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## Abstract

The effects of credit constraints on university participation are investigated in a setting where income contingent tuition loans are available to students. Students most likely to face credit constraints have the same or higher probability of attending university as all other students, given their high school achievement. A novel approach to handle potential bias arising from unobserved heterogeneity is proposed. An estimate of unobservable heterogeneity based on post-secondary plans reported during ninth grade is constructed. This estimate is found to explain university attendance but does not overturn results regarding the effects of credit constraints.



**JEL classification:** I21, I22, I28

**Keywords:** University participation, credit constraints, unobservables

# 1 Introduction

The role of credit constraints is a central issue in higher education. Governments and universities worldwide recognise the significance of credit constraints and many offer a diverse range of policies and solutions to resolve such issues and enable students to attend university. Forms of support range from full public funding of higher education and generous income support in Scandinavian countries such as Denmark, Finland, Iceland, Norway and Sweden, through to a diverse collection of grants, loans and work-study that form the federal aid system in the US; see OECD (2013).

One of the challenges in providing support for higher education is how to most effectively utilise scarce resources. Students from relatively wealthy backgrounds may be able to draw on family support, so funding policies that benefit such students might be seen as inequitable and possibly inefficient. Conversely, tight targeting towards disadvantaged students might see some students in need miss out on support and opportunities and others come away with large and unmanageable student debt.

This is the topic of much recent debate in the US where Avery and Turner (2012) and Stiglitz (2013) highlight the growing disparity between graduate earning prospects and student debt and repayment levels. Stiglitz (2013) suggests the Australian income contingent loan scheme (Higher Education Contribution Scheme, hereafter HECS) offers appealing features such as income contingency and a fixed repayment burden that could address concerns about student debt. Repayments are only required if graduates earn above an income threshold and repayments are a fixed proportion of earnings. Importantly, the repayment dollar amount rises and falls with income so graduates are less likely to end up with unmanageable repayments that could drive them to default.

This debate has led to the introduction of the Investing in Student Success Act of 2014 (Income Sharing Agreements) to the US Senate and Congress by Senator Marco Rubio and Representative Tom Petri respectively on 9 April 2014. The critical feature is that the repayment burden is exogenous to the loan size and varies with graduate income. The proposed scheme would recover loans where financially feasible and, as a matter of course, the repayment burden would fall in times of unemployment.

In this paper we study the effects of credit constraints on university attendance of students under the world's first income contingent loan scheme, in place in Australia since 1989. Students face a tuition charge for which they have access to a universal income contingent loan scheme, HECS, which is further described below with more details available in Chapman (1997). Students in need have access to an income support scheme based on a parental means test.

In order to identify credit constrained students we exploit the fact that 35% of students attend private schools in Australia. Based on private school attendance, supplemented with socioeconomic status (SES) data, we form three categories of students, those unlikely and likely to be constrained and those that are potentially constrained; more detail is provided below. The strategy infers that families that were able and willing to pay for private education when students were in ninth grade are unlikely to face credit constraints. Over the relevant period for our data, average tuition fees in private independent secondary schools were higher than university tution charges; for example in 1998, average school fees were $6,123 while the highest university charge was $5,772 in 2000. Given the income HECS loan scheme in place, credit constraints are more likely to operate on the costs of books and other study materials along with day to day living costs.

We find very little difference in university participation between credit constraint groups. What differences we do find depend on high school achievement and are opposite to what might be expected. At low levels of high school achievement, likely constrained students are up to 11% more likely to attend university than unlikely constrained students. At higher levels of high school achievement, these differences are not present. These results suggest that the HECS income contingent loan scheme and other institutions in place in Australia effectively deal with any short term credit constraints students may face in deciding to attend university. The results also suggest that lower achieving likely constrained high school graduates are more optimistic about university study than similar students who are unlikely or potentially constrained.

Given these results, one might speculate that likely constrained students choosing to attend university might be more motivated or have some other unobservable characteristics that lead to our finding. We devise a strategy to address concerns these results might be driven by selection on unobservables. Students are first surveyed in ninth grade and answer questions about plans for post-secondary study. We estimate a model of these plans, controlling for a range of ninth grade observed characteristics. The residuals in such a model reflect some of the unobservable characteristics that might drive students to university attendance so we construct a ranking of these unobservables to include in our model of university attendance. Upon re-estimation of our baseline model with these estimated unobservables included, we find that the unobservables are indeed significant in explaining the university attendance probability. However, the effects of credit constraint group membership on university participation are qualitatively unchanged and robust to the inclusion of these unobservables.

As a further robustness check, we estimate a constrained bivariate probit model where student decisions to complete high school and qualify for university and the decision to attend university are modelled jointly. We impose assumptions about unobservables affecting the decisions to qualify for and attend university respectively. The results suggest that even if a strong (40%) correlation between the disturbance terms of the models of these two outcomes is assumed, the effects of credit constraint group membership on university attendance are unchanged. The implication is the possible omission of any unobservables is unlikely to lead to biases that would change our conclusions about credit constraints.

These findings are consistent with a range of results about credit constraints in the US. Studies by Carneiro and Heckman (2002), Cameron and Taber (2004) and Keane and Wolpin (2001) all find little evidence of credit constraints hindering university attendance in the US, based on the NLSY 79 cohort.[1] However, Belley and Lochner (2007) study the importance

[1] In a study using UK data, Dearden et al. (2004) find little evidence that credit constraints affected university attendance.

of credit constraints using the more recent NLSY 97 cohort and find that youth from high income families are 16% more likely to attend university than those from low income families, after conditioning on a range of factors. After accounting for wealth along with income, the difference in attendance between high and low groups is 30 percentage points. They also find strong evidence of an ability gradient in attendance which is consistent across all income levels and both NLSY cohorts.

These studies focus on parental income as a measure of credit constraints. In a related study, Brown et al. (2012) show that parental income might not be the best indicator of credit constraints if parents are unwilling or unable to contribute to college costs of the student. They exploit information on federal aid rules in the US, sibling spacing and financial gifts from parents to identify the effects of credit constraints. They find that many students who might not be thought to be constrained on the basis of income do indeed face constraints. In a similar vain, the approach adopted here does not rely on income but rather the ability and willingness of parents to invest in their child's education. Another identification strategy is employed by Coelli (2011) who studies unexpected job loss among Canadian fathers. He finds large negative effects on university attendance for those who were 16 to 17 years old when the father's job loss was experienced, indicating negative effects of short term credit constraints even in the presence of student loans.

As we find credit constraints do not play an important role in the university attendance decision, we analyse our results further presenting a decomposition of what are the most important factors in explaining differences between the university attendance decisions of high and low SES students. The decomposition exploits observables, ninth grade test scores, the estimate unobservables described above and high school achievement. The key message is that the SES gradient is driven overwhelmingly by high school achievement rather than credit constraints, suggesting for those students that qualify for university, the funding institutions in place are able to adequately deal with any credit constraint issues that students might face.[2]

[2] In related work by Cardak and Vecci (2014) it is found that credit constrained students exhibit a greater

In Section 2, we provide a brief description of the educational institutions in place in Australia that are relevant to our study, including the HECS and income support schemes. The empirical strategy, including our approach to controlling for the possible effects of unobservables, is presented in Section 3. We describe the data in Section 4, providing definitions of the credit constraint groups. The results, including several tests of robustness, are presented in Section 5. We summarise our key results and conclude in Section 6.

## 2 Overview of School to University Transition

University admission in Australia is similar to other countries. In order to gain a university place, students are required to (i) demonstrate academic achievement or aptitude and (ii) be willing and able to pay any tuition charges. However, there are idiosyncracies that are important for our analysis which we outline below.

In order to demonstrate academic achievement or aptitude, students need to complete high school, receiving the relevant certificate from their state body. University applications are typically handled by a state based central admissions body. Students are required to apply for an Equivalent National Tertiary Entrance Rank (ENTER) score which is supplied to the central admissions body. The ENTER score is based on their achievement in statewide examinations and other assessment tasks and reflects the student's percentile rank in the graduating cohort for their home state. It is the primary mechanism by which university places are rationed.[3] Courses of study in higher demand typically have higher ENTER score cut-offs for admission, thus these ENTER scores may be considered part of the price of admission to a program.[4]

risk of dropout. This is in contrast with Stinebrickner and Stinebrickner (2008) who find that dropout is not affected by credit constraints for Berea College students in the US.

[3] The ENTER score was specific to the state of Victoria. However, each state provided graduating students with an equivalent ranking, for example a Universities Admissions Index (UAI) in New South Wales. These rankings could be used to apply for university places out of the student's home state. We use the term ENTER score as a generic name for these entrance ranks which are calibrated to a common, Australian-wide scale that ranges from 30 to 99.95. Since 2010, these percentile ranks have been renamed Australian Tertiary Admission Rank (ATAR) for all states and territories except Queensland.

