

## **Student Outcomes at University in Australia: A Quantile Regression Approach**

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### **Abstract**

*Students' success during their first year at university is largely influenced by their university entrance score. Personal characteristics and secondary school characteristics also impact on success. This paper uses quantile regression to investigate how the effects of these factors vary along the grade distribution. It finds that the factors which influence grades have a more pronounced impact on the success of low-achieving students than on that of high-achieving students. These results have implications for student selection and also for the way scholarships may be used to attract talented high school students.*

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# **Student Outcomes at University in Australia: A Quantile Regression Approach**

## **I. Introduction**

Many factors combine to determine success and failure at university. Personal characteristics, such as age and gender, appear to be of modest importance in this regard. Contemporary work patterns (for example, classes missed and hours spent studying) have a greater influence. However, students' prior academic achievement has been shown in many empirical studies to be the main influence on how well they perform at university. Studies for the United States that have found a positive relationship between students' university grades and prior academic achievement include Gist, *et al.* (1996), Robst and Keil (2000) and Stinebrickner and Stinebrickner (2003). Similar findings have been reported for Australia by Birch and Miller (2005), Dancer and Fiebig (2004), Dobson and Skuja (2005), Everett and Robins (1991) and Win and Miller (2005), for Canada by Robb and Robb (1999), for the United Kingdom by Johnes (1997), Johnes and McNabb (2004) and Smith and Naylor (2005), and for Singapore by Tay (1994).

There is also variation in performance at university according to the type of high school attended, with graduates of government schools in both the United Kingdom (*e.g.*, Smith and Naylor, 2005) and Australia (Birch and Miller, 2005; Dobson and Skuja, 2005; Win and Miller, 2005) reported as outperforming graduates from private schools, when high school achievements are held constant.

The strong relationship between student outcomes at university and prior academic achievement seemingly vindicates the use of high school results in university admission policies. Other determinants of university performance, such as the variation with high school attended, have also been used in university admission policies, though the practice is under legal challenge (see Smith and Naylor, 2005).

Another way of looking at success and failure at university is to separate out a focus on groups of low-achievers at university from that on high-achievers. Such a focus may be important to a number of basic operational procedures within universities. For example, many universities use poor performance in the early stages of the university program to identify students at risk of failure, and possible sanction or exclusion from

the university. Knowing the impact of various determinants of academic success in the lower part of the results distribution may assist policy making in this regard. Similarly, some universities identify high performing students for streaming into pre-honours classes, and having information on the marginal effects of the determinants of university performance among such students may be helpful.

This paper examines the way the impacts of prior academic achievement and other key determinants of academic performance vary across the distribution of first-year marks. In doing this it uses quantile regression, a statistical technique that has recently become popular in economics owing to improved efficiency of the computer algorithms required for its estimation, and a greater realisation of the range of applications of the technique that extend well beyond the traditional use for assessing whether a set of OLS estimates are sensitive to outliers. For example Garcia, *et al.* (2001) and Sakellariou (2004) have used quantile regression to examine gender wage effects, Eide, *et al.* (2002) and Martins and Pereira (2004) have used this methodology to study the rates of return to education, while Nielsen and Rosholm (2001) and Mueller (1998) study public/private sector wage differentials using a quantile regression approach. Applications to the study of scholastic achievements include Eide and Showalter (1998) and Bassett, *et al.* (2002).

This paper is structured as follows. Section II provides a brief overview of research on the links between scholastic achievement at university and prior academic achievement. Section III presents information on the quantile regression methodology that is used in this study, and informs on the limited applications of this methodology to date in the study of university students' academic performance. Section IV reports on a quantile regression analysis of the first-year academic performance of students at the University of Western Australia in 2001. Section V concludes, with discussion of the additional insights into university students' academic performance that can be gained through use of the quantile regression methodology.

## **II. Scholastic Outcomes at University and Prior Academic Achievement**

The relationship between students' tertiary academic performance and their academic achievements at high school has, as mentioned in the introduction, been extensively studied in the economics of education literature. There are a number of key patterns in

the findings of these studies. Most studies report a strong, positive correlation between university grades and university entrance scores. In the Australian literature, for example, the recent studies by Birch and Miller (2005), Dobson and Skuja (2005) and Win and Miller (2005) show that each increment on the Tertiary Entrance Rank<sup>1</sup> is typically associated with an increase of between 0.5 and 1.0 in the average first-year mark at university. There has also been debate in Australia over the links between performance at university and TER scores (or equivalent) in the region around the minimum scores institutions set for entrance. West and Slamowicz (1976), in a study of first-year students enrolled at Monash University in 1970, found that the relationship between the mean first-year university mark and the mean score in the final year of high school (Higher School Certificate or HSC) was negative at low levels of HSC. Using more recent data (for 2001), Win and Miller (2005) report that the relationship between first-year university performance and the TER is flat at lower values of the TER.<sup>2</sup>

The studies reviewed have a focus on the links between the TER and the conditional mean of the first-year university performance. However, the impact of the TER on first-year performance may not be constant across the marks scale. Indeed, for many policy purposes it may be more important to know how the TER impacts on outcomes around the pass-fail marks, and at any thresholds that are used for selection of students into various streams (*e.g.*, honours streams) or the more prestigious programs (*e.g.*, combined degrees, law).

A method that is well suited to the analysis of how the effects of an independent variable may vary across the different conditional quantiles of a distribution is quantile regression. This method was first developed by Koenker and Bassett (1978) and later extended by Buchinsky (1998). It differs from standard OLS regression as it allows for the analysis of the dependent variable at distinct quantiles of the distribution, whereas OLS regression only allows the analysis of the dependent variable at the conditional mean.

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<sup>1</sup> The Tertiary Entrance Rank is a number between 0 and 99.95 that measures each year's group of Year 12 students against each other (on the basis of external examinations and school assessment).

<sup>2</sup> An implication of this is that a composite selection index might be used instead of using the HSC or TER as a sole university entrance criterion (see West and Slamowicz, 1976; Everett and Robins, 1991).

### III. Quantile Regression and its Use in the Economic Education Literature

Following Buchinsky (1998), and assuming  $(y_i, x_i)$ ,  $i = 1, \dots, n$  is a sample of the population,  $y_i$  is the dependent variable and  $x_i$  is the  $k$  by 1 vector of explanatory variables, a simple quantile regression model can be written as:

$$Quant_{\theta}(y_i|x_i) = x_i'\beta_{\theta}, \quad (1)$$

where  $Quant_{\theta}(y_i|x_i)$  refers to the conditional quantile of  $y_i$ , conditional on the vector of the explanatory variables  $x_i$ . It is assumed that the  $\theta^{\text{th}}$  conditional quantile cannot be less than zero or greater than one ( $0 < \theta < 1$ ).

Equation 1 implies:

$$y_i = x_i'\beta_{\theta} + u_{\theta}, \quad (2)$$

where  $Quant_{\theta}(u_{\theta}|x_i) = 0$ .

