# Does academic success affect outcomes in graduate labour markets?

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# Declaration

Except where appropriately acknowledged, this thesis is my own work, has been expressed in my own words and has not previously been submitted for assessment.

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## Abstract

This thesis explores the impact that university grades have on the labour market outcomes of Australian students graduating from undergraduate study. Using cross-sectional data of students from the University of Adelaide, we investigate the effect that a student's grade point average has on both the likelihood of employment and expected wages. We build on previous literature by using instrumental variable estimation and sample-selection models to correct for potential biases in the model, which also allows us to look at these two measures simultaneously. Our results suggest that when the models of these two outcomes are estimated simultaneously, area of study is the main source of variability in wages amongst individuals. Students' grades and employment history, which may have been expected to also influence wages, were found to only have a significant impact on employment probability. This challenges previous studies on graduate starting wages, which find positive impacts of these measures on wages when they were looked at in isolation of employment outcomes.

# Contents

# 1. Introduction

The university sector in Australia has grown strongly over the previous few decades. Between 1982 and 2015, the proportion of Australians who hold a bachelor level degree or higher has increased from 5.8 per cent to 25.4 per cent [Australian Bureau of Statistics, 2015a]. As the supply of university graduates increases, the return to these degrees appears to be decreasing. While individuals with at least undergraduate qualifications have increased labour force participation, lower rates of unemployment, and higher salaries than those without tertiary qualifications, the gap in each of these areas has fallen since 2010 [Australian Bureau of Statistics, 2015b].

Studies on the return to educational attainment tend to focus on the impact on expected wages. However, if the gap in employment levels between groups who do and *do not* hold a bachelor's degree are potentially diminishing, it is worth considering the labour market outcomes of graduates in the context of employability, not just wages. Although wages and employability are highly connected, factors may affect them differently. For example, an area of study with an over-supply of graduates may provide high wages for those who find employment, but also be associated with low levels of employment. Different students may also place different weights on wages and employment likelihood. It therefore is beneficial to look at both of these measures of labour market success.

This thesis aims to show the ways in which academic success, as measured by a student's grade point average (GPA), can influence both expected wages and employment probability. Although we may expect area of study to be the main cause of variation in wages and aggregate employment levels of graduates, signals of ability could be expected to explain differences amongst graduates with similar qualifications. Previous studies have found a significant positive relationship between GPA and starting salaries for Australian graduates (e.g. Chia and Miller [2008]). However, these results were based only on the wage measure of graduate outcomes, ignoring the potential endogeneity of GPA due to unobserved factors that affect employment outcomes (e.g. relevant work experience or extracurricular activities), or sample selection bias from ignoring graduates not in full-time employment.

This thesis aims to build on the current literature by applying different methodologies to address these issues of endogeneity and sample selection bias. The presence of endogeneity is explored through instrumental variable (IV) estimation, with *'degree satisfaction'* introduced as an instrument for GPA. We also apply a multinomial selection model to correct for sample selection bias within our model. This multinomial selection approach has the advantage of answering our questions on both wages and employment outcomes simultaneously. To the best of our knowledge, the multinomial selection approach has not been applied to the analysis of wage returns in the graduate labour market.

We use 2010-2015 data from the Australian Graduate Survey on undergraduate students from the University of Adelaide, combined with university data on academic performance, to answer our question. This dataset provides useful information on graduate wages, as well as outcomes of those who were not in employment at the time of the survey.

Our results suggest that our baseline model, which closely mirrored those used in other studies, suffers from sample selection bias, but not endogeneity. Once this sample selection issue is corrected, area of study is the main source of variability in wages. Academic success and work experience were found to only have a significant impact on employment status.

The rest of this thesis proceeds as follows. Section 2 provides a summary of the literature on the returns to education and graduate labour markets. Section 3 introduces the econometric model, discusses the issues of endogeneity and sample selection bias in the model, and introduces the estimation techniques used to deal with these issues. Section 4 describes the data. Section 5 presents the estimation results and the key findings. Finally, Section 6 concludes the thesis.

## 2. Literature Review

The relationship between educational attainment and labour market outcomes has been the focus of a considerable amount of economic research. There are a number of explanations for this relationship. The first is the human capital theory of Becker [1962], which states that individuals invest in themselves in order to increase their labour productivity. Education is assumed to lead to increases in individual productivity, and so investing in education is expected to lead to an increase in wages. This idea was applied by Mincer [1974], who theorised a log-linear relationship between an individual's wage, their total level of educational attainment and their labour market experience. This relationship has been used widely in empirical work on the determinants of wages (e.g. Card [1993], Angrist and Krueger [1990]).

An alternative explanation of the relationship is the signalling theory of Spence [1973]. This theory suggests that even if education provided no human capital benefits, education could still positively impact wages through signalling. Those with a higher ability are assumed to have a lower cost/effort of attaining education, creating a stable equilibrium in which only high ability individuals enrol in higher education. This allows firms to identify ability through level of education, even if this education has not increased labour productivity. This argument is particularly relevant in graduate labour markets, as graduates likely have limited relevant labour market experience from which their productivity can be observed.