[4] Admission to university on the basis of ENTER scores is the dominant mode for matriculating students in Australia. Other criteria are used for mature aged entrants which form a smaller part of the student body and are not the focus of our analysis.

Virtually all universities in Australia are public and since 1989 students have faced a tuition charge. This tuition charge may be paid up front or students could defer payment by agreeing to an income contingent loan provided by the federal government. These income contingent loans were referred to as Higher Education Contribution Scheme (HECS) loans.[5] HECS loan balances are indexed to inflation, thereby offering students a zero real interest rate. Repayments are administered through the federal tax system and are only required when taxable income exceeds a legislated level; see Chapman (1997) for more details. In addition to HECS, students could apply for means tested government support (called AUSTUDY) while studying. This means tested support is based on parental income and available in the later years of high school and through university. It takes the form of regular government payments while studying, essentially a stipend, where the amount varies with the level of assessed need. However, only small proportions of university students are eligible for such support (34% in our sample); see Ryan (2013) for a detailed discussion of these payments.

While the institutional and policy environment in Australia seems to address short term credit constraints at least to some degree, we still observe a strong socioeconomic status (SES) gradient in university attendance. Potential students may be credit constrained if they are unable to fund costs such as books, study materials and living expenses that are not covered by the HECS scheme, or if they do not qualify for sufficient income support while studying. The SES gradient is illustrated using the Longitudinal Surveys of Australian Youth (LSAY) data in Figure 1. A nonparametric estimate of the probability of university attendance conditional on SES is presented and highlights the highest SES students are nearly 3 times more likely to attend university than the lowest SES students.[6]

In order to identify students that are credit constrained, we exploit the fact that 35% of students attend some form of private school in Australia.[7] Thus, while public education is the dominant mode of school education in Australia, a large proportion of the population is

[5] Since 2005, the HECS scheme has been renamed the Higher Education Loan Program (HELP).

[6] The conditional means shown in figures in this paper were all estimated using the *lowess* or *mlowess* programs in *stata*.

[7] The non-government school sector is typically divided into the Catholic sector (20%) and the independent sector (15%).

willing and able to pay for education, indicating these households might not face educational credit constraints. As the private school sector exhibits a wide variety of schools with different fee structures, we cannot rely entirely on private school attendance as an indicator of the absence of credit constraints. Instead, we complement private school attendance with other data to identify households that are less likely to face credit constraints. We use additional information about the SES of the student's parents and about the average SES of the school attended. We define three groups. The first comprises students who are least likely to face credit constraints. They have relatively high SES backgrounds and attend private schools where the average SES of the school's students is also high. The second group comprises students most likely to face credit constraints, with relatively low SES and attending schools where the average SES of the school's students is also low. The third comprises all other students and is referred to as potentially constrained. We define an indicator variable for membership of each of these three groups, using group membership to investigate the impact of credit constraints on university participation. We provide further details below when describing our empirical approach and data.

# 3 Empirical Method

Optimizing students making the decision to attend university face a number of constraints and trade-offs and will choose to attend university if they believe the benefits from attending will make it worthwhile relative to any costs they face. The student's assessment of this will depend on their attitude towards education, a range of personal attributes related to university study and their personal circumstances at the time they decide to undertake university study, including the likelihood that they are credit constrained. These factors comprise both 'permanent'and 'temporary'components, some possibly unobserved, that may influence the decision to attend university.

Individuals with similar observed demographic characteristics may make different decisions if their underlying unobserved attitudes towards education differ or if their circumstances at critical times (current or past) differ. The following empirical model reflects these various features of the university participation decision:

$$u_{it}^{*} = \alpha + y_{it}\kappa + G_{it}'\tau + (y_{it} \times G_{it}')\varphi + X_{it}'\beta + c_i\gamma + e_{it}. \tag{1}$$

The desired level of university participation by individual $i$ at time $t$ is latent and given by $u_{it}^{*}$. This desired level of participation depends on a range of factors observed at time $t$. These include a vector of demographic characteristics, $X_{it}$, and the student's high school achievement (ENTER score) given by $y_{it}$. It also depends on whether the student faces credit constraints. This is captured by $G_{it}$ which indicates whether a student is likely or unlikely to face credit constraints based on the groups described in the previous section and formally defined below. Along with these observed factors, participation depends on unobserved factors. We divide these unobserved factors into transitory and permanent components. Transitory unobserved factors operate at the time of the attendance decision and are denoted $e_{it}$. The permanent factors are denoted $c_i$ and reflect unobserved attitudes towards education, individual motivation and ambition along with personal discount rates. We distinguish these two components as we outline and implement a strategy to account for permanent unobserved factors below.

The observed university participation decision is denoted $u_{it}$ and modelled using a probit specification where university attendance conditional on $y_{it}$, $G_{it}$ and $X_{it}$ is given by:

$$P(u_{it} = 1 | X_{it}, y_{it}, G_{it}, c_i) = \Phi(\alpha + y_{it}\kappa + G_{it}'\tau + (y_{it} \times G_{it}')\varphi + X_{it}'\beta + c_i\gamma), \tag{2}$$

where $\Phi$ denotes the standard Normal cumulative distribution function (*cdf*). As in equation (1), this specification highlights the importance, for university participation, of high school achievement in the form of ENTER score, $y_{it}$, and ability to pay any costs of university education captured by the group membership dummies, $G_{it}$. Testing the significance of $\tau$ indicates whether group membership affects the level of university participation independent of ENTER score. In addition to this level effect, we allow for the effect of credit constraint group membership to vary by ENTER score by including the interaction term $(y_{it} \times G_{it}')$

and testing the significance of $\varphi$.

As noted above, unobserved heterogeneity in individual attitudes towards university education that are consistently held through time are captured by $c_i$. Typically, equation (2) will be estimated without data on $c_i$. Exclusion of $c_i$ from equation (2) will lead to biased parameter estimates, most notably to attenuated estimates of all parameters, though the ratios of one parameter to another are not affected; Wooldridge (2010). In our case, however, there are grounds for more specific concerns. Suppose members of each group are differentially likely to complete school and obtain an ENTER score, possibly because their attitudes towards university education differ. In this case, parameter estimates of group effects ($\tau$ and $\varphi$) will be influenced by these differences in average group attitudes.

To illustrate the potential problem, consider all students who complete high school and obtain an ENTER score. Suppose those students from the most likely to face credit constraints group do indeed have much more positive attitudes towards university education than those from the unlikely to face credit constraints group. These different attitudes could confound estimates of the impact of group membership and thus credit constraints. The presence of such unobserved heterogeneity may lead to estimates of little difference in participation between groups, but only because the effect of heterogeneous attitudes offsets the impact of group membership on university participation.

We adopt two approaches in this paper to deal with this potential problem. First, we obtain an estimate of $c_i$ based on post school educational plans individuals reveal about themselves in Year 9 (ninth grade). The second approach is to assume that the individual heterogeneity induces positive correlation between the decisions to obtain an ENTER score and to attend university. We estimate these decisions jointly with a bivariate probit, both unconditionally and by making explicit assumptions about the extent of the correlation. Each approach is described below in turn.

In the LSAY data used in this study, subjects report their post-school study plans in Year 9. Our approach uses information on whether or not individuals plan to attend university to obtain an estimate of $c_i$. These plans are likely to be influenced by the same kind of individual characteristics as those included in equation (2), but observed in the first wave of the survey, $X_{i1}$, rather than at the time of the university attendance decision. Plans will also be influenced by academic achievement measured in the first wave, $p_{i1}$. Idiosyncratic factors such as motivation, ambition and aspects of credit constraints not related to SES will also influence whether young people plan to attend university. These factors are unrelated to $X_{i1}$ and are expected to be reflected in $c_i$. We therefore estimate an equation of the form:

$$u_{i1}^{plan} = P(u_{i1}^{plan} = 1|X_{i1}, p_{i1}) + \epsilon_{i1} = \Phi(X_{i1}'\delta + p_{i1}\lambda) + \epsilon_{i1}, \tag{3}$$

where $u_{i1}^{plan}$ is a dichotomous variable that reflects reported post-school study plans, $X_{i1}$ and $p_{i1}$ are as noted above and $\epsilon_{i1}$ is an error that reflects the unobserved idiosyncratic factors that influence whether young people *plan* to attend university. This error term will tend to be more positive (negative) where students with poorer (stronger) $X_{i1}$ and $p_{i1}$ values *unexpectedly* report that they intend (do not intend) to go to university. It should be noted that $X_{i1}$ does not include the constrained/unconstrained group identifiers as we do not wish to impose any group-based structure on these parameter estimates. However, $X_{i1}$ does include parental SES since this is an important determinant of student plans.[8]