The quantile regression estimates are achieved by minimising the weighted sum of the absolute value of the errors (see Bedard, 2003). In other words, the  $\theta^{\text{th}}$  conditional quantile regression estimator for  $\beta$  is estimated by minimising:

$$\min \beta \left[ \sum_{\{i: y_i \geq x_i\beta\}} \theta |y_i - x_i\beta| + \sum_{\{i: y_i < x_i\beta\}} (1-\theta) |y_i - x_i\beta| \right]. \quad (3)$$

While the main benefit of quantile regression is that it allows for the impact of explanatory variables on the dependent variable to be analysed along the total distribution of a data sample, Buchinsky (1998) points out there are two other main advantages of the estimating procedure. First, as quantile regression is based on a weighted sum of absolute deviations, the approach gives a robust measure of location on the distribution scale. In turn, this ensures that the estimated coefficients on the explanatory variables are not sensitive to outlier observations in the data sample. Second, when the error term in the regression is of a non-normal distribution, the estimates obtained from quantile regression may be more valid than those obtained using OLS. Various extensions of this quantile regression approach are covered in Eide, *et al.* (2002).

While quantile regression has been used extensively in the economics literature to analyse gender wage differentials, the rates of return to education and other labour market outcomes, there are only a few studies that examine the determinants of scholastic achievements using this method. Relevant studies from the United States are summarised in Table 1.<sup>3</sup>

**Table 1**  
**Summary of Studies Examining the Determinants of Scholastic Achievements Using Quantile Regression**

| Study/Country/Sample/<br>Quantiles Analysed  | Variables  | Main Findings <sup>(a)</sup>  |
|--|--|---|
| Eide and Showalter (1998)<br>United States of America.<br>Secondary school students.<br>0.05, 0.25, 0.50, 0.75 and 0.95.   | Dependent Variable: Changes in students' maths score from sophomore to senior year.<br><br>Independent Variables: Student-teacher ratio, length of the school year, proportion of teachers with advanced degrees, schools' expenditure per student, initial math score, family size, proportion of non-white students, proportion of Hispanic students, race, gender, parents' educational attainment, family income and schools' locality.  | Attending a school which had a longer school year had a larger impact on students' maths scores at the middle and upper quantiles than at the lower quantiles.<br><br>Attending a school with a larger number of students had a larger impact on students' maths scores at the lower quantiles than at the middle and upper quantiles.  |
| Ng and Pinto (2003)<br>The United States of America.<br>University students enrolled in a business unit.<br>0.15, 0.20, 0.25, 0.30, 0.40, 0.45, 0.50, 0.80 and 0.85. | Dependent Variable: Students' score on their final exam for the unit.<br><br>Independent Variables: Number of classes missed, mark for the unit's quiz, mark for unit's project and various 'learning styles'.   | Students' mark for the unit's quiz had a larger impact on students' exam score at the lower quantiles than at the middle and upper quantiles.<br><br>Students' mark for the unit's project had a larger impact on students' exam scores at the middle and upper quantiles than at the lower quantiles.  |
| Bassett, <i>et al.</i> (2002)<br>United States of America.<br>Students in their final of high school.<br>0.10 to 0.90 with 0.20 intervals.                           | Dependent Variable: Students' score on their college entrance exams.<br><br>Independent Variables: Proportion of teachers with higher degrees, student-teacher ratio, schools' expenditure per student, school size, proportion of students who are white, the proportion of students who are non-white, the proportion of students who are Asian, schools' attendance rates, schools' mobility rates, schools' dropout rates, schools' average score for the college entrance exam, schools' locality, family income, parents' and family's educational attainment. | Schools' proportion of teachers with higher degrees, school size, schools' proportion of white students, schools' proportion of non-white students and attending a school in the capital city had a larger impact on students' college entrance exam score at the lower quantiles than at the middle and upper quantiles.<br><br>The student-teacher ratio, schools' expenditure per student, family's education, schools' proportion of Asian students, attendance rates, dropout rates and the schools' average score for the college entrance exam had a larger impact on students' college entrance exam score at the upper quantiles than at the middle and lower quantiles. |

<sup>3</sup> Quantile regression has been also been used to estimate the determinants of academic performance in Austria (see Schnessweis and Winter-Ebmer, 2005); Denmark (see Schindler, 2003); Germany (see Fertig, 2003); China (see Ding and Lehrer, 2004); Holland (see Levin, 2001) and in cross country analysis (see Fertig and Schmidt, 2002).

**Table 1**  
**Summary of Studies Examining the Determinants of Scholastic**  
**Achievements Using Quantile Regression**

| Study/Country/Sample/<br>Quantiles Analysed  | Variables   | Main Findings <sup>(a)</sup>   |
|--|---|--|
| Kremer and Levy (2003)<br>United States of America<br>University students enrolled in<br>first year.<br>0.10, 0.25, 0.50, 0.75 and 0.90.   | Dependent Variable: Students' GPA<br><br>Independent Variables: Has a college room mate<br>who drinks alcohol frequency and has a college<br>room mate who drinks alcohol occasionally.                       | Living with roommates who drink<br>alcohol frequently or drink alcohol<br>occasionally had a larger impact on<br>students' GPA in the lower quantiles<br>than in the upper quantiles.                          |
| Tam, <i>et al.</i> (2002)<br>United States of America<br>University students enrolled in<br>first year.<br>05 to 0.95 with 0.05 intervals. | Dependent Variable: Students' GPA<br><br>Independent Variables: High school percentile<br>rank, students; national college admission score<br>(ACT) and the average ACT score of the high<br>school attended. | Students' ACT score, high school<br>percentile rank and the average ACT<br>score of the high school attended had a<br>larger impact on students' GPA in the<br>lower quantiles than in the upper<br>quantiles. |

Notes: <sup>(a)</sup> The main findings only summarise the findings for variables of statistical significance.

As shown in the table, the studies differ in a two main respects.<sup>4</sup> First, they vary in terms of the general approach followed. Hence, Tam, *et al.* (2002) examine the relationship between students' grades and selected characteristics at every 5<sup>th</sup> quantile of the distribution (starting at quantile 0.05). In comparison, Edie and Showalter (1998) and Basset, *et al.* (2002) consider the determinants of students' grades at every 20<sup>th</sup> percentile or 25<sup>th</sup> percentile of the distribution. The theory does not offer any ideal or optimal approach in this regard, and the differences across studies appear to represent no more than the preferences of the researchers over the number of quantiles that need to be analysed to adequately characterise the impacts of the main explanatory variables across the marks distribution. Given the smooth patterns in the estimated effect across the percentiles of the scholastic achievements distribution (see, for example, Figure 2 below), it appears reasonable to focus on a small number of quantiles in the statistical analysis.