A major stream of the literature on education has focused on using the work of Becker [1962] and Mincer [1974] to estimate the marginal wage return to an additional year of educational attainment. This question has received particular interest due to the issue of self-selection of high ability individuals into education. Griliches [1977] discusses the issue in which ability is unobserved, and must either be omitted or proxied by some measure of ability/intelligence such as an IQ test. If there is no strong proxy for ability, this self-selection into education can lead to 'ability bias', in which the estimated return to education is endogenous, as it is correlated with the unobserved ability variable that is captured through the error term. If this model is estimated using least- squares, the true impact of ability is partially captured by the education variable due to the correlation between them, which would be expected to cause an upward bias on estimates of the return to education.

This problem of endogeneity in the estimated returns to education has been explored in a number of studies. Angrist and Krueger [1990] used quarter of birth as an instrument for education, noting that compulsory education laws based upon age have an asymmetric impact on the education levels of individuals depending on their birth month. The impact on educational attainment arises as some students reach this age at which they can leave school earlier in their education than others, and so on average those born in certain quarters of the year have lower levels of educational attainment. They argue that birth month should not impact earnings through any other channel, and therefore should be a valid instrument for education. A number of other studies have used alternative instruments to address this problem. Angrist and Krueger [1992] used Vietnam War lottery numbers as an instrument for educational attainment. Within the national service lottery, certain numbers were more probable than others, so the likelihood of being drafted varied across individuals. Students were given a pardon from conscription, which is believed to have increased the number of university enrolments during this period. The choice of instrument was therefore based on the hypothesis that individuals who otherwise would not have enrolled in college would do so to avoid conscription, and that the likelihood of this occurring increased with the likelihood of their lottery number being selected. Butcher and Case [1994] use the sibling composition of females as an instrument, as they present evidence that females with more siblings (particularly other sisters) are less likely to receive a college education. Card [1993] used the presence of a nearby college as an instrument for educational attainment. This was chosen as college proximity is expected to encourage education by minimising the costs of attainment, but should otherwise be uncorrelated with ability. Kane and Rouse [1993] use a similar approach, in which distance to the nearest 2-year and 4-year colleges and state specific tuition rates were used as instruments for educational attainment.

These studies all reported increased returns to education in the instrumental variable estimates compared with the least-squares results. This contradicts the perceived upward bias on the return to education that the omission of ability is expected to cause. Using the microeconomic model of educational attainment developed by Becker [1967], which assumes the human-capital returns to education exhibit diminishing returns, Card [1995] suggests that the reason for this counter-intuitive result is that the individuals that many of these instruments target (those whose educational attainment is increased by some treatment) are potentially receiving less education due to higher discounting of future benefits. This could be the result of lack of financing options, or distaste for education. If higher discounting is the cause, these individuals will stop receiving education when their marginal return to education is higher than those who undertake further study. Since those individuals whose level of education were affected by the treatments had higher marginal returns to education at the point they stopped studying, estimates for the return to education increased when these instruments are used. The other issue with these instrument choices is that they are weak, i.e. they are poorly related to ability. The introduction of the literature on weak IVs has raised concerns about the quality of many empirical applications of IV methods. For example, Bound et al. [1995] show that the quarter of birth instrument is only weakly correlated to educational attainment, and therefore its use as an instrument leads to a bias that is on the same scale as the original endogeneity bias. These studies therefore highlight not only the potential endogeneity that arises in studies on the return to education, but also the importance of selecting good instrument variables.

One shortfall of the standard wage equation of Mincer [1974] is that it treats additional years of education identically. This ignores the variation in the wage returns of different education programs. Tertiary education is one such area where comparisons amongst individuals with similar levels of attainment are important. Card and Krueger [1990] have found that the quality of an institution providing university education has a significant impact on the return to education. The content of university education has also been shown to be an important determinant of earnings [Del Rossi and Hersch, 2008].

Comparisons between individuals with similar education may be advantageous if this education provides proxies to compare ability between individuals. Within the context of university graduate labour markets, the most obvious measure of ability is a student's grades. A positive relationship between GPA and wages has been found in a number of studies. Thomas [2000] studied wages of college graduates from a number of U.S. universities. He found that GPA and area of study were strong predictors of wages.

A number of studies have been produced on the Australian graduate labour market. These studies tend to be dominated by the Australian Graduate Survey (AGS),[1] which provides information on graduate starting wages. This survey does not have any suitable measures of ability though. As a result, research questions are not based

[1]The AGS is a survey of graduates from Australian universities, taken at the time of graduation

on issues of ability, but rather target other issues that are feasible given the dataset, such as over-education[2] or wage discrimination against particular demographics.