The unobserved factors that influence university study plans $\left(u_{i1}^{plan}\right)$ will be reflected in the estimated residual $(\widehat{\epsilon}_{i1})$ from equation (3). This estimated residual includes the unobserved permanent factors that influence the decision to attend university $(c_i)$, that we wish to include in equation (2). In structure, equation (3) is similar to the first stage of a Heckman selection model, except students are not selected out of attending university if, in ninth grade, they say they do not *intend* to go to university. Unlike the case of a Heckman selection model, we do not impose normality assumptions on the derived variable to be calculated based on equation (3). Instead we rank individuals in terms of their residual value to emphasize the most surprising responses given their characteristics. That is, we construct

[8]The parameters from equation (3) allow us to estimate the contributions of individual characteristics and achievement levels to student plans. In post-estimation analysis below, we use these estimates to rank individuals in terms of their observed personal characteristics and achievement levels. That is, we use: $\tilde{T}_{i1} = rank(X_{i1}'\widehat{\delta})$, and $\tilde{p}_{i1} = rank(p_{i1}\widehat{\lambda}) = rank(p_{i1})$, to illustrate differences in university participation by individual rank in these predicted characteristics.

a variable based on the rank of the residual $\widehat{\epsilon}_{i1}$ given by:

$$\tilde{\epsilon}_{i1} = rank(\widehat{\epsilon}_{i1}) = rank(u_{i1}^{plan} - \Phi(X_{i1}'\widehat{\delta} + p_{i1}\widehat{\lambda})), \tag{4}$$

and assume that it provides a good measure of the permanent unobserved heterogeneity term, $c_i$. The variable $\tilde{\epsilon}_{i1}$ is included in the estimation of equation (2) in order to address any possible bias in parameter estimates resulting from the omission of $c_i$. Intuitively, the highest (lowest) ranked $\tilde{\epsilon}_{i1}$ will correspond to students with poor (good) characteristics who *surprisingly* plan (not) to attend university.[9]

Our second approach to dealing with concerns about the unobserved heterogeneity embodied in $c_i$ makes use of the reasons for obtaining an ENTER score. Given that the primary reason to acquire an ENTER score is to qualify for university (along with some vocational education courses), we consider the possibility that the decision to acquire an ENTER score and university attendance are jointly determined. We jointly estimate models of both decisions as

$$u_{it} = P\left(\alpha_1 + y_{it}\kappa_1 + G_{it}'\tau_1 + (y_{it} \times G_{it}')\varphi_1 + X_{it}'\beta_1\right) + \left(c_i + \xi_{it}\right), \tag{5}$$

$$E_{it} = P\left(\alpha_2 + p_{i1}\kappa_2 + G_{it}'\tau_2 + (p_{i1} \times G_{it}')\varphi_2 + X_{it}'\beta_2\right) + \left(c_i + \zeta_{it}\right), \tag{6}$$

via a bivariate Probit model, where $E_{it}$ is an indicator of whether a student acquires an ENTER score, $\xi_{it}$ and $\zeta_{it}$ are standard normal disturbance terms and all other variables are as already defined. In this case, $(c_i + \xi_{it})$ and $(c_i + \zeta_{it})$ are the respective disturbance terms that include the permanent unobserved heterogeneity reflected in $c_i$. Ideally we would test for the independence of $(c_i + \xi_{it})$ and $(c_i + \zeta_{it})$, implying $\rho_{uE} = 0$. However, without suitable exclusion restrictions to identify the parameters in equation (5), we are unable to test this assumption. Instead we undertake a constrained maximum likelihood estimation where we assume different values of $\rho_{uE} > 0$. The higher is $\rho_{uE}$, the greater the role of $c_i$

[9]In addition to $rank(\widehat{\epsilon}_{i1})$, we consider various transformations of $\widehat{\epsilon}_{i1}$ with little change in results. More detail is provided below. We also make use of a different estimate of $c_i$, given by $(u_{i1}^{plan} - \overline{u}_{i1}^{plan})$, where the average plan is calculated for students in the same school as individual $i$. In a simple non-parametric way, it reflects how different the individual is from her peers. Again, results are unchanged by this alternative estimate of $c_i$.

in $(c_i + \zeta_{it})$ and the more likely estimates of $\tau_1$ and $\varphi_1$ are biased because of the omission of $c_i$. If estimates of $\tau_1$ and $\varphi_1$ are unchanged for different assumed values of $\rho_{uE}$, we argue that the parameter estimates are robust to the omission of the unobserved heterogeneity in $c_i$. This approach draws on work by Altonji *et al.* (2005) and Imbens (2003).

# 4 Data

The data used in this paper is drawn from the Longitudinal Surveys of Australian Youth (LSAY). The similarity between the 1995 (LSAY 95) and 1998 (LSAY 98) cohorts along with the absence of any major institutional changes around the times when these cohorts made university decisions allows us to pool these two cohorts in our analysis, while we include dummies in order to control for cohort effects.[10]

These cohorts are drawn from two-stage cluster samples of Australian school children. In the first stage, schools were randomly selected. In the second stage, intact classes of Year 9 students from those schools were randomly selected. The samples were stratified by school sector (government, Catholic or independent private schools). Population means in this paper are estimated with weighted data to account for this stratification along with attrition. In the first survey year, when students were in Year 9, they completed literacy and numeracy tests at their schools, along with a short questionnaire to elicit background information.[11] Participants were surveyed in subsequent years by mail and/or telephone questionnaires. In their fifth and subsequent contact years in both surveys, subjects were asked whether they had received the relevant certificate from their jurisdiction to indicate they had completed Year 12, whether they had obtained an ENTER score and whether they were studying at university.

[10] Descriptive statistics for the pooled and seperate LSAY 95 and LSAY 98 cohorts are provided in Table A.1 of Appendix A, showing the similarities between the two cohorts. When we repeated the analysis below for a more recent but smaller LSAY 06 cohort, the results and conclusions are unchanged.

[11] Student performance in ninth grade literacy and numeracy tests were used by Rothman (2002) to construct achievement scales. The individual literacy and numeracy scales were constructed to have a mean of 50 and standard deviation of 10. In this paper, we use the average of these two scales to reflect individual student achievement. This average has a standard deviation of 8.5. Where only one of the literacy and numeracy scales is available, it was used as the achievement score. This affected about 1.9% of observations used in the analysis.

We define three groups of students who face differing degrees of credit constraints. The first group is *unlikely* to face credit constraints and is defined to include students who in ninth grade (i) were in the top SES quartile, based on their parent's occupation;[12] (ii) attended a school in the top SES quartile of schools, based on the average of parents' occupation in schools; and (iii) attended a non-government school. The third criterion ensures that only individuals whose families had already demonstrated a preparedness to pay for at least part of their child's education were included in this group. The first two criteria are designed to pick out those students with the highest social backgrounds at the schools where such students are most concentrated. This group constitutes 8.1% of the weighted sample data.

In contrast, the second group is *likely* to face credit constraints and includes students who in ninth grade (i) were in the lowest SES quartile; and (ii) attended schools in the lowest average SES quartile of schools. This group constitutes 10.8% of the weighted sample data.

The third group comprises students who are *potentially* constrained and is defined as all students who are not members of the *unlikely* and *likely* to be credit constrained groups.[13]

The size of and summary statistics for these groups are presented in Panel A of Table 1. Consistent with the Australian and international evidence, members of the high SES, *unlikely* constrained group had the highest university participation rate and the highest average ENTER score. In turn, the middle group had a lower average ENTER score and university participation rate, while the low SES and *likely* constrained group had the lowest average ENTER score and university participation rate.

As a cross check, we provide evidence on how well these criteria have partitioned ninth grade students according to other indicators of wealth and social background in Panel B of Table 1. These other indicators include a social status index based on parental edu-

[12] The Australian National University (ANU) 3 scale is used for the two cohorts; Jones (1989). The scale is a status-based occupational prestige measure that lies between 0 and 100. The relevant 'parent' is the student's father unless information about his occupation is missing. In those circumstances, information on the occupation of the student's mother is used.

[13] Variations in these definitions were used to test how sensitive the results reported below are to the specific SES variable and the group selection criteria used here. Partitioning students according to alternative SES measures, such as the Australian Bureau of Statistics (ABS) neighbourhood based SES measures or measures based on average taxable incomes within postcodes, did not change the qualitative features of the results.

cation and occupation constructed by the Australian Bureau of Statistics (ABS 1998), and whether students received government student income support (AUSTUDY) while attending university.