Second, the studies also vary according to the specification of the estimating equation, the significant variables and the way the explanatory variables influence students' grades across the quantiles of distribution. There is an absence of a consensus finding in this regard, though whether this is due to the variation in the specification of the estimating equation or the infancy of this line of research is not clear.

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<sup>4</sup> Obvious differences in the studies summarised in Table 1, and also the related literature noted in Footnote 3, are the samples and the variables included in the models.

#### **IV. Quantile Regression Analysis of University Performance in Australia**

The empirical analysis below uses quantile regression to estimate the determinants of students' tertiary academic grades. The analysis draws on data on first-year students studying at the University of Western Australia (UWA). The focus on outcomes during the first year of study follows the theme of recent research on university performance in Australia (*e.g.*, see Rodgers, 2002; Dancer and Fiebig, 2004; Dobson and Skuja, 2005; Win and Miller, 2005 and Birch and Miller, 2005). This focus in large part appears to be because of the problems of categorising students to specific years of study beyond the first year, and possibly because of concerns over the need to model attrition when looking at years of study beyond first year. It is not clear from the Australian literature whether the findings based on analysis of outcomes for first-year students carry over to higher years of study. Some comment on the determinants of students marks in years of study other than first year is provided below, though the primary focus is, in line with the Australian literature, on the determinants of the marks of first-year students.

A related issue is the extent to which the findings for UWA, which is one of the more selective universities, in terms of its capacity to attract Year 12 students with high TER scores, will generalise to the tertiary sector as a whole. While comment on this matter from the perspective of a quantile regression approach is not possible at this stage, the findings reported from a conventional (OLS) analysis of the determinants of first-year marks at UWA are remarkably similar to findings reported for Monash University (Dobson and Skuja, 2005, and the references therein) and for another large, comprehensive university in Australia (Birch and Miller, 2005) and also in the British literature (Smith and Naylor, 2005).

The data set employed below is the same as that used in Win and Miller (2005). Specifically, it relates to students who were in their first year at university in 2001 and who graduated from high school in 2000. Win and Miller (2005) present details on the derivation of the data set. Specifically, they note that the first year intake at UWA is approximately 3,300. Nearly 24 per cent of this intake were not considered because they had a gap of more than one year between leaving school and commencing university, 10 per cent were omitted because they were full-fee paying overseas students and a further 10 per cent were purged from the sample because they had

missing marks. The latter group comprises those who withdrew from university, had deferred exams or had marks that had not been finalised at the time the data were extracted from the student record system. The tabular analysis in Win and Miller (2005, Table 2) shows that students with missing information on their first-year marks are more likely to be female, to be from rural areas and to have attended a rural school than other students. However, in terms of the other characteristics considered in the statistical work, including their TER, the two groups of students are quite similar.

The data sample contains information on students' personal and demographic characteristics, such as gender and locality of residence, tertiary academic characteristics, such as university grades and courses studied, and characteristics of the secondary school attended, such as school type and school size. Following Win and Miller (2005), the sample is restricted to students who attended a secondary school in Western Australia, had a TER score and had valid information on their first-year academic performance. Overall, the data sample is comprised of 1,803 students. The analysis measures students' tertiary academic performance by their first-year weighted average mark at university. This represents the marks that students obtained in all of the units of study they were enrolled in.<sup>5</sup> Each mark is weighted to the relative contribution of the unit studied towards the students' degree.

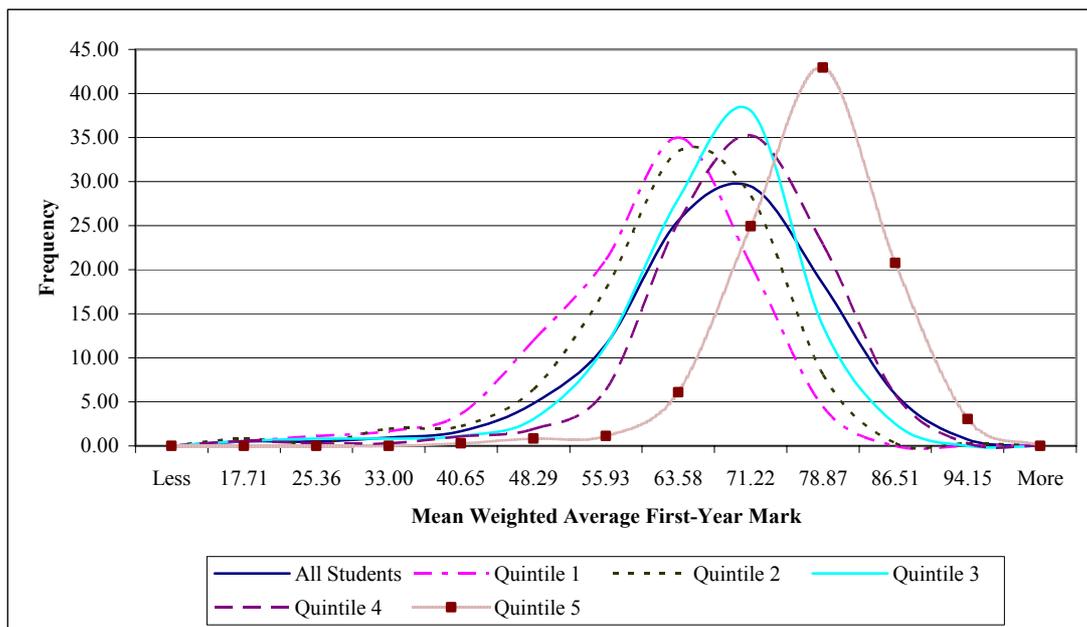
Some preliminary information on the sample is presented in Figure 1, which presents the frequency distribution of the weighted average first-year marks for students with different TER scores. The distribution for all students has a mean of 63.6. The median is 64.5. These characteristics of the distribution of first-year marks vary considerably by students' TER scores. Students with a lower TER score have, on average, lower first-year grades than students with a higher TER score. For example, the mean weighted average first-year marks for students with a TER score in the lowest two quintiles recognised in the figure are 56.5 and 59.2. The medians for these groups are 57.9 and 60.8. In comparison, the grades of students who had a TER score in the top two quintiles in the figure are 65.8 and 73.6 (medians of 66.7 and 73.7).

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<sup>5</sup> It relates to students' marks obtained after the dates specified for withdrawal from a unit.

Figure 1 also shows variations in the spread of the first-year marks according to TER score. The tightest distribution, as measured by the standard deviation, is for the fifth quintile (standard deviation of only 7.7). The most dispersed distribution is that for the first quintile (standard deviation of 10.4). Related to this is the variation across quintiles in the range of the first-year marks. For all students, the first-year marks range from 2 to 91. The spread of the average weighted first-year marks is slightly larger for students whose TER scores were in the lower quintiles than for students whose TER scores are in the higher quintiles. For example, the first-year grades of students whose TER scores are in the bottom quintile (Quintile 1) range from 12 to 78. In contrast, the grades of students whose TER score are in the top quintile (Quintile 5) range from 40 to 91.