The concept of over-education refers to the case in which an individual's qualifications are above what is required for their current employment. The associated wage penalty is a comparison between the wages of these graduates and equally skilled graduates who are working in areas that require this level of education. Carroll and Tani [2013] combine AGS data with a follow up survey taken three years after graduation. Results show that over-education was most prevalent in science, society & culture, and creative arts. Many of those who considered themselves over-educated at the time of graduation were no longer uneducated three years later, suggesting they were able to move up to positions relevant to their qualifications. The escape from over-education was particularly high for the younger respondents. The survey found a large significant wage penalty for those working in positions where they were considered over-educated of around 10 per cent. This penalty did not appear to be significantly different between areas of study though.

Gender wage discrimination has also been explored using AGS data. Graduate Carers Australia [2014] have shown recent evidence of gender discrimination in graduate labour markets. The extent of this discrimination was reduced when information about courses was included, giving some credence to the suggestion that apparent gender discrimination is the result of women selecting degrees with lower expected graduate salaries. However, even after controlling for course choice and non-gender personal characteristics, the study found graduate salaries of women were 4.4 per cent lower.

Despite being a less explored issue, there is some evidence of a relationship between

[2]The AGS has a question regarding whether university qualifications were necessary for the individuals current employment

academic success and graduate wages in Australia. Chia and Miller [2008] combine the AGS dataset with background information of students from the University Of Western Australia. Their results suggest that academic achievement, as measured by a student's weighted average mark, was one of the strongest predictors of graduate employment, alongside area of study. They also found that high school characteristics and achievements were not useful predictors of starting salaries.

Although a positive relationship between academic ability and wages seems unsurprising, it is worth considering at what stage of employment the wage premium for those with high ability become noticeable. Murnane et al. [1995] investigated the impacts of cognitive ability (as measured by test scores) on high school graduates. They found that wage impacts of cognitive ability were not significant two years after graduation, but they did have a significant positive impact six years after. This relationship held amongst varying education levels. Although high school graduates and university graduates may face different types of labour markets, they are both characterised by limited relevant experience. This could suggest that wage differentials are limited until sufficient experience has been gained, leaving little room for ability to dictate wage differentials in early graduate employment.

Wages are not the only way to measure graduate outcomes though. Employment outcomes have also been modelled by likelihood of employment. Ballarino and Bratti [2009] use data from graduates of Italian universities between 1992–2001 about their employment (or study) outcomes three years after graduation to fit a multinomial logit model of graduate outcomes. The outcomes were classified as: stable employment, unstable employment, further study and unemployment. Separate results were fitted for each year of graduation. The results from this paper suggest that graduates from hard sciences, engineering and 'hard social sciences' (e.g. statistics, economics) were significantly more likely to be in stable employment three years after graduation.

Given the primary industries in Italy, these differences were assigned to the low supply of graduates within these sectors, rather than high demand. The report also found evidence of significant changes in these estimates over the sample.

The issue of sample selectivity bias in labour markets was introduced by Gronau [1973]. This paper developed a model of wages for married women. Married women were perceived as more likely to have reservation wages than other workers, as the household was likely to already have one income from their husbands. To correct for the women who did not enter the labour market due to their reservation wage being above their wage offers, the model was estimated using the sample selection correction of Heckman [1979]. Results suggested that estimates that failed to make this correction underestimated the returns to human capital attainment. Gronau [1973] suggested that such sample selection corrections for wage equations are necessary whenever the population of interest had a significant portion not in the labour market.

Multinomial selection models have been used to estimate the returns to educational attainment in previous literature. For example, Meer [2007] explored the wage returns to different pathways of schooling: academic, technical, general and business. A multinomial logit model was fitted to predict which of these pathways a particular individual would choose. Correction terms for each of these pathways was then added to each of the pathway wage equations. This model was used to identify whether students were enrolling in the course that maximised their expected earnings. On average, the model suggested that students studying in the academic or technical pathways had correctly self-selected. Those in the general pathway would, on average, have a higher expected wage if they enrolled in the technical pathway, while those studying in the business pathway would have a higher expected wage if they enrolled in the academic pathway. This model was used to argue against the proposed removal of technical stream from U.S. schools during the early 2000's.

Blacklow and Nicholas [2008] use Australian Graduate Survey data for graduates of the University of Tasmania to estimate the probability of having found employment by graduation date using a probit estimation. They apply a multinomial-selection treatment to account for self-selection of students into degrees based upon ability. They also use a Heckman sample-selection correction to their probit model to account for those who did not enter the labour force. The issue of self-selection into degrees is important in this context as no ability proxies were available in their dataset. The results of this paper find a negative correlation between the errors determining further study and initial graduate employment probability. The authors use these results to suggest that, in their sample, those undertaking further study would not be expected to have otherwise performed well in the labour market. Rather, further study may be the chosen due to poor labour market potential. Self-selection and sample selection bias were found to be present in their data, as their estimates changed significantly after the corrections were applied.

This thesis aims to build on this existing studies of the Australian graduate labour market by applying methods to correct for endogeneity and sample selection bias that have been used in the aforementioned literature.