The ABS social status index provides an indication of the average social backgrounds of the neighbourhoods in which each student lived in the first wave of their respective survey cohorts. It shows that two thirds of the *unlikely* constrained group are in the top quartile of the ABS social status index, with one third in the top decile and 3.9% in the bottom quartile. Conversely, 57.3% of the *likely* constrained group are in the bottom quartile of the ABS social status index with only 2.2% of these students in the top quartile. The rate of receipt of AUSTUDY is also in line with expectations, with 55.3% (13.7%) of the *likely* (*unlikely*) constrained group in receipt of government support. These indicators demonstrate that members of the *unlikely* constrained group come from more privileged backgrounds than the *potentially* constrained group, who in turn have substantially higher social backgrounds than members of the *likely* constrained group.

Descriptive statistics for the set of variables used in the regression equations for the three groups are shown in Table A.2 of Appendix A. These confirm the advantaged nature of the social background of the *unlikely* constrained group relative to the other groups. Their parents are much more highly educated, and the individuals themselves are more likely to be non-Indigenous and to live in urban areas.

Preliminary analysis of the role of credit constraints is presented in Figure 2 where non-parametric estimates of the probability of university attendance conditional on ENTER score are presented for each credit constraint group. The key result is that the curves for each group are virtually on top of each other. The implication is, given high school achievement as reflected in ENTER scores, students who are *likely* to face credit constraints have the same probability of attending university as students who are *unlikely* to face credit constraints. The analysis below introduces a full set of covariates and addresses unobserved heterogeneity in modelling university attendance. However, the results are consistent with those in Figure 2 and there is no evidence that *likely* constrained students are less likely to attend university.

We now proceed to the more detailed empirical analysis.

# 5 Results

The results of estimation of equation (2) are presented in Table 2. The first column presents parameter estimates where no measures have been taken to deal with unobservables denoted by $c_i$. We find strong positive effects of parental education, student NESB immigrant status and a negative male gender effect, all consistent with expectations based on existing literature. We also find a small negative LSAY 98 cohort effect, consistent with the stronger labour market conditions that cohort experienced after 2000, and unsurprising state effects which are excluded to save space.

In addition to these standard controls, linear, quadratic and cubic ENTER score terms are included. The overall effect of ENTER score is positive, the stronger the high school achievement of a student the more likely they are to attend university. Given the nonlinear effect of ENTER score, we present the overall marginal effects evaluated at different ENTER scores in the first column of Table 3. This shows the marginal effect of ENTER score is significant at the 1% level across the full range of ENTER scores and is highest at the 60-80 range, declining at higher and lower ENTER scores. The implication is that in these higher and lower ranges, changes in ENTER score are less likely to change the decision to attend or not attend university.

Our research question is, are the students who are likely to be credit constrained less likely to attend university? The overall marginal effects of credit constraint group membership are presented in the second column of Table 2 and imply no statistically significant average effects. Since the model in equation (2) includes an interaction term between ENTER score and group membership, the effect of group membership at different ENTER scores is presented in Table 4 and Figure 3.[14] The first two columns of Table 4 show group membership effects corresponding to parameter estimates in the first column of Table 3, where no

[14] Tests of the inclusion of higher order interaction terms between ENTER score and group membership did not reject that those effects were zero.

measures have been taken to deal with unobservables. Relative to the group that is *most likely* to be credit constrained, the marginal effects of group membership are only significant at low ENTER scores, 40-60. The *unlikely* to be constrained group is 9-11% less likely to attend university, significant at the 1% level, while the *potentially* constrained group is 5-6% less likely to attend university. The average marginal effects are small and not significantly different from zero.

Figure 3 plots predicted values for the three groups at different values of the ENTER score using average group characteristics. Consistent with Table 4, this figure shows that the difference in attendance probabilities is greatest at low ENTER scores, but in favour of the *likely* to be constrained group with the gap narrowing as high school achievement increases. This gap is particularly evident for ENTER scores up to around 60. Above that point, there are no differences between groups until the very top of the ENTER distribution, though there are very few observations from the *likely* constrained group with scores of 95 or higher. Since the question remains whether unobserved differences in the strength of attitudes towards university held between the groups drives our results among those who obtained an ENTER score, the next subsection focusses on approaches to deal with unobserved heterogeneity in attitudes towards university.

## 5.1 Sensitivity analysis

The initial results indicate that students who are expected to face credit constraints are not less likely to attend university than students in the other two groups. In this subsection we report on the outcomes of three extensions to our main results. First, we report on results where we add estimates of otherwise unobserved heterogeneity to our main regression equation. Second, we report unconstrained bivariate probit estimates also designed to deal with unobserved heterogeneity revealed through the correlation between obtaining an ENTER score and attending university. Finally, we report on the constrained estimation in the bivariate probit framework, to assess how high the correlation between the unobserved elements of those two decisions would need to be to change our main results, that the likely constrained group are not less likely to attend university than the *unlikely* constrained group.

We begin by developing an estimate of $c_i$ that can be included in the estimation of equation (2) to deal with the potential impact of permanent unobservables on our base estimates. The estimate is based on the model of ninth grade plans to attend university in equation (3). The results are presented in Table B.1 in Appendix B. A range of characteristics reported in ninth grade are included ($X_{i1}$) along with linear, quadratic and cubic functions of ninth grade achievement ($p_{i1}$). As expected, most of these variables are very important for these plans. These estimates are used to construct $\tilde{\epsilon}_{i1}$ given in equation (4).[15]

In the first column of Table 5, we present the average value of $\tilde{\epsilon}_{i1}$ for each of the three credit constraint groups, based on the full sample of students. The most notable point is that this average value is similar for each group. The second column presents averages of the same estimated variable, but only for students who completed high school and acquired an ENTER score. Compared to the full sample, these estimates suggest some selection into obtaining an ENTER score based on ninth grade plans to attend university. That is, among those who obtain an ENTER score, the *likely* constrained students had stronger plans to attend university than the potentially constrained students who in turn had slightly stronger plans to attend university than the *unlikely* constrained students. The interpretation is that of the students who obtain an ENTER score and qualify for university entrance, the *likely* constrained students are on average more motivated to undertake university study. It also signals that our measure of unobservables is consistent with expectations about the direction of potential biases in the baseline results.

This rank of unobservables data is included as a measure of $c_i$ in the estimation of equation (2), with results presented in the colums headed 'unobservables included' in Table 2.[16] The rank of unobservables is significant at the 1% level and clearly very important in explaining

[15] Variations in the construction of the heterogeneity indicator, $\tilde{\epsilon}_{i1}$, as $rank(\widehat{\epsilon}_{i1})$ included linear, quadratic and cubic splines with parameters for positive values of $\widehat{\epsilon}_{i1}$ allowed to differ from those associated with negative values, use of the Inverse Mills Ratio and allowing its effect to also be different for positive and negative values. These alternative measures did not produce qualitatively different estimates to those presented.

[16] The standard errors of the parameters in the second column are taken from bootstrapped estimates of the equation, based on 50 replications.

university participation. Notwithstanding the inclusion of the rank of unobservables data, relative to the first columns of Table 2, the set of significant parameters remains unchanged while the parameter estimates are notably similar. This suggests that while the rank of unobservables variable indeed captures important factors that explain university participation compared to the first columns of Table 2, these factors are largely uncorrelated with the other explanatory variables included in equation (2).

To emphasise the similarity between results, we present the overall effect of ENTER score in the second column of Table 3. This table shows that the marginal effect of ENTER score is virtually unchanged by the inclusion of the rank of unobservables data, with very small reductions in the marginal effect apparent only at the ENTER scores of 60 and 70.

Returning to our principal question of the effect of credit constraints on university attendance. We present the overall effect of group membership for these unobservable adjusted parameter estimates in the third and fourth columns of Table 4. These results imply some of the higher propensity to attend university among the low ENTER score, *likely* constrained students is related to unobservables. The new results indicate students from the *potentially* constrained group are as likely to attend university as students from the *likely* constrained group. Students from the *unlikely* constrained group are still 8-10% less likely to attend university for ENTER scores under 60, while the average marginal effects are positive but not significantly different from zero. Hence, while differences in unobservables explain some of the difference in university participation between the groups, they do not mask any lower 'true' levels of participation among the *likely* constrained group of students.