**Figure 1**  
**Frequency Distribution of Mean Average Weighted First-Year Mark by**  
**Students' TER Score for the University of Western Australia, 2001**



These variations in the first-year marks are examined below using both OLS and quantile regression. In each instance a reasonably parsimonious specification of the estimating equation is adopted. This follows from findings reported by Birch and Miller (2005), which show that while additional insights can be gained from adopting richer specifications, the addition of further regressors or even the employment of alternative methodology (for example, random effects models and random parameters

models) does not impact on the findings relating to the core of the variables considered here. Moreover, the model does not include information on the courses the students were studying. At first glance this would seem like a significant omission, given that the tertiary cut-off ranks for courses differ appreciably, and there may be factors that affect both students' course choice and their academic performance in first year. The sensitivity of the basic estimating equation to this exclusion was examined by Win and Miller (2005). They conclude (p. 11) that "when course variables were added to the model, few were associated with statistically significant effects, and among those that were, estimated effects were quite small". In addition, it was noted in this particular study that the addition of the course type variables did not lead to any material changes to the estimated coefficients for the core variables included in equation (4) above.

Accordingly, the explanatory variables included in the model to estimate the determinants of students' tertiary academic success include the students' TER score, gender, locality of residence, socio-economic status<sup>6</sup> and school type. The code names and a description of these variables are presented in Table 2.

**Table 2**  
**Description of the Variables in Models of the Determinants of Students' Grades**

| Variable/<br>Variable<br>Code | Description   | All Students |          | Quantile 0.05<br>Students |          | Quantile 0.95<br>Students |          |
|-------------------------------|---|--------------|----------|---------------------------|----------|---------------------------|----------|
|                               |   | Mean         | Std Dev. | Mean                      | Std Dev. | Mean                      | Std Dev. |
| Students' Grades              |   |              |          |                           |          |                           |          |
| <i>Grade</i>                  | Continuous variable for students' weighted average first-year mark measured as a mark out of one hundred. | 63.58        | 11.47    | 42.36                     | 4.69     | 79.46                     | 1.83     |
| TER Score                     |   |              |          |                           |          |                           |          |
| <i>TER</i>                    | Continuous variable for students TER score measured as a mark out of one hundred.                         | 91.76        | 5.90     | 86.20                     | 6.13     | 97.57                     | 2.66     |
| Gender                        |   |              |          |                           |          |                           |          |
| <i>Female</i>                 | Dummy variable for female students.   | 0.53         | 0.50     | 0.40                      | 0.49     | 0.46                      | 0.50     |
| <i>Male</i>                   | Omitted category.   | 0.47         | 0.50     | 0.60                      | 0.49     | 0.54                      | 0.50     |

<sup>6</sup> The socio-economic status of students' home neighbourhoods is based on information on students' permanent home postcodes and is measured by the Australian Bureau of Statistics's (ABS) *Index of Economic Resources*. The index considers the level of income, expenditure, home ownership, dwelling size and car ownership of households in particular regions. A high score on the index indicates that a region contains a larger proportion of households on high incomes, a larger proportion of families owning or purchasing their home and a larger proportion of families living in large houses (for more discussion, see ABS 2001).

**Table 2**  
**Description of the Variables in Models of the Determinants of Students' Grades**

| Variable/<br>Variable<br>Code | Description  | All Students |          | Quantile 0.05<br>Students |          | Quantile 0.95<br>Students |          |
|-------------------------------|--|--------------|----------|---------------------------|----------|---------------------------|----------|
|                               |  | Mean         | Std Dev. | Mean                      | Std Dev. | Mean                      | Std Dev. |
| Home Location                 |  |              |          |                           |          |                           |          |
| <i>Rural</i>                  | Dummy variable for students who live in the regions of Central, Kimberly, Midlands, Pilbara, Southwest, Lower Great Southern and Upper Great Southern.                             | 0.12         | 0.32     | 0.15                      | 0.36     | 0.07                      | 0.25     |
| <i>Urban</i>                  | Omitted category.  | 0.88         | 0.32     | 0.85                      | 0.36     | 0.93                      | 0.25     |
| Socio-Economic Status         |  |              |          |                           |          |                           |          |
| <i>SES</i>                    | Continuous variable for students' socio-economic status. It is measured by the ABS's <i>Index of Economic Resources</i> and is derived from the students' permanent home postcode. | 1067.50      | 71.79    | 1073.20                   | 69.68    | 1065.80                   | 73.64    |
| School Type                   |  |              |          |                           |          |                           |          |
| <i>Catholic</i>               | Dummy variable for attending a Catholic secondary school.  | 0.23         | 0.42     | 0.33                      | 0.47     | 0.14                      | 0.35     |
| <i>Independent</i>            | Dummy variable for attending an Independent secondary school.  | 0.35         | 0.48     | 0.34                      | 0.47     | 0.35                      | 0.48     |
| <i>Government</i>             | Omitted category.  | 0.42         | 0.49     | 0.33                      | 0.47     | 0.51                      | 0.50     |

Using the mnemonics presented in Table 2, the estimating equation may be written as:

$$Grade_i = \beta_0 + \beta_1 TER_i + \beta_2 Female_i + \beta_3 Rural_i + \beta_4 SES_i + \beta_5 Catholic_i + \beta_6 Independent_i + \varepsilon_i. \quad (4)$$

Consistent with Ding and Lehrer (2004), equation (4) is estimated using the quantile regression approach at every fifth percentile on the grade distribution (starting at Quantile 0.05).

The results from equation (4) estimated using OLS and quantile regression are presented in Tables 3 and 4, respectively. The results using OLS are consistent with the findings in the empirical literature on the determinants of academic success. Hence they show that students' weighted average first-year marks are positively correlated with their TER score (*TER*) and being female (*Female*).<sup>7</sup> The analysis shows that, on average, students' university grades increase by 1 percentage point for

<sup>7</sup> The results from the estimation of the determinants of students' grades using OLS also suggest that students' home location and the socio-economic status of their home neighbourhoods influence their grades at university. Students living in rural areas (*Rural*) were found to have grades that are 1.4 percentage points lower than the grades of students living in the metropolitan area. Socio-economic status (*Index*) was found to be slightly negatively correlated with students' university grades. However, as these variables are only of statistical significance at a small number of the quantiles on the grade distribution, discussion on how these variables influence students' grades at university has been kept to a minimum.

every 1 point increase in their TER score. Female students, on average, have grades that are 2.4 percentage points higher than the grades of their male counterparts.<sup>8</sup>

**Table 3**  
**Results From the Estimation of the Determinants of Students' Tertiary Academic Success, OLS**

| Variable                            | School Type and Personal Characteristics<br>Coefficient                                    |
|-------------------------------------|--|
| <i>Constant</i>                     | -22.212<br>(-4.226)*   |
| TER Score<br><i>TER</i>             | 1.022<br>(25.770)*   |
| Gender<br><i>Female</i>             | 2.387<br>(5.187)*  |
| Home Location<br><i>Rural</i>       | -1.754<br>(-2.178)**   |
| Socio-Economic Status<br><i>SES</i> | -0.006<br>(-1.795)***  |
| School Type<br><i>Catholic</i>      | -3.319<br>(-5.577)*  |
| <i>Independent</i>                  | -3.983<br>(-7.502)*  |
|                                     | Adjusted $r^2 = 0.285$<br>Log Likelihood Function = -6651.30<br>Mean <i>Grade</i> = 63.578 |

Notes: (a) The 't'-values are in parentheses. The symbol \* refers to significance at the 1 per cent level, \*\* refers to significance at the 5 per cent level and \*\*\* refers to significance at the 10 per cent level.

