8.22</td>
</tr>
<tr>
<td>Some calculus yr 11 or higher</td>
<td>Mean</td>
<td>8.56</td>
</tr>
<tr>
<td>95% CI</td>
<td>Lower Bound</td>
<td>7.80</td>
</tr>
<tr>
<td>Median</td>
<td>Upper Bound</td>
<td>9.32</td>
</tr>
<tr>
<td>Median</td>
<td></td>
<td>8.00</td>
</tr>
</tbody>
</table>
Figure 5
Box Plot Summary of the Two Distributions for Pre-test Performance

Table 8
Academic Performance and Attendance

<table>
<thead>
<tr>
<th>Attend_factor</th>
<th>Performance Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>total_100 low (0-3)</td>
<td>Mean 48.12 3.11</td>
</tr>
<tr>
<td></td>
<td>95% CI (41.8,54.5)</td>
</tr>
<tr>
<td>medium(4-7)</td>
<td>Mean 52.26 2.39</td>
</tr>
<tr>
<td></td>
<td>95% CI (47.5,57.0)</td>
</tr>
<tr>
<td>high(8-11)</td>
<td>Mean 60.85 1.31</td>
</tr>
<tr>
<td></td>
<td>95% CI (58.3,63.4)</td>
</tr>
</tbody>
</table>

(number of tutorials attended in brackets)
Figure 6
Box Plot Summary of the Three-level Attendance Factor Distributions for Overall Performance

![Box Plot](image)

Table 9
Final Model for Academic Performance

<table>
<thead>
<tr>
<th>Parameter</th>
<th>B</th>
<th>Std. Error</th>
<th>t</th>
<th>Sig.</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>35.628</td>
<td>3.515</td>
<td>10.135</td>
<td>.000</td>
<td>28.701 - 42.554</td>
</tr>
<tr>
<td>AttendTotal_11</td>
<td>1.855</td>
<td>.360</td>
<td>5.155</td>
<td>.000</td>
<td>1.146 - 2.564</td>
</tr>
<tr>
<td>Pretest_18</td>
<td>0.859</td>
<td>0.224</td>
<td>3.837</td>
<td>.000</td>
<td>0.418 - 1.300</td>
</tr>
</tbody>
</table>

Table 10
Average Performance Total for the Course (%)  
(Standard error in brackets)

<table>
<thead>
<tr>
<th>Respondent Group</th>
<th>Non Respondent Group (Did not sit Pre-test)</th>
<th>All Completing the Course</th>
</tr>
</thead>
<tbody>
<tr>
<td>57 (n=231) (1.1)</td>
<td>51.3 (n=121) (1.6)</td>
<td>55 (n=352) (0.9)</td>
</tr>
</tbody>
</table>
Table 11  
Average Total Attendance/11 Weekly Sessions for the Course (%)  
(Standard error in brackets)

<table>
<thead>
<tr>
<th>Non Respondent Group (Did not sit Pre-test)</th>
<th>Respondent Group</th>
<th>All Completing the Course</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.9 (0.3) (n=121)</td>
<td>7.6 (0.2) (n=231)</td>
<td>7.0 (0.66) (n=352)</td>
</tr>
</tbody>
</table>

Figure 7  
Box Plot Summary: Distributions for Attendance of Respondents/Nonrespondents

Table 12  
Average Performance Totals for the Course (%) by Gender  
for the Pre-test Respondents vs. Non-Respondents  
(Standard error in brackets)

<table>
<thead>
<tr>
<th>Pre-test Respondents</th>
<th>Non-Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>Male</td>
</tr>
<tr>
<td>55.9 (n=102) (1.7)</td>
<td>49.7 (n=53) (2.6)</td>
</tr>
</tbody>
</table>
Table 13
Average Pre-test Score (out of 18)
(Standard error in brackets)

<table>
<thead>
<tr>
<th>Respondent Group (Completed the Course)</th>
<th>Non Respondent Group (Did not Complete the Course)</th>
<th>All Pre-tested</th>
</tr>
</thead>
<tbody>
<tr>
<td>8.4 (n=231) (0.3)</td>
<td>6.1(n=46) (0.6)</td>
<td>8.0 (n=277) (0.3)</td>
</tr>
</tbody>
</table>

In practice, teaching and learning effectiveness remains predominantly determined by student performance in the recall and application of learnt concepts and skills (Webster and Hackley, 1997).