This is confirmed in simple matching estimates presented in the lower panel of Table 4. In the first two columns, mahalanobis matching estimates of group membership effects using ENTER scores alone are presented. Both Average Treatment on the Treated (the *unlikely* constrained group matched to those with ENTER scores most like them in the *likely* constrained group) and Average Treatment on the Untreated (the *likely* constrained group matched to those with ENTER scores most like them in the *unlikely* constrained group) are presented. These do not suggest university participation rates are higher in either the *unlikely* or potentially constrained groups than the *likely* constrained group. In the third and fourth columns, the matching takes place on ENTER scores and on $\tilde{\epsilon}_{i1}$. This generally pushes the estimates to be more in favour of the idea participation is higher among the *unlikely* and potentially constrained groups compared to the *likely* constrained group. However, none of the estimates are significantly different from zero.

The overall picture is confirmed in both our constrained and unconstrained bivariate probit estimates, where the two dependent variables are whether or not individuals obtained an ENTER score and whether they attend university. The results of this analysis are presented in Table 6. The top row shows the results from the unconstrained estimation, while the lower rows show the results where we force the correlation between the errors of the two equations (denoted by $\rho$)) to take the specific values in the first column of the table. Note that the $\rho = 0$ results coincide with the results for the univariate university participation probit presented in the first two columns of Table 2.

The results in the first row of Table 6 indicate that in the unconstrained estimation, the estimate of $\rho$ is positive, as might be expected if similar unobserved factors affect both the decision to obtain an ENTER score and whether people attend university. However, the estimate of $\rho$ is small and not statistically different from zero and therefore suggests we could rely solely on the univariate university participation probit results.[17] The estimated parameters on (and marginal effects of) the group membership indicators and their interaction with the ENTER scores are also very close to those of the univariate university participation probit.

The remaining rows of Table 6, where we impose particular values on $\rho$ indicate that that negative values for $\rho$ increase the apparently higher university participation of the *likely* constrained group over the other groups, while higher positive values for $\rho$ reduce them. However, even correlation values as high as $\rho = 0.4$ are not strong enough to lead to estimates where the *likely* constrained group is less likely to attend university than the other

[17] If the estimate of $c_i$ given by $\tilde{\epsilon}_{i1}$, is used as an explantory variable in both equations the resulting estimate of $\rho$ becomes negative, but again is small – about the same absolute value as the estimate reported when $\tilde{\epsilon}_{i1}$ is not included – and not significantly different from zero.

groups. [18]

## 5.2 What really matters for university attendance?

We now present the university participation decision in a slightly different way that highlights why we find the *likely* constrained group of students are at least as likely to attend university as the other groups. The university participation decision will be decomposed into four broad components. Three of these components will be based on the results reported in Table B.1, which relate a set of ninth grade individual characteristics to the plans of individuals to attend university, also revealed in ninth grade.

First, we make use of the rank of the unobservables $\tilde{\epsilon}_{i1}$, computed from equation (4). Second, based on the estimates in Table B.1, we also construct the ranks of ninth grade achievement ($\tilde{T}_{i1}$) and a composite index of the other variables used to explain the Year 9 plans multiplied by their respective estimated parameters ($\tilde{p}_{i1}$); see footnote 8 for formal definitions. These two ranks are referred to as 'Year 9 achievement' and 'Year 9 observables' respectively.

The fourth component is based on the rank of individuals' ENTER scores. We impute a value for those individuals who do not obtain an ENTER score.[19] In the imputation process we assume the estimated effects of all factors determining the ENTER score are the same for those students who did and did not obtain an ENTER score. Thus, those individuals who did not obtain an ENTER score may only receive a lower imputed score than those who did obtain an ENTER score because of poorer characteristics. Nevertheless, the average imputed ENTER score of those who did not obtain an ENTER score was 46 compared with 65 for those who did. Further, 64 percent of those who did not obtain an ENTER score were imputed to have an ENTER score of below 50, compared with 34 percent of those who did obtain an ENTER score.

[18] The estimated marginal effect of the unconstrained group variable is 2.2 but is not significantly different from zero.

[19] The imputation of missing ENTER score values was based on OLS using the following variables: group membership, achievement, parental occupational SES, gender, completed parental education, student born overseas, Indigenous, metropolitan area, state indicators, individual self-confidence and cohort.

We estimate the effects of these four rank variables on the probability an individual attends university using a non-parametric smoother, conditional on the other rank variables. The results are shown in Figure 4. The line for any of the individual ranks take account of the impact of the other ranks, so it is akin to the marginal effects we estimate from a regression equation. Panel A shows the estimated relationships when only the ranks of Year 9 observables, unobservables and achievement are included, while Panel B also includes the ENTER rank.

A number of features of the two figures and their comparison are noteworthy. First, Year 9 observables and achievement predominantly affect university attendance via their impact on ENTER scores. In Panel B, the effects of moving from the bottom to the top rank of those variables is demonstrated to be much smaller once ENTER ranks are taken into account. Second, the unobservables also have an impact on attending university, though it is less affected by the inclusion of the ENTER rank. Third, the ENTER rank strongly dominates the explanation of who goes to university. Some people with low ENTER scores do attend university, but marginal increases in ENTER ranks in the bottom half of the distribution do not affect the probability of attendance. However, moving from the half way point of the distribution to the top increases the probability by about 80 percentage points. Beyond the ENTER ranks of individuals, very little else seems to matter in explaining differences in university attendance.

The implications of these figures for our central research question is that credit constraint group membership must be less important than ENTER scores in the determination of university attendance. The observables curve in Panel B of Figure 4 includes an SES variable and reflects the information in our credit constraint group variables. Comparing the effect of observables between the top and bottom 10 percent ranked individuals, which is what our earlier analysis effectively does, the difference in university attendance is very small. Given this decomposition, it is not surprising that there are no differences between the likely and unlikely constrained groups in university attendance once we condition on ENTER scores, as our main results suggest.

# 6 Conclusions

We have studied the effects of credit constraints on the university attendance decisions of students facing an income contingent loan scheme (HECS-HELP) in Australia. Conditional on high school achievement, the results show no differences in the probability of university attendance between students likely to face credit constraints and those unlikely to face constraints. It is surprisingly found that lower in the high school achievement distribution, likely credit constrained students have a greater probability of attending university than students unlikely to face constraints.

We also devised an innovative approach to address any possible bias that might arise from the omission of unobservables. The approach exploited responses collected in ninth grade to questions about study plans after high school and led to the estimation of unobservable effects. These unobservables were found to be very important in explaining university attendance decisions of students. However, our key conclusions were unaffected by their inclusion. Credit constraints do not appear to be a factor that leads to differences in the probability of university attendance.

These results imply that the institutions in place in Australia, comprised of income contingent loans (HECS-HELP) for tuition and means tested government support for living expenses (AUSTUDY), are relatively successful in relaxing any credit constraints that disadvantaged students may face when making decisions to attend university. In response to these findings we decompose the probability of university attendance in order to identify most important factor affecting differences in university attendance. The dominant factor is found to be high school achievement as measured by ENTER, the key mechanism by which university places are rationed.

Given these results, policies targeting the SES gradient in university participation are best focused on factors that affect qualifying for university admission. These factors may appear early in childhood, certainly before the age of 15 when we first see the subjects in the LSAY surveys. Importantly, this shift of attention and the resulting research cannot ignore the evolution of the institutional support in place to alleviate credit constraints as our results are conditional on those institutions. If policy strategies succeed in qualifying more low SES students for university admission, the question of credit constraints may need to be revisited.

The current higher education policy debate in Australia includes a range of proposals such as lower government subsidies per student, deregulated and potentially higher tuition charges and higher interest rate charges on any debts accrued. All of these changes are likely to lead to higher costs for all students. Our results focus on differences in attendance between groups with different levels of access to resources and are positive in that we do not find differences in attendance. However, estimates of demand elasticities would be needed in order to predict how these different groups will respond to large changes in the cost of higher education.

Income contingent loan features have been advocated by Stiglitz (2013) as a way to deal with growing debt burdens faced by college students in the US. Legislation before the US Senate and Congress in the form of Investing in Student Success Act of 2014 (Income Sharing Agreements) seeks to incorporate income contingent features into college loan arrangements in the US. Our findings suggest that income contingent loans do not deter qualified students from disadvantaged backgrounds from attending university. If anything, the risk mitigation insurance features of HECS-HELP seem to be encouraging greater numbers of lower ability students to attempt university than otherwise similar but non-constrained students.