The OLS results also show that the type of secondary school attended by students has a significant impact on their grades at university. Students who attended Catholic (*Catholic*) or Independent (*Independent*) secondary schools were found to have grades that are 3.3 and 4.0 percentage points lower than the grades of students attending Government schools. These findings are consistent with the majority of results in the Australian empirical literature (see Table 2 in Birch and Miller, 2005 for a summary on the findings of Australian studies which consider the impact of school type on grades), and with evidence for the United Kingdom (see Smith and Naylor, 2005).

<sup>8</sup> The grade advantage that female students have over male students has largely been linked to female's favourable attitudes towards study (Hewitt, 2003) and their ability to meet numeracy and literacy standards in primary school (Nowicki, 2003).

**Table 4**  
**Results From the Estimation of the Determinants of Students' Tertiary Academic Success:**  
**School Type and Personal Characteristics, Quantile Regression**

|                                      | Quantile 0.05<br>Coefficient                                 | Quantile 0.10<br>Coefficient                                 | Quantile 0.15<br>Coefficient                                 | Quantile 0.20<br>Coefficient                                 | Quantile 0.25<br>Coefficient                                 | Quantile 0.30<br>Coefficient                                 | Quantile 0.35<br>Coefficient                                 | Quantile 0.40<br>Coefficient                                 | Quantile 0.45<br>Coefficient                                 |
|--------------------------------------|--|--|--|--|--|--|--|--|--|
| <i>Constant</i>                      | -62.823<br>(-1.116)  | -55.491<br>(-2.862) *  | -37.119<br>(-2.842) *  | -31.236<br>(-2.156) **                                       | -33.926<br>(-3.727) *  | -34.631<br>(-4.597) *  | -28.508<br>(-4.338) *  | -27.575<br>(-4.466) *  | -290.576<br>(-5.092) *                                       |
| TER Score<br><i>TER</i>              | 1.290<br>(3.037) *   | 1.231<br>(8.416) *   | 1.133<br>(11.490) *  | 1.067<br>(9.763) *   | 1.069<br>(15.560) *  | 1.075<br>(18.900) *  | 1.061<br>(21.400) *  | 1.069<br>(22.950) *  | 1.038<br>(23.690) *  |
| Gender<br><i>Female</i>              | 3.525<br>(0.715)   | 3.404<br>(2.005) **  | 3.165<br>(2.767) *   | 2.962<br>(2.335) **  | 2.893<br>(3.629) *   | 2.637<br>(3.997) *   | 2.841<br>(4.936) *   | 2.653<br>(4.908) *   | 2.266<br>(4.455) *   |
| Home Loc.<br><i>Rural</i>            | -7.947<br>(-0.921)   | -2.882<br>(-0.970)   | -2.205<br>(-1.102)   | -2.147<br>(-0.967)   | -1.642<br>(-1.177)   | -1.250<br>(-1.083)   | -1.079<br>(-1.071)   | -0.727<br>(-0.769)   | -0.398<br>(-0.447)   |
| SES<br><i>SES</i>                    | -0.006<br>(-0.163)   | -0.003<br>(-0.255)   | -0.010<br>(-1.095)   | -0.008<br>(-0.766)   | -0.004<br>(-0.668)   | -0.003<br>(-0.540)   | -0.006<br>(-1.388)   | -0.007<br>(-1.587)   | -0.001<br>(-0.279)   |
| School Type<br><i>Catholic</i>       | -2.984<br>(-0.468)   | -3.525<br>(-1.606)   | -3.139<br>(-2.122) **  | -4.032<br>(-2.457) **  | -3.387<br>(-3.286) *   | -3.333<br>(-3.907) *   | -3.550<br>(-4.771) *   | -3.310<br>(-4.735) *   | -3.184<br>(-4.841) *   |
| <i>Independent</i>                   | -3.832<br>(-0.674)   | -5.042<br>(-2.574) *   | -4.602<br>(-3.487) *   | -4.441<br>(-3.034) *   | -4.374<br>(-4.574) *   | -4.173<br>(-5.482) *   | -4.178<br>(-6.294) *   | -3.794<br>(-6.084) *   | -3.427<br>(-5.840) *   |
| Summary<br>Statistics <sup>(b)</sup> | Mean <i>Grade</i> =<br>47.242<br>Mean <i>TER</i> =<br>86.203 | Mean <i>Grade</i> =<br>52.165<br>Mean <i>TER</i> =<br>87.607 | Mean <i>Grade</i> =<br>55.346<br>Mean <i>TER</i> =<br>88.128 | Mean <i>Grade</i> =<br>57.004<br>Mean <i>TER</i> =<br>88.271 | Mean <i>Grade</i> =<br>58.823<br>Mean <i>TER</i> =<br>89.062 | Mean <i>Grade</i> =<br>60.209<br>Mean <i>TER</i> =<br>89.777 | Mean <i>Grade</i> =<br>61.450<br>Mean <i>TER</i> =<br>89.444 | Mean <i>Grade</i> =<br>62.539<br>Mean <i>TER</i> =<br>90.388 | Mean <i>Grade</i> =<br>63.599<br>Mean <i>TER</i> =<br>91.041 |

Notes: <sup>(a)</sup> The symbol \* refers to significance at the 1 per cent level, <sup>(b)</sup> computed on the basis of 500 draws (with replacement) of 100 individuals from the sample, \*\* refers to significance at the 5 per cent level and \*\*\* refers to significance at the 10 per cent level.