# 3. Econometric Specification and Methodology

## 3.1 Model Specification

The model used in this thesis is based upon the classic wage equation of Mincer [1974], with the inclusion of ability proposed by Griliches [1977]. Modifying the Mincer equation to make it more relevant to the graduate labour market, the following model was chosen:

$$\begin{aligned} log(Wage_i) &= \beta_0 + \beta_1 GPA_i + \beta_2 SEX_i + \beta_3 WKFY_i + \beta_4 INT \\ &\quad + \theta' DEG_i + \phi' DATE_i + \varepsilon_i, \end{aligned} \tag{3.1}$$

where Wage is the salary,[3] the grade point average (GPA) is used as a proxy for ability, SEX is a dummy variable indicating that the individual is female, WKFY is a dummy indicating whether the individual was employed during their final year of study, INT is a dummy variable indicating whether the individual was an international student, DEG is a vector of dummy variables for different areas of study, DATE is a dummy indicating which semester the student graduated, $\varepsilon$ is an error term, $\beta_j$ for $j = 0, ..., 4$, $\theta$, and $\phi$ are unknown coefficients to be estimated.

As discussed earlier, GPA is used to approximate ability in a number of studies of graduate starting wages (e.g. Chia and Miller [2008], Thomas [2000]). Although GPA may not be a perfect measure of ability, we expect it to be a reasonable proxy in the graduate labour market, as it is one of the main signals of ability available to employers. This may be less relevant in labour markets where workers have considerable

[3] Although we use annual salary rather than hourly wage as a measure of earnings, we refer to these earnings as wages for the rest of the paper to maintain consistency with the wage equation literature

experience, as previous work quality provides an alternative signal of ability.

Lack of relevant employment experience is a key characteristic of the graduate labour market. However, non-relevant work experience may still signal to employers that an applicant has desirable personal characteristics. A dummy variable indicating whether the student worked during their final year of study is therefore used as a proxy for experience. Unfortunately, this variable gives no indication on whether this work was relevant to a graduate's eventual employment.

Our focus in this thesis is on students graduating with an undergraduate degree(s). There is therefore minimal variability in years of educational attainment, which motivated the inclusion of education in the Mincer equation. To account for the importance that Mincer placed on education in wage determination, dummies for areas of study, as well as degree type (such as honours and advanced degrees), are included to capture the effect of differences in educational attainment. A dummy for double degrees is also included, although this variable is acting as a control for the fact that multiple study area dummies were selected, and thus should not be interpreted as the return to studying a double degree. A vector of dummies indicating which semester an individual graduated was included to control for variations in aggregate labour market conditions. A dummy variable was also included for international students due to employment restrictions placed on non-citizens (non-citizens are not permitted to work in the Australian Public Sector,[4] and private businesses face large visa costs of employing non-citizens [5]). Finally, a dummy variable were included for female students to account for the gender bias that has been found in previous studies of the Australian graduate labour market [Graduate Carers Australia, 2014].

[4] http://www.apsc.gov.au/publications-and-media/archive/publications-archive/citizenship-in-the-australian-public-service

[5] https://www.border.gov.au/Trav/Visa/Fees

## 3.2 Specification Issues

One potential pitfall in estimating our model is that our GPA variable may be endogenous. If GPA is correlated with unobserved factors that affect the quality of job that a person obtains, then the estimated marginal effect of GPA may be biased. For example, our weak proxy for experience does not distinguish between relevant and irrelevant experience. Individuals with strong preferences for employment may seek out more relevant work experience or extracurricular activities, while also putting in more effort to achieve high grades during university. This could create endogeneity problems in estimating the return to GPA if these unobserved experience/extracurricular activities factors are the actual causes of higher wages.

We propose two methods to deal with such issues. The first is to use instrumental variables (IVs) to obtain the exogenous component of our GPA variables, in order to estimate the true marginal return. If suitable instruments that are correlated with GPA but uncorrelated with these unobserved factors are available, it is possible to identify the return to GPA.

The second treatment of the issues in model (3.1) is related to sample selection. Within our dataset, about 26.3 per cent of bachelor degree graduates were in full-time employment by the date of graduation (see Table 4.1). If we expect that those who have those unobserved factors are more likely to be in the sub-sample who have found employment (so these factors affect both employment likelihood and quality), then there is a sample selection problem, which creates biases in the model estimates. Corrections for sample selection bias are therefore required.

Section 3.3 details our methodology to deal with these problems.

## 3.3 Methodology

### 3.3.1 Identification of the marginal effect of GPA

Identifying the marginal return to GPA using an IV estimator requires suitable instrumental variables. These variables must be correlated with GPA, but must be uncorrelated with the unobserved effects that are causing the endogeneity, and should not affect wages themselves. In this thesis, we use *entry score* and *degree satisfaction* as instruments for GPA.

Entry score is measured by the individual's high school results, which were used to gain entrance to university. Birch and Miller [2006] have found a strong positive relationship between high school and university grades for Australian students. The results of Chia and Miller [2008] suggest that high school grades were not a significant determinant of graduate starting wages, once university grades are accounted for. Therefore, if high school grades are not correlated with these same unobserved factors, we expect that they are a suitable choice.