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Table 1: Group sizes and summary statistics.

| | Groups | | | |
|---|---|---|---|---|
| | Unlikely Constrained | Potentially Constrained | Likely Constrained | Total |
| **Panel A: Summary statistics for pooled LSAY 95 and LSAY 98 sample.** | | | | |
| Observations | | | | |
| Unweighted | 1,614 | 13,086 | 1,307 | 16,007 |
| Weighted | 1,323 | 12,861 | 1,770 | 15,954 |
| Weighted observations with ENTER score | 1,138 | 7,462 | 700 | 9,300 |
| Proportion with ENTER score (%) | 86.4 | 58.3 | 39.8 | 58.6 |
| Proportion with ENTER score if Year 12 (%) | 92.7 | 75.2 | 61.9 | 76.7 |
| Proportion female (%) | 54.0 | 48.9 | 48.7 | 49.3 |
| University participation rate (%) | 67.9 | 35.3 | 19.9 | 36.3 |
| Average ENTER score (if had one) | 83.1 | 72.0 | 62.4 | 72.6 |
| Year 12 participation rate (%) | 95.7 | 82.7 | 73.3 | 82.8 |
| Proportion at Government school | 0.0 | 70.8 | 93.4 | 67.6 |
| Proportion at Catholic school | 40.9 | 19.8 | 6.6 | 20.1 |
| Proportion at Independent school | 59.1 | 9.4 | 0.0 | 12.3 |
| **Panel B: Social background and government support for each group.** | | | | |
| ABS education/occupation SES index | | | | |
| Proportion in top quartile(%) | 63.0 | 20.8 | 2.2 | |
| Proportion in top decile(%) | 34.6 | 6.1 | 0.3 | |
| Proportion in bottom quartile(%) | 3.9 | 25.0 | 57.3 | |
| Proportion who received AUSTUDY/Youth Allowance at university (%) | 13.7 | 35.9 | 55.3 | |

Source: Estimated from LSAY 95 and LSAY 98.

Table 2: University participation probit estimates: Without and with the inclusion of ninth grade unobservables.

| | Unobservables | | | |
|---|---|---|---|---|
| | Excluded | | Included | |
| | Parameters | Marg. eff. | Parameters | Marg. eff. |
| Unlikely constrained group | -1.243*** | -0.02 | -1.111*** | -0.01 |
| | (0.386) | (0.02) | (0.367) | (0.02) |
| Potentially constrained group | -0.472* | -0.02 | -0.418 | -0.02 |
| | (0.257) | (0.02) | (0.282) | (0.02) |
| Unlikely constrained × ENTER | 0.016*** | | 0.014*** | |
| | (0.005) | | (0.005) | |
| Potentially constrained × ENTER | 0.005 | | 0.005 | |
| | (0.004) | | (0.004) | |
| ENTER | -0.087** | 0.01*** | -0.095** | 0.01*** |
| | (0.040) | (0.00) | (0.045) | (0.00) |
| $(\text{ENTER})^2$ | 0.002*** | | 0.002*** | |
| | (0.001) | | (0.001) | |
| $(\text{ENTER})^3$ | -0.000*** | | -0.000*** | |
| | (0.000) | | (0.000) | |
| Male | -0.083*** | -0.02*** | -0.102*** | -0.03*** |
| | (0.031) | (0.01) | (0.023) | (0.01) |
| Student overseas born | | | | |
| English speaking country | -0.011 | 0.00 | -0.014 | 0.00 |
| | (0.094) | (0.02) | (0.096) | (0.02) |
| Non-English speaking country | 0.419*** | 0.11*** | 0.448*** | 0.11*** |
| | (0.060) | (0.02) | (0.063) | (0.01) |
| Father has degree | 0.098*** | 0.03*** | 0.136*** | 0.03*** |
| | (0.037) | (0.01) | (0.037) | (0.01) |
| Mother has degree | 0.092** | 0.02** | 0.110** | 0.03** |
| | (0.040) | (0.01) | (0.043) | (0.01) |
| Self-confidence | 0.005 | 0.00 | 0.006 | 0.00 |
| | (0.005) | (0.00) | (0.005) | (0.00) |
| Indigenous | 0.233 | 0.06 | 0.209 | 0.05 |
| | (0.149) | (0.04) | (0.156) | (0.04) |
| Metropolitan | -0.036 | -0.01 | -0.025 | -0.01 |
| | (0.037) | (0.01) | (0.041) | (0.01) |
| Y98 cohort | -0.122*** | -0.03*** | -0.124*** | -0.03*** |
| | (0.034) | (0.01) | (0.036) | (0.01) |
| Rank of unobservables | | | 0.603*** | 0.15*** |
| | | | (0.051) | (0.01) |
| Constant | -0.700 | | -0.959 | |
| | (0.905) | | (1.091) | |
| State indicators | **Yes** | | **Yes** | |
| Observations | 9,898 | | 9,898 | |

Table 3: Marginal effect of ENTER scores on university participation at different points of the ENTER distribution.

| | Unobservables | |
|---|---|---|
| Enter | Excluded | Included |
| 40 | 0.7*** | 0.7*** |
| 50 | 1.4*** | 1.3*** |
| 60 | 2.0*** | 2.0*** |
| 70 | 2.1*** | 2.0*** |
| 80 | 1.4*** | 1.4*** |
| 90 | 0.7*** | 0.7*** |
| 95 | 0.4*** | 0.4*** |
| 99 | 0.3*** | 0.3*** |

Table 4: Differences in university participation rates for cases where ninth grade unobservables have been included and excluded. Results are university participation rates relative to the likely constrained group at different points of the ENTER distribution.

| | Unobservables excluded | | Unobservables included | |
|---|---|---|---|---|
| Enter | Unlikely Constrained | Potentially Constrained | Unlikely Constrained | Potentially Constrained |
| 40 | -8.9*** | -5.3** | -8.3*** | -4.6 |
| 50 | -11.2*** | -6.0** | -9.8*** | -5.1* |
| 60 | -10.5*** | -5.6** | -8.7*** | -4.6* |
| 70 | -5.2 | -3.6 | -3.7 | -2.8 |
| 80 | 0.5 | -1.2 | 1.2 | -0.8 |
| 90 | 3.1 | 0.2 | 3.3 | 0.4 |
| 95 | 3.5* | 0.6 | 3.6* | 0.7 |
| 99 | 3.7** | 0.8 | 3.8** | 0.9 |
| Average marginal effect | -2.4 | -2.3 | 2.0 | 2.1 |
| Matching estimate | | | | |
| ATT | -2.1 | -3.5 | 4.4 | 1.4 |
| ATU | -7.0 | -1.5 | 4.4 | -5.3 |

Table 5: Average ninth grade unobservables by group: For the full sample, observed in ninth grade and for only those students with ENTER scores, observed after high school graduation.

| | Ninth grade unobservables | |
|---|---|---|
| | Full sample | Only students with an ENTER score |
| Likely Constrained | 0.50 | 0.60 |
| Potentially Constrained | 0.50 | 0.55 |
| Unlikely constrained | 0.51 | 0.52 |

Table 6: Constrained and unconstrained estimates of group effects from bivariate probit estimation.

| $\rho$ | Unlikely Constrained | Potentially Constrained | ENTER× Unlikely Constrained | ENTER× Potentially Constrained |
|---|---|---|---|---|
| **Unconstrained estimates** | | | | |
| 0.045 | -1.209*** | -0.460* | 0.016*** | 0.005 |
| (0.063) | (0.388) | (0.258) | (0.005) | (0.004) |
| **Altonji et al. constrained estimates** | | | | |
| -0.5 | -1.664*** | -0.625*** | 0.019*** | 0.006* |
| | (0.364) | (0.237) | (0.005) | (0.004) |
| -0.4 | -1.573*** | -0.592** | 0.018*** | 0.006 |
| | (0.371) | (0.244) | (0.005) | (0.004) |
| -0.3 | -1.485*** | -0.561** | 0.017*** | 0.006 |
| | (0.377) | (0.249) | (0.005) | (0.004) |
| -0.2 | -1.401*** | -0.531** | 0.017*** | 0.006 |
| | (0.382) | (0.253) | (0.005) | (0.004) |
| -0.1 | -1.320*** | -0.501* | 0.016*** | 0.005 |
| | (0.384) | (0.256) | (0.005) | (0.004) |
| 0 | -1.243*** | -0.472* | 0.016*** | 0.005 |
| | (0.386) | (0.257) | (0.005) | (0.004) |
| 0.1 | -1.169*** | -0.444* | 0.015*** | 0.005 |
| | (0.386) | (0.258) | (0.005) | (0.004) |
| 0.2 | -1.097*** | -0.417 | 0.015*** | 0.005 |
| | (0.384) | (0.257) | (0.005) | (0.004) |
| 0.3 | -1.030*** | -0.39 | 0.015*** | 0.005 |
| | (0.381) | (0.254) | (0.005) | (0.004) |
| 0.4 | -0.966** | -0.364 | 0.014*** | 0.005 |
| | (0.376) | (0.251) | (0.005) | (0.004) |