**Table 4**  
**Results From the Estimation of the Determinants of Students' Tertiary Academic Success:**  
**School Type and Personal Characteristics, Quantile Regression**

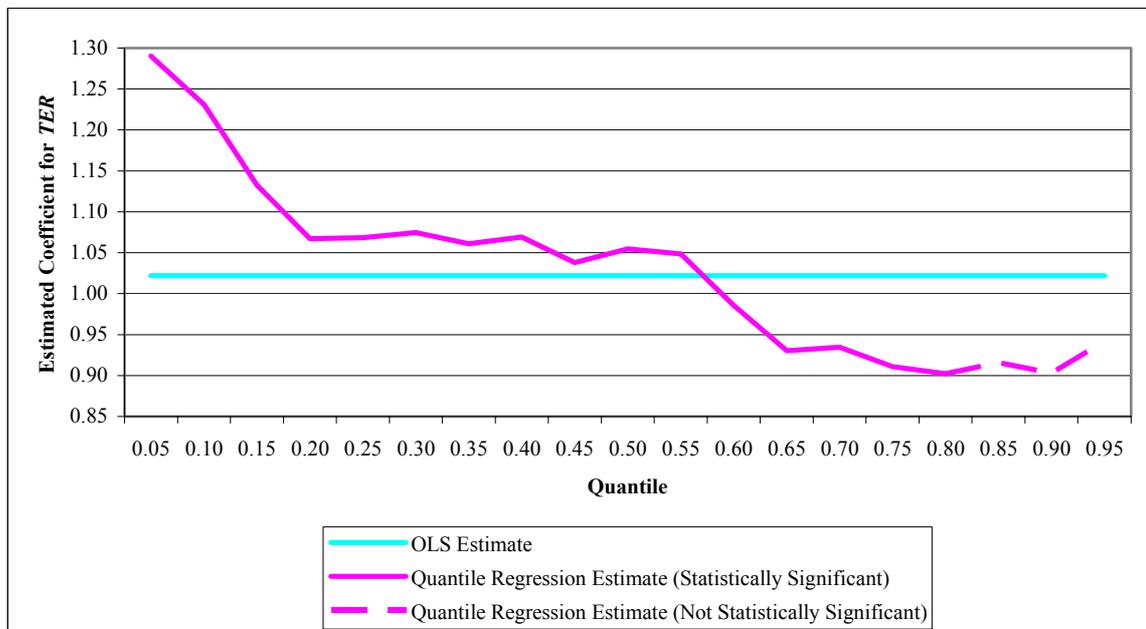
|                                      | Quantile 0.50<br>Coefficient                                 | Quantile 0.55<br>Coefficient                                 | Quantile 0.60<br>Coefficient                                 | Quantile 0.65<br>Coefficient                                 | Quantile 0.70<br>Coefficient                                 | Quantile 0.75<br>Coefficient                                 | Quantile 0.80<br>Coefficient                                 | Quantile 0.85<br>Coefficient                                 | Quantile 0.90<br>Coefficient                                 | Quantile 0.95<br>Coefficient                                 |
|--------------------------------------|--|--|--|--|--|--|--|--|--|--|
| <i>Constant</i>                      | -28.660<br>(-5.003)*   | -26.257<br>(-4.691)*   | -19.281<br>(-3.511)*   | -11.979<br>(-2.126)**  | -9.946<br>(-1.655)**   | -8.571<br>(-1.268)   | -4.499<br>(-0.562)   | -1.803<br>(-0.013)   | 2.644<br>(0.013)   | 1.914<br>(0.008)   |
| TER Score<br><i>TER</i>              | 1.055<br>(24.400)*   | 1.048<br>(24.830)*   | 0.986<br>(23.790)*   | 0.930<br>(21.891)*   | 0.934<br>(20.610)  | 0.911<br>(17.850)*   | 0.902<br>(14.940)*   | 0.916<br>(0.864)   | 0.903<br>(0.572)   | 0.942<br>(0.490)   |
| Gender<br><i>Female</i>              | 2.158<br>(4.302)*  | 2.029<br>(4.141)*  | 1.872<br>(3.892)*  | 1.634<br>(3.313)*  | 1.559<br>(2.962)   | 1.699<br>(2.870)*  | 2.040<br>(2.910)*  | 2.008<br>(0.163)   | 1.288<br>(0.070)   | 1.257<br>(0.056)   |
| Home Loc.<br><i>Rural</i>            | -0.233<br>(-0.265)   | 0.122<br>(0.143)   | -0.200<br>(-0.238)   | -0.319<br>(-0.369)   | -1.114<br>(-1.207)   | -1.414<br>(-1.365)   | -1.733<br>(-1.413)   | -2.462<br>(-0.114)   | -1.149<br>(-0.036)   | -0.941<br>(-0.024)   |
| SES<br><i>SES</i>                    | -0.002<br>(-0.597)   | -0.003<br>(-0.742)   | -0.003<br>(-0.822)   | -0.047<br>(-1.065)   | -0.005<br>(-1.265)   | -0.003<br>(-0.734)   | -0.006<br>(-1.038)   | -0.008<br>(-0.084)   | -0.010<br>(-0.066)   | -0.010<br>(-0.058)   |
| School Type<br><i>Catholic</i>       | -3.414<br>(-5.263)*  | -3.568<br>(-5.629)*  | -3.654<br>(-5.875)*  | -3.410<br>(-5.346)*  | -3.613<br>(-5.308)   | -3.882<br>(-5.070)*  | -3.416<br>(-3.769)*  | -3.347<br>(-0.210)   | -1.901<br>(-0.080)   | -2.567<br>(-0.089)   |
| <i>Independent</i>                   | -3.937<br>(-6.803)*  | -3.870<br>(-6.845)*  | -3.874<br>(-6.983)*  | -3.764<br>(-6.614)*  | -3.761<br>(-6.194)   | -3.988<br>(-5.839)*  | -4.016<br>(-4.967)*  | -3.677<br>(-0.259)   | -3.002<br>(-0.142)   | -3.187<br>(0.007)  |
| Summary<br>Statistics <sup>(b)</sup> | Mean <i>Grade</i> =<br>62.539<br>Mean <i>TER</i> =<br>90.388 | Mean <i>Grade</i> =<br>63.599<br>Mean <i>TER</i> =<br>91.041 | Mean <i>Grade</i> =<br>64.737<br>Mean <i>TER</i> =<br>91.121 | Mean <i>Grade</i> =<br>65.515<br>Mean <i>TER</i> =<br>92.016 | Mean <i>Grade</i> =<br>68.818<br>Mean <i>TER</i> =<br>93.196 | Mean <i>Grade</i> =<br>69.907<br>Mean <i>TER</i> =<br>94.544 | Mean <i>Grade</i> =<br>71.386<br>Mean <i>TER</i> =<br>94.704 | Mean <i>Grade</i> =<br>72.847<br>Mean <i>TER</i> =<br>95.793 | Mean <i>Grade</i> =<br>74.519<br>Mean <i>TER</i> =<br>96.761 | Mean <i>Grade</i> =<br>76.348<br>Mean <i>TER</i> =<br>97.567 |

Notes: <sup>(a)</sup> The symbol \* refers to significance at the 1 per cent level, <sup>(b)</sup> computed on the basis of 500 draws (with replacement) of 100 individuals from the sample, \*\* refers to significance at the 5 per cent level and \*\*\* refers to significance at the 10 per cent level.