Degree satisfaction is measured through individual ratings on the quality of their university program. There are a number of ways that satisfaction could be related to GPA. If courses are better at meeting students' needs, they are likely to be more satisfied with their degrees. This may also improve student engagement and effort, which could be expected to increase grades. Alternatively, higher satisfaction could be driven by grades. A number of studies [Langbein, 2008] [Krautmann and Sander, 1999], have found students rate staff who gives higher grades more favourably in performance reviews. Since we only seek a correlation between the IV and endogenous variable, it is not relevant for our purpose which way this relationship is driven. We would not expect student satisfaction to be affecting wages through any other channel, and have no reason to believe it would be correlated with any other unobserved factors. We can therefore expect that degree satisfaction is a suitable instrument for GPA.

Let $Z_1$ denote all explanatory variables in (3.1) except GPA, and $Z_2$ denote a vector containing our IVs, then the problem can be written as a set of simultaneous equations:

$$\begin{aligned} log(Wage_i) &= \beta_0 + \beta_1 GPA_i + \beta_2 SEX_i + \beta_3 WKFY_i + \beta_4 INT \\ &\quad + \theta' DEG_i + \phi' DATE_i + \varepsilon_i, \qquad (3.2) \\ GPA_i &= \delta Z_1 + \eta Z_2 + v_i, \qquad (3.3) \end{aligned}$$

This model in (3.2) and (3.3) can be estimated using two-stage least-squares (2SLS). As the elements of both $Z_1$ and $Z_2$ are orthogonal to $\varepsilon_i$, (3.3) is capturing the component of our GPA variable that is orthogonal to the errors, with the endogenous component captured in the error term $v_i$. The original GPA variable is then replaced in (3.2) by the fitted value of GPA from (3.3). Since this fitted GPA variable is orthogonal to $\varepsilon_i$, the endogeneity problem is removed, and (3.2) can be estimated consistently using least-squares estimation.

### 3.3.2 Correcting for sample selection

The large proportion of students not in full-time employment in the period following the completion of studies could be a source of sample selection bias. A test for sample-selection bias in (3.1) is therefore required. This thesis will employ two types of sample selection corrections. First, a Tobit II correction is applied, using the two-step method of Heckman [1979] to test for sample selection bias. Next, a multinomial logit sample-selection correction is applied to (3.1). This expands on the Tobit II model by exploiting information regarding the different reasons for not being in full-time employment.

The correction model of Heckman [1979] is first used to test if the estimates of (3.1) are biased from using only those who are employed full-time in the sample. In this model, we must first specify a selection rule, which denotes whether an individual is in full time employment. The wage of an individual is therefore only observed if the selection rule is satisfied. This selection model should be fitted with all explanatory variables from the wage equations, as well as at least one variable excluded from the wage equation to avoid multicollinearity issues. We have chosen a quadratic age term and home postcode socioeconomic ranking as the exclusionary restriction variables. Letting $X$ denote a vector containing all explanatory variables from (3.1) and $Z_3$ contain the age and postcode socio-economic background variables, the following system describes our employment-wage model:

$$\begin{aligned} log(Wage_i^*) &= X_i'\beta + \varepsilon_{1i}, && (3.4) \\ h_i^* &= X_i'\gamma + Z_{3i}\Pi + \varepsilon_{2i}, && (3.5) \end{aligned}$$

where (3.5) is a binary choice model describing whether an individual is employed full-time. Let $h_i = 1$ denote that individual $i$ is in full time employment, and $h_i = 0$ if not. The wage observation rule can then be described as:

$$\begin{aligned} log(Wage_i) &= log(Wage_i^*), h_i = 1 \text{ if } h_i^* > 0 \\ log(Wage_i) &\quad \text{not observed}, h_i = 0 \text{ if } h_i^* \leq 0 \qquad (3.6) \end{aligned}$$

The parameters from (3.4) can be estimated consistently by conditioning on the selection rule, since only the data that follows the selection rule is observed. The conditional expectation of wages is:

$$E[log(wage_i)|h_i = 1] = X_i'\beta + E[\varepsilon_{1i}|h_i = 1] \qquad (3.7)$$

Heckman [1979] showed that if binary choice model in (3.5) is fitted using a probit model, the conditional expectation of the error in (3.7) can be written as:

$$\begin{aligned} E[\varepsilon_{1i}|h_i = 1] &= E[\varepsilon_{1i}|h_i^* = X_i'\gamma + Z_{3i}'\Pi + \varepsilon_{2i} > 0] \\ &= \sigma_{12}\frac{\phi(X_i'\gamma + Z_{3i}'\Pi)}{\Phi(X_i'\gamma + Z_{3i}'\Pi)} \end{aligned} \tag{3.8}$$

where $\phi(.)$ is the standard normal probability density function (PDF), and $\Phi(.)$ is the standard normal cumulative distribution function (CDF). If $\sigma_{12}$ is non-zero, the error term has a non-zero expectation, which leads to biased least-squares estimates. Let us define the inverse Mills ratio (IMR) as:

$$\lambda_i = \frac{\phi(X_i'\gamma + Z_{3i}'\Pi)}{\Phi(X_i'\gamma + Z_{3i}'\Pi)} \tag{3.9}$$