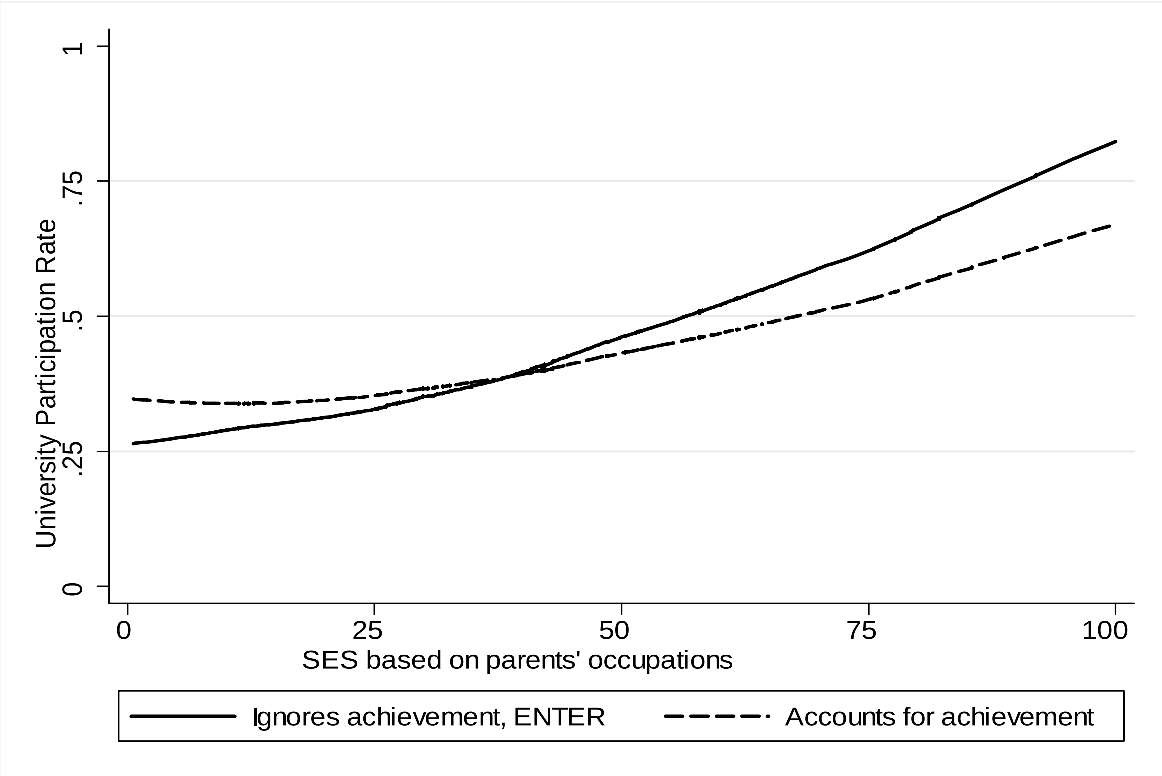


Figure 1: Probability of university participation in Australia by SES background before and after adjustment for studnet ability based on ninth grade school achievement.

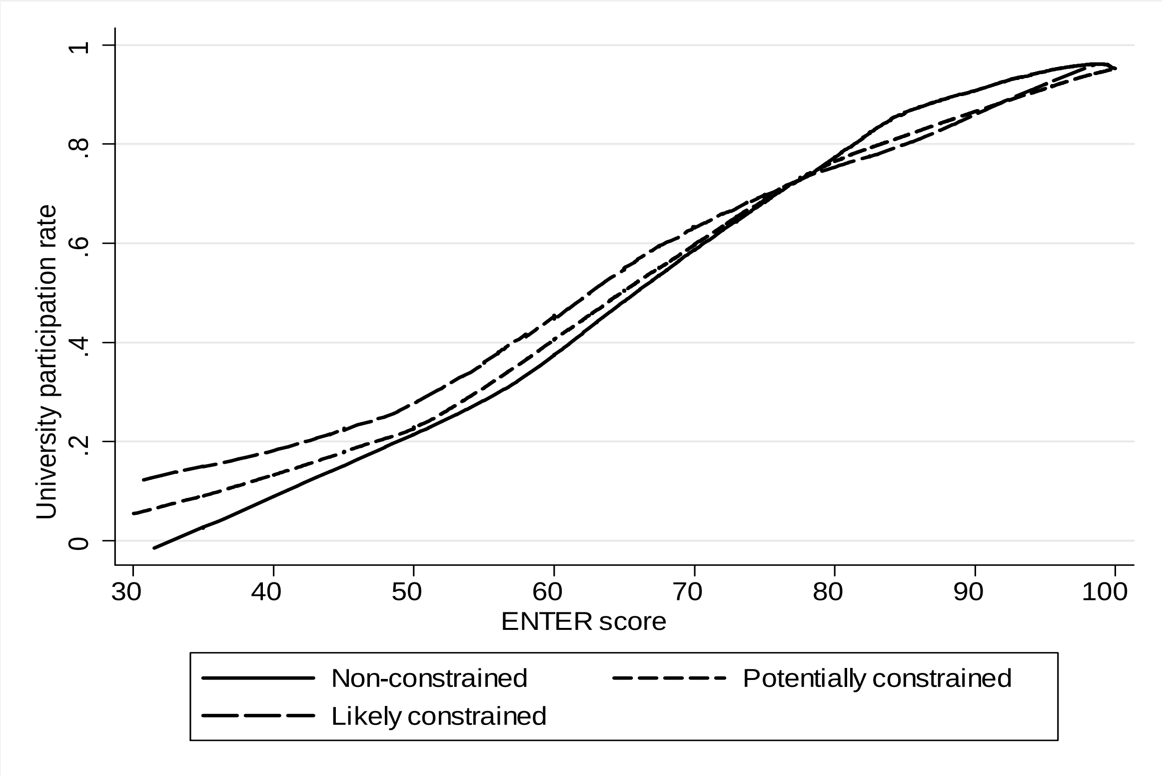


Figure 2: Probability of university participation by ENTER score

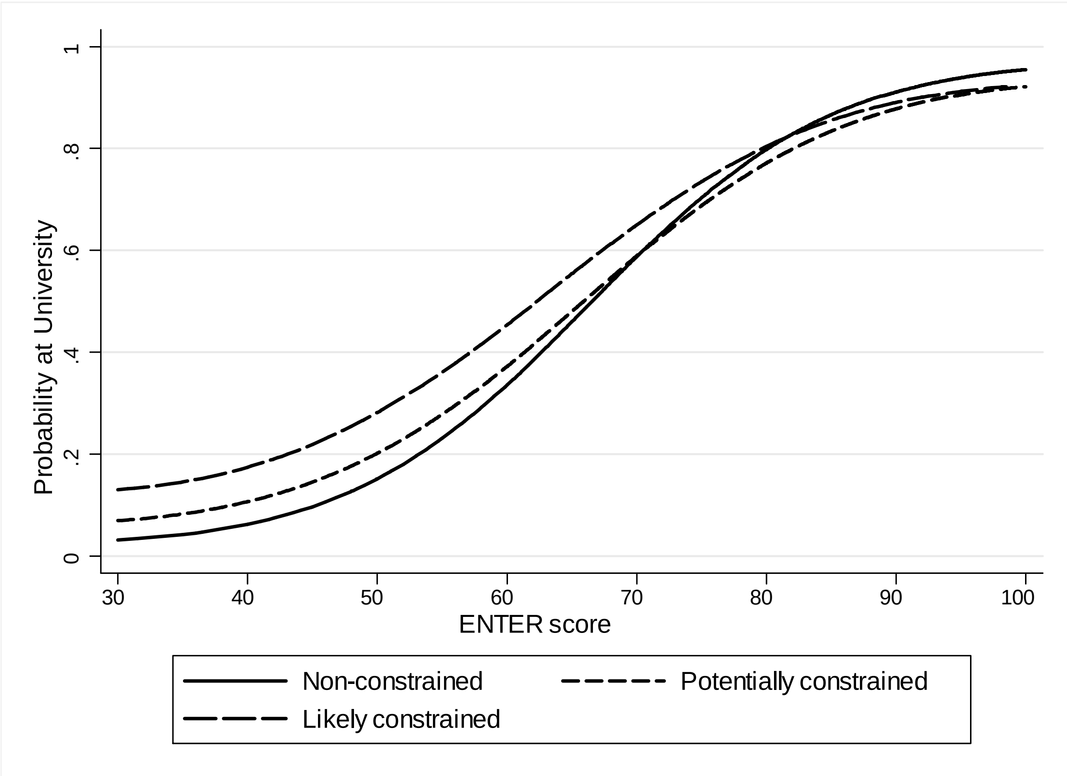


Figure 3: Predicted probabilities of university attendance for different credit constraint groups by ENTER score, based on estimates in first two columns of Table 2.