The results from the estimation of equation (4) using quantile regression show that the impact of these variables on weighted average first-year marks varies across the grade distribution. While this can be seen from reading across the rows of Table 4, the pattern of effects can be illustrated clearly using a series of diagrams.

Figure 2 plots the estimated coefficients for TER score using both the quantile regression and OLS approaches to estimating the determinants of students' grades. By construction, the estimated coefficient for TER score obtained from OLS remains constant at 1.02 across the grade distribution. In contrast, the estimated coefficients for TER score obtained using quantile regression decline over the grade distribution, from 1.29 (Quantile 0.05) to 0.90 (Quantile 0.90). In other words, having one point higher TER is worth more among low-achieving students than it is among high-achieving students. This can also be seen in the conditional summary statistics (for TER and first-year grades) presented at the foot of Table 4. These exhibit much greater change in conditional mean first-year marks between adjacent quantiles for low-achieving students than for high-achieving students.

**Figure 2**  
**Estimated Coefficients for TER Score, OLS and Quantile Regression**



The quantile regression at the median ( $\theta = 0.50$ ) is 1.05, which is quite close to the OLS estimate of 1.02. This suggests that the OLS method is robust, and that the

quantile regression might be adopted simply for the fuller characterisation of the distributions under consideration that it offers. In this regard, the estimated coefficients for the TER variable between (and including) the 5<sup>th</sup> and 60<sup>th</sup> quantiles are not significantly different from the OLS estimate. However, the estimates obtained for the 65<sup>th</sup> through to the 80<sup>th</sup> quantiles are significantly different from the OLS estimate. The significant estimates obtained with the quantile regression approach for the higher quantiles are significantly different from that obtained for the 5<sup>th</sup> quantile.

The quantile regression approach to estimating the determinants of students' tertiary grades also found that TER score did not significantly influence the grades of students performing extremely well at university (that is, students in Quantiles 0.85, 0.90 and 0.95). This finding may imply that other factors, perhaps such as grades for a particular secondary school subject or natural ability, may influence the grades of students who perform very well at university. Inspection of the TERs for the top fifty students indicates that these range from 90.25 to 99.95. The median and mode are each over 99, but 10 percent of this high-achieving group have TERs below 95.

The statistical insignificance of the quantile regression coefficients for students in the top fifteen per cent of the grade distribution is consistent with the findings in the study by Levin (2001), who reported that the scholastic achievements of high school students in America with grades in the 90<sup>th</sup> quantile could not be explained by the independent variables included in the model. It differs, however, from the findings of two other studies of the determinants of students' academic grades (Fertig, 2003 and Bassett, *et al.*, 2002).<sup>9</sup> The finding may indicate a high degree of homogeneity among students who perform very well at university. Alternatively, unobserved factors, such as motive and study habits, may account for these students' tertiary marks.

The larger sized quantile regression estimates of TER score for students at the lower-end of the grade distribution, as well as TER score being an insignificant determinant of the grades of students at the upper-end of the grade distribution, suggests that students' TER score is a better predictor of grades for students who have below average to average first-year marks than it is for students who have above average

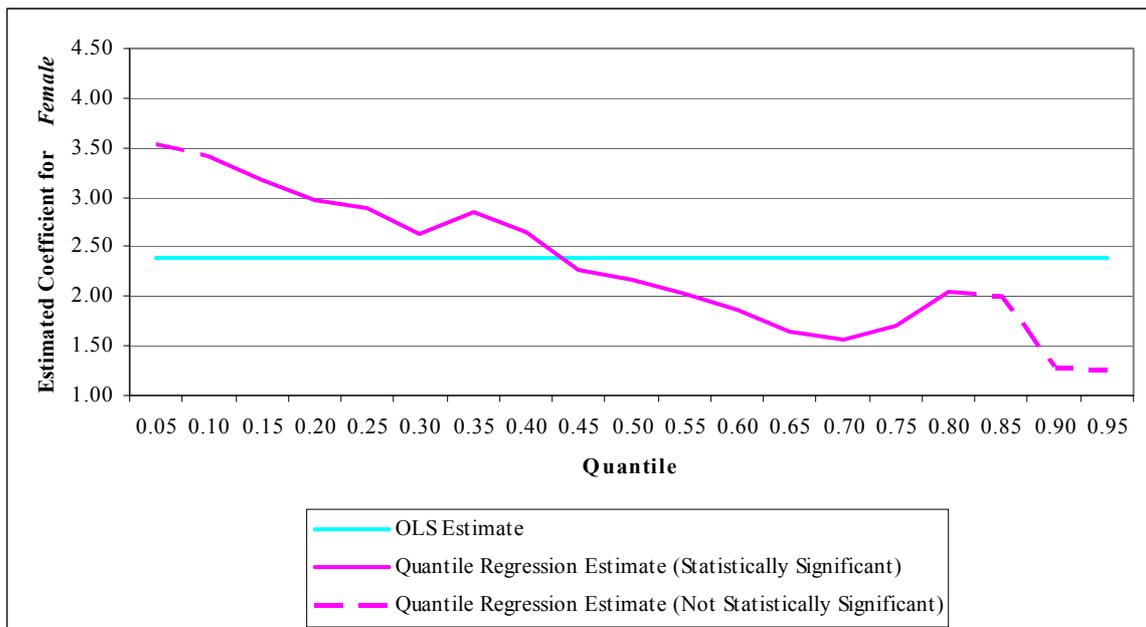
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<sup>9</sup> Most studies using quantile regression in other applications also report significant regressors at the top end of the distributions (*e.g.*, Garcia, *et al.*, 2001; Arulampalam, *et al.*, 2004 and Buchinsky, 1998).

grades. This finding seemingly contradicts the proposition in Win and Miller (2005), to the effect that TER is a better predictor of the first-year performance of university students among high-achieving students than it is among lower-achieving students. However, the pattern of effects that arises in the quantile regression analysis summarised in Figure 2 is consistent with findings reported in Ng and Pinto's (2003) study of the links between students' score on their final exam for a unit and their mark in the unit's within-semester quiz.

Figure 3 graphs the estimated coefficients for the dummy variable for female students (*Female*) obtained using OLS and quantile regression. Similar to the findings regarding the quantile regression estimates of TER score, the estimated coefficients for female students fall as one moves from the lower-end of the grade distribution to the upper-end of the distribution. Hence, for students with grades in Quantile 0.05 the estimated coefficient for the '*Female*' variable is 3.53. In comparison, the coefficient is 1.26 for students with grades in Quantile 0.95. This finding implies that the grade advantage that female students have over their male counterparts is larger for below average to average students than it is for above average students.