Heckman's method involves fitting the selection rule using a probit model, and using the above expectation to correct the wage equation by including the IMR term as a separate variable, giving the following model:

$$log(Wage_i) = X_i'\beta + \alpha\lambda_i + e_i \tag{3.10}$$

The remaining error term $e_i$ now has a zero conditional mean, so (3.10) can be estimated consistently using least-squares estimation. The coefficient $\alpha$ on the IMR in (3.10) is an estimate for $\sigma_{12}$. We can therefore conclude that the errors of the wage and selection equations are correlated if this coefficient is statistically significant, which would imply that the original model suffered from sample selection bias.

If sample selection bias is present, then we can obtain a more informative model by using the full information on graduates who were not in full time employment at the time of graduation. This group can be split in four categories: unemployed, part-time workers, further study and not in the labour force.

The Heckman model's correction term is formed by exploiting the correlation between the errors in the first and second stage of the model, where these correlations are unobserved determinants of the two models. However, we may expect that the unobserved factors that affect the likelihood of individuals being in different employment statuses would not be correlated with wages in the same way. Personality characteristics that make an individual more inclined to enrol in further study, such as work ethic, may be positively correlated with wages. Factors that instead increase the likelihood of not being in the labour force, such as distaste for employment, may negatively affect wages. We would therefore expect a model that treated these employment categories as different outcomes to be more accurate as it fully exploits the correlation between errors in the selection process and wages.

In order to exploit this additional information about those not in full time employment, the model will be estimated using a multinomial logit selection model. This model follows the same intuition as the Heckman model. The first stage of this model again describes the selection rule, except where the first stage is a multinomial logit model, rather than a probit. The wage is observed only if an individual is working full time, although now there are separate outcomes in the selection stage for each of the four other employment categories. The correlation between the errors in each of the equations of the multinomial model and the second stage creates a bias in the second stage that must be corrected. This model will use the same exclusionary restrictions as the Heckman estimation, and can therefore be denoted as:

$$log(Wage_i^*) = X_i\beta + \varepsilon_{1i} \quad (3.11)$$

$$h_{ij}^* = X_i'\gamma_j + Z_{3i}'\Pi_j + v_{ij}, \quad \forall j = 1, ..., 5 \quad (3.12)$$

where (3.12) is a multinomial outcome model describing individual *i's* employment status, where $j$ denotes the employment categories. Let outcome 1 denote full-time employment, while part time employment, unemployment, not in the labour force and further study are categorised as 2,...,5 respectively. Then if we define $h_i^{max} =$

$\max_{j\neq 1}(h_i^j)$, the observation rule is described by:

$$\begin{aligned} log(Wage_i) &= log(Wage_i^*), h_{i,1} = 1 \text{ if } h_{i,1}^* > h_i^{max} \\ log(Wage_i) &\quad \text{not observed}, h_{i,1} = 0 \text{ if } h_{i,1}^* < h_i^{max} \end{aligned} \tag{3.13}$$

McFadden et al. [1973] showed that when the selection process is fitted using a multinomial logit, the probability of individual $i$ being in category $k$ can be re-written as:

$$\begin{aligned} P_i^k &= P(h_i = k|Z) \\ &= \frac{exp(\eta_k' Z_i)}{\sum_j exp(\eta_j' Z_i)} \end{aligned} \tag{3.14}$$

The multinomial logit selection model was originally proposed by Lee [1983]. However, this estimation method placed strong assumptions on the errors of the multinomial selection model; namely that the correlation between each of the errors in the selection models and the second stage error have the same sign. Given that the advantage of the multinomial selection model was that it allowed us to exploit different correlations between employment statuses and potential wages, this assumption is overly restrictive for this context.

Dubin and McFadden [1984] proposed an estimation technique, that instead relied on the assumption that the correlation between multinomial selection errors and errors in the second stage were linear, and that these correlations summed to zero. Again, this restriction could be overly restrictive.