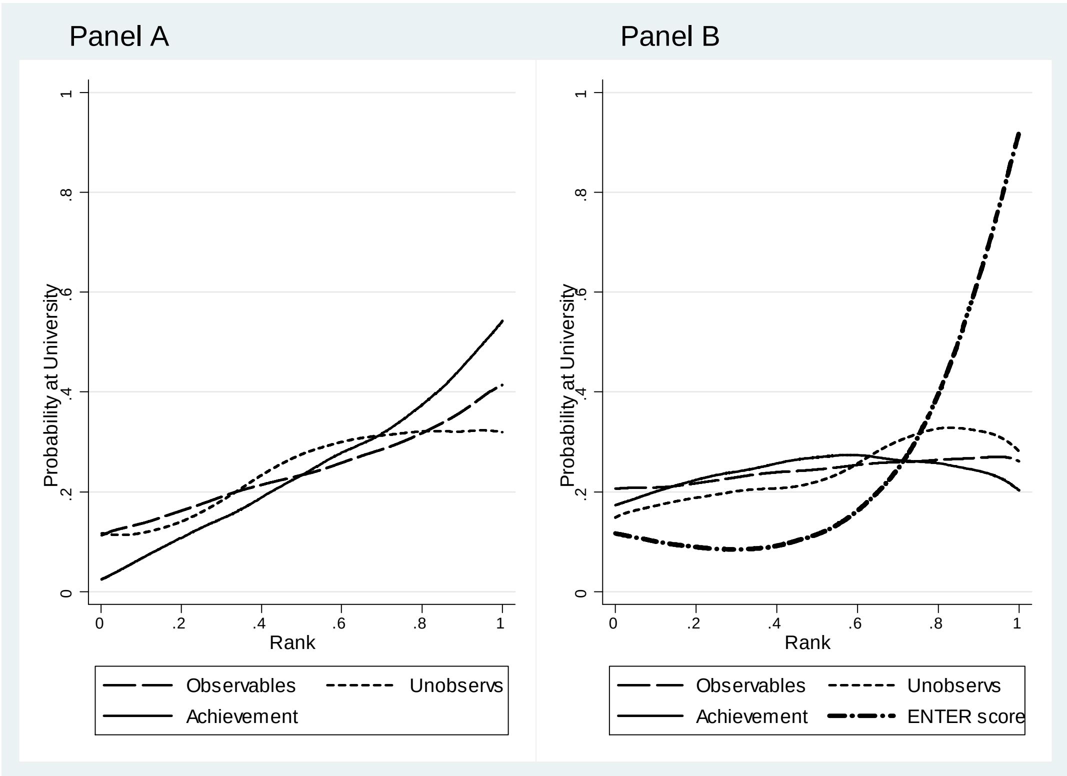


Figure 4: Estimates of the impact of ninth grade academic achievement, other observables and estimated unobservables on university participation in Panel A, and with ENTER score accounted for in Panel B.

# Appendix A Supplementary Summary Statistics

Table A.1: Descriptive statistics by LSAY cohort and pooled.

| | Y95 Mean | Y98 Mean | Pooled Mean | Pooled Std dev. |
|---|---|---|---|---|
| University Participation | 0.364 | 0.361 | 0.363 | 0.481 |
| Proportion with an ENTER score | 0.580 | 0.592 | 0.586 | 0.493 |
| ENTER score (if had one) | 72.30 | 72.90 | 72.60 | 17.80 |
| Achievement | 50.50 | 50.30 | 50.40 | 8.30 |
| Non-constrained group | 0.080 | 0.086 | 0.083 | 0.276 |
| Potentially constrained group | 0.809 | 0.804 | 0.806 | 0.395 |
| Likely constrained group | 0.111 | 0.110 | 0.111 | 0.314 |
| Male | 0.478 | 0.509 | 0.493 | 0.500 |
| Student born overseas | | | | |
| English speaking country | 0.029 | 0.024 | 0.027 | 0.161 |
| Non-English speaking country | 0.069 | 0.069 | 0.069 | 0.254 |
| Father has degree | 0.190 | 0.213 | 0.201 | 0.401 |
| Mother has degree | 0.177 | 0.194 | 0.185 | 0.388 |
| Indigenous | 0.023 | 0.024 | 0.023 | 0.151 |
| Metropolitan | 0.545 | 0.535 | 0.540 | 0.498 |
| New South Wales | 0.332 | 0.328 | 0.330 | 0.470 |
| Victoria | 0.245 | 0.234 | 0.240 | 0.427 |
| Queensland | 0.183 | 0.201 | 0.192 | 0.394 |
| South Australia | 0.075 | 0.077 | 0.076 | 0.264 |
| Western Australia | 0.107 | 0.106 | 0.106 | 0.308 |
| Tasmania | 0.030 | 0.027 | 0.029 | 0.167 |
| Northern Territory | 0.008 | 0.008 | 0.008 | 0.089 |
| Australian Capital Territory | 0.019 | 0.019 | 0.019 | 0.137 |
| Self-confidence | 49.90 | 50.30 | 50.10 | 3.19 |
| Observations | 8,320 | 7,687 | 16,007 | |

Source: Estimated from LSAY 95 and LSAY 98.

Table A.2: Descriptive statistics by credit constraint group.

| | Groups | | | |
|---|---|---|---|---|
| | Unlikely Constrained | Potentially Constrained | Likely Constrained | Total Mean (Std.Dev.) |
| University Participation | 0.679 | 0.353 | 0.199 | 0.363 (0.481) |
| Proportion with an ENTER score | 0.864 | 0.583 | 0.398 | 0.586 (0.493) |
| ENTER score (if had one) | 83.10 | 72.00 | 62.40 | 72.60 (17.80) |
| Achievement | 55.80 | 50.40 | 46.00 | 50.40 (8.30) |
| Male | 0.540 | 0.489 | 0.487 | 0.493 (0.500) |
| Student born overseas | | | | |
| English speaking country | 0.048 | 0.027 | 0.012 | 0.027 (0.161) |
| Non-English speaking country | 0.060 | 0.065 | 0.105 | 0.069 (0.254) |
| Father has degree | 0.628 | 0.178 | 0.045 | 0.201 (0.401) |
| Mother has degree | 0.451 | 0.176 | 0.050 | 0.185 (0.388) |
| Indigenous | 0.004 | 0.023 | 0.042 | 0.023 (0.151) |
| Metropolitan | 0.813 | 0.504 | 0.598 | 0.540 (0.498) |
| New South Wales | 0.348 | 0.331 | 0.308 | 0.330 (0.470) |
| Victoria | 0.269 | 0.235 | 0.251 | 0.240 (0.427) |
| Queensland | 0.128 | 0.195 | 0.215 | 0.192 (0.394) |
| South Australia | 0.086 | 0.076 | 0.067 | 0.076 (0.264) |
| Western Australia | 0.137 | 0.105 | 0.095 | 0.106 (0.308) |
| Tasmania | 0.012 | 0.027 | 0.052 | 0.029 (0.167) |
| Northern Territory | 0.000 | 0.009 | 0.005 | 0.008 (0.089) |
| Australian Capital Territory | 0.019 | 0.021 | 0.005 | 0.019 (0.137) |
| Self-confidence | 49.90 | 50.00 | 50.70 | 50.10 (3.19) |
| Observations | 1,614 | 13,086 | 1,307 | 16,007 |

Source: Estimated from LSAY 95 and LSAY 98.

# Appendix B Supplementary Results

Table B.1: Parameter estimates of model explaining student plans to attend university when surveyed in ninth grade.

| Variable | Parameter Estimate |
|---|---|
| Achievement | -0.139** |
| | (0.058) |
| $(\text{Achievement})^2$ | 0.004*** |
| | (0.001) |
| $(\text{Achievement})^3/100$ | -0.003*** |
| | (0.001) |
| Male | -0.416*** |
| | (0.021) |
| Student overseas born | |
| English speaking country | 0.104** |
| | (0.048) |
| Non-English speaking country | 0.769*** |
| | (0.043) |
| Father has degree | 0.365*** |
| | (0.028) |
| Mother has degree | 0.308*** |
| | (0.024) |
| SES (parents' occupations) | 0.005*** |
| | (0.000) |
| Self-confidence scale | 0.038*** |
| | (0.004) |
| Indigenous | -0.082 |
| | (0.060) |
| Metropolitan | 0.214*** |
| | (0.024) |
| Y98 cohort | 0.097*** |
| | (0.024) |
| Constant | -1.752* |
| | (0.959) |
| State indicators | **Yes** |
| Observations | 26,717 |