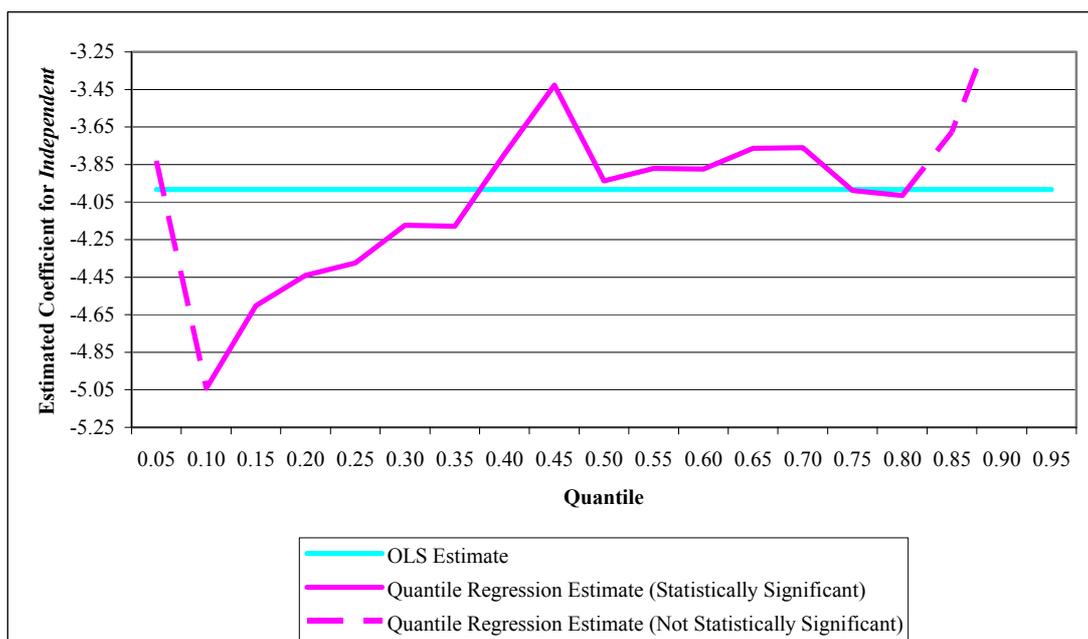
**Figure 3**  
**Estimated Coefficient for Being a Female Student, OLS and Quantile Regression**



The results from the quantile regression analysis show that students who attended Catholic or Independent schools have lower grades than their counterparts who attended Government schools over the entire distribution of university grades. The impact of attending non-government schools also varies substantially across the grade distribution. However, the estimated coefficients for the ‘*Catholic*’ variable in the quantile regression vary within a small range, and further analysis does not appear to be revealing.

The pattern in the quantile regression coefficients for the ‘*Independent*’ schools variable, however, is quite interesting. As shown in Figure 4, the differences in the first-year marks of students from Independent schools and Government schools is larger among students who have grades in the bottom third of the grade distribution than it is among students who have grades in the top two-thirds of the distribution. Hence, for students in Quantiles 0.10 to 0.35, the quantile regression estimates for attendance at an Independent school are larger (in absolute terms) than the estimate obtained at the conditional mean (the OLS estimate of -3.89). For students with grades in the upper two-thirds of the grade distribution, the quantile regression estimates for the variable ‘*Independent*’ are smaller than that obtained at the conditional mean.

**Figure 4**  
**Estimated Coefficient for Attending an Independent School,**  
**OLS and Quantile Regression**



In summary, there are two main points that arise from the above analyses. First, for the most part, the estimated coefficients obtained using quantile regression are of the same sign as the estimates obtained using OLS. In other words, the variables that have positive (negative) impacts on students' grades measured at the condition mean generally have positive (negative) impacts on grades across most of the grade distribution.

Second, the extent to which students' TER score, gender and school type influence grades at university varies across the distribution of first-year marks. The variables associated with TER score, being a female student and attending an Independent school have a more pronounced impact on the grades of students who are segmented in the lower third to one-half section of the grade distribution. This may imply that factors which are not captured in the data set may play a larger role in determining the grades of above average tertiary students.

## **V. Concluding Comments**

This study has used a quantile regression approach to examine success and failure during the first year of study at the University of Western Australian for the 2001 entrance cohort. It shows that the impact of most explanatory variables varies across the grade distribution. Of particular note are the findings in relation to the impact of the TER, gender and type of high school attended, as these impacts have attracted considerable interest in the literature. It is shown that the marginal effect of TER is greatest in the lower quantiles of the grade distribution (being as high as a 1.29 increase in mean first-year marks per increment in TER in the lowest quantile, compared to effects of 0.90 in the higher quantiles). The TER is insignificant in the highest three quantiles considered (0.85, 0.90 and 0.95).

Previous research has established that females do better during their first year at university than males, holding other influences, including TER, constant. The analyses above show that this is particularly the case when examining the lower quantiles of the mark distributions for males and females. Among better performing students, there is little difference in the conditional quantiles of males and females.

Finally, the results from the quantile regression analysis show that students from Independent high schools have poorer first-year performance at university across most of the marks distribution. The difference in marks, however, is greatest among the lowest quantiles of the marks distribution.

These results show, therefore, that TER is of greatest importance among those students most prone to failure. This suggests that a focus on TER in admission policies is justified. The results also suggest that in situations where a university lowers its entrance scores, then, *ceteris paribus*, there should be a clustering of marks at the bottom of the distribution.<sup>10</sup>

The insignificance of TER among the top 15 percentiles of the grade distribution is presumably accounted for by particular talents of these students in the subjects studied (*e.g.*, a talent for science when studying science). An implication of this is that relying upon the TER in the allocation of prestigious scholarships to commencing students may not be desirable if the primary objective is to attract students who will be the best, academically, during their first year of study. Yet this is the direction that a number of Australian universities have taken. Moreover, work-in-progress suggests that the first-year outcomes are highly likely to be repeated in later years of study, as TER diminishes in status as a predictor of academic performance and the marks in earlier years of study become the key variables in models of the determinants of students' marks. These analyses indicate that the patterns reported in this paper on the links between first-year outcomes and the TER are likely to characterise the relationship between outcomes in second year and first-year marks, and also the relationship between outcomes in third year and second-year marks. The relationship between marks in the higher years of study and the TER appears to be attenuated compared to that reported in this paper, though it is significant and the dominant part of the explanation of students' grades provided prior university results are not accounted for in the statistical analysis. In other words, the basic framework presented in this study appears to be applicable to higher years of study.

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<sup>10</sup> This might be offset, however, by any tendency to mark to a distribution.

The results show that TER, gender, school type and other variables have sizeable impacts on the conditional quantiles throughout most of the marks distribution. These variables will thus impact on a large number of internal decisions by universities, on course transfers, intake into honours programs, scholarships etc. They are, therefore, important to the main dimensions that might be held to constitute success and failure at university. Understanding the reasons for the effects, and knowing whether they generalise to later years of study, and to students at other institutions, are important directions for future research.

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