Bourguignon et al. [2007] propose an adaptation to the estimator of Dubin and McFadden [1984] that relaxes the requirement of correlations summing to zero, but retain the linearity assumption. In their paper, the three methods are compared through Monte-Carlo simulations. The Bourguignon et al. [2007] adaption is shown to outperform both earlier estimators, except in the case when the restrictive assumptions of these models were valid. The Monte-Carlo simulations also showed that the correction performs well even when the independence of irrelevant alternatives (IIA) assumption of the multinomial logit model is not valid. This result is important in our context, as it seems unlikely that the probability of entering a particular employment category would maintain a consistent relative probability with another category if a third category were no longer available. For these reason, the method of Bourguignon, Fournier and Gurgand will be used in this thesis. This method offers the following correction method:

$$y_i = x_i\beta + \sigma\left[r_1^* m(P_i^1) + \sum_{j=2,\ldots,M} r_j^* m(P_i^j)\frac{P_i^j}{P_i^j - 1}\right] + w_i \tag{3.15}$$

where $r_j^*$ is the fitted correlation between the error of the j$^{th}$ selection equation $e_j$ and the wage equation error $\varepsilon$,

$$m(P_j) = \int J(v - logP_j)g(v)dv, \tag{3.16}$$

$g(.)$ is the density function of the Gumbel distribution, and $J(.) = \Phi^{-1}(G(.))$, where $\Phi(.)$ is the standard normal c.d.f and $G(.)$ is the c.d.f of the Gumbel distribution. As with the Heckman model, significance and sign of the $r_j^*$ correlation terms helps identify the source and direction of sample selection bias.

# 4. Data

## 4.1 Data Sources

Our dataset is a combination of two datasets from graduates of the University of Adelaide (UoA) between 2010-2015. The first dataset is from the Australian Graduate Survey (AGS). The AGS is an optional survey given to all students who graduate from an Australian university. The questions relate to their studies at university and their satisfaction with their degree, as well as their post-study labour market outcomes. This dataset was matched with a second dataset, provided by the University of Adelaide, which gave more detailed information about individual students' grades and background.

## 4.2 Model Variables

The dependant variables used in this thesis are graduate outcomes, measured by both wages and employment status.

The wage data available is based on a survey question on the estimated yearly salary of those in employment, with no information on hours worked. For this reason, those working part time are excluded from the sample, as they cannot be directly compared through an hourly wage. Full time workers with a wage below the 2010 Australian minimum wage of $29,600 [Fair Work Australia, 2010] were excluded as potential false responses,[6] as were those whose responses were deemed to be unrealistically high.[7]

[6] Most of these responses appear to be within the range of realistic weekly or monthly salaries

[7] The amount chosen as unrealistically high was an annual salary $\geq \$300,000$, which resulted in

For the first stage of our multinomial selection model, individuals are classified into particular employment status categories, based on work hours, study and job seeking. Using responses to questions from the AGS survey, graduate employment status variables were classified into the following five categories: working full-time, working part-time, unemployed, not participating in the labour market and continuing with further study. Individuals were classified as working part-time, working full-time or studying using responses to questions about employment status and further study from the AGS survey. Unemployed workers were categorised as those who were not in any of the employment or study categories, but indicated that they had applied for work. Graduates not participating in the labour force were classified as those not in any of the employment or study categories who indicated that they had not sought employment.

Graduates continuing with undergraduate study that was enrolled in before completion of a previous degree (e.g. students enrolled in a double degree who were graduating from the first of their two degrees) were also excluded, as this study decision was not considered to be an equivalent decision to true graduates.

Table 4.1 below shows the distribution of employment status within our dataset. These data shows that only a relatively low proportion of graduates from our dataset have entered full time employment at the date of graduation.

Table 4.1: **Graduate employment status**

| **Category** | **Number** | **Percentage** |
|---|---|---|
| Working Full-Time | 3805 | 26.25 |
| Working Part-Time | 2998 | 20.68 |
| Unemployed | 1589 | 10.96 |
| Not Participating | 1643 | 11.33 |
| Further Study | 4462 | 30.78 |
| Total | 14497 | 100.00 |

the removal of 45 observations from the dataset

The explanatory variables are those used in (3.1). The primary explanatory variable of interest in this thesis is GPA. Grade data was available for each year of study, although this was not split between courses or degrees undertaken. These variables were combined as a weighted average to form an overall GPA variable.[8]

To measure the impact of different fields of study, a set of dummy variables were included in the baseline model. The dataset contains graduates from a range of degree types. For ease of comparison, only the data for students graduating with undergraduate degrees (bachelor or honours) were used. These degrees were merged into twelve different categories; agricultural science, architecture, business and economics, engineering, health sciences, law, mathematics and physical sciences, medicine and dentistry, music, and teaching. Any double/concurrent combination of degrees were classified as having a value of one for the dummy variables associated with each individual degree. For full details of how these degrees were categorised, see Table A.1. A dummy variable for honours and advanced degrees was also included.[9]

As a measure of employment experience, a dummy variable was formed from the AGS survey questions indicating whether or not the respondent was employed during their final year of university. Gender was controlled for through a dummy variable indicating whether the respondent was a female. International student information was provided as a response to the AGS survey. This was included as a dummy variable indicating whether a student had responded that they were not a permanent resident of Australia.

Finally, dummy variables indicating the semester of graduation were obtained from the AGS data set. The University of Adelaide (UoA) has two graduation ceremonies

[8] To see how GPA is calculated, see https://www.adelaide.edu.au/enrol/gpa/

[9] Advanced Degrees are a type of degree offered at the University of Adelaide to high ability students. They are modified versions of regular degrees (e.g. Bachelor of Science (Advanced)) that follow the typical structure of standard degree, but may involve special courses or have stricter course requirements. See https://www.adelaide.edu.au/study/high-school/whatcanistudy/degree-types/

each year, one in April (semester 1 graduation) and one in September (semester 2 graduation). These graduation ceremonies occur several month after students complete their final courses. The variables used here refer to these dates, rather than the time at which students finished their final courses.

The instrumental variables used in this thesis were *degree satisfaction* and *entry score*. The degree satisfaction variable is measured using the survey response questions relating to university experience (see Appendix A.1.1). 29 questions were available on degree satisfaction, each rated on a Likert scale from 1-5 (strongly disagree to strongly agree). These responses were combined to form a satisfaction dummy indicator, which took the value of 1 if the median of these responses was 4 or greater, and 0 if the median was 3 or below.[10] For students with multiple surveys (those who may have graduated multiple degrees), all responses to the university experience questions were included in this median.

The entry score variable was measured using the student's TER/ATAR (high school graduation score used to gain enrolment into university). Although this was not available for all students in our dataset, approximately 80 per cent of the sample of those working full time were maintained. While this excluded a higher proportion of international students, we do not expect this to be an issue as the distribution of GPA between the two groups is close.

The exclusionary restrictions used in this thesis were age (included in quadratic form) and socio-economic background of the individual's home postcode. The age variable was measured in years, but was accurate up to the months relative to the month of graduation. The socio-economic background variable was measured from

[10]Using the mean of responses to form a continuous variable was also considered. However, this instrument performed worse on orthogonality tests. This could be the results of reverse causality between satisfaction and wages, where those who found higher paying jobs rated their degrees more favourably as a result. The fact that this only shows up on the continuous measurement suggests this effect may have been persistent but of low magnitude.

the individual's home postcode registered on the UoA student database. These data come with a socio-economic ranking of postcodes into three categories: low, medium and high. The medium case is treated in this study as the base case, so the estimated effects of the low and high dummy variables are interpreted as relative to being from a medium socio-economic area. There were a number of postcodes where the socio-economic background was unknown, however this was mostly related to international students, so this variable was removed to avoid multicollinearity with the international student variable.

## 4.3 Data Description

We now investigate whether the correlations between variables that we have previously discussed are present in our dataset.

Our question is formulated on the expectation that GPA has a positive relationship with labour market outcomes. Table A.3 shows a positive correlation between GPA and wages, particularly amongst those with a GPA above 6. Table A.6 shows a positive relationship between GPA and employment. Those with higher GPA appear more likely to either be working full-time or enrolled in further study, and are less likely to be unemployed or not participating in the labour market. Again, this correlation appears to hold between most bands of GPA, but is most noticeable for those with a GPA above 6. These observations lend support to the expected positive relationship between GPA and labour market outcomes.

As we observe in Table A.5, there are noticeable differences between average starting wages of graduates between areas of study. Medicine graduates have the highest average starting wages while architecture and arts and social sciences have the lowest starting wages amongst graduates with a bachelor degree. There are also considerable differences in the distribution of graduates into different employment statuses between areas of study. Table A.4 shows that engineering and medicine students, as well as having the highest average starting wages, are also the most likely to find employment. Business & economics are the most likely to be unemployed or not in the labour force at the time of graduation. Meanwhile, those studying science-related degrees or architecture are the most likely to undertake further study after completion of their bachelor, potentially indicating the need for post-graduate qualifications in employment relevant to these areas of study.

Looking at Table A.2, the grade distribution varies significantly between areas of study. As such, we might expect that GPA is not an accurate measure of ability for comparison of individuals between areas of study. This would suggest that the effect of the GPA variable would mostly be explaining variations in wage within areas of study.

In Table A.7 we see a significant correlation between degree satisfaction and GPA. However, Table A.8 shows negligible difference in wages between those who were and were not satisfied with their degree. Given that our satisfaction variable is positively correlated with GPA but not wages, it appears to be a suitable instrument choice.

There is also a strong correlation between entry score and GPA. In Table A.9, we see that students with an entry score above 90 were more likely to have a GPA of 5 or greater, while those with an entry score below 90 had a larger clustering of students with a GPA between 4 and 5. This lends support to the use of GPA as an instrument.

# 5. Results

The results of the estimations introduced earlier are presented below. Section 5.1 presents the results of estimations of the determinants of graduate wages. These include the results of the baseline model in (3.1), the IV estimation of (3.2), and the second stages of the two selection models from (3.4) and (3.11). The determinants of graduate employment status are presented in Section 5.2. These are estimated using the first stages of the two selection models in (3.5) and (3.12).

## 5.1 Graduate Starting Wages

As discussed in Section 3.1, previous studies have found a positive relationship between university grades and graduate starting salaries. In Table 5.1, the least-squares findings suggest that GPA has a significant positive impact on expected graduate starting wages, in line with this previous literature. A unit increase in GPA predicted to increase wages by 1.01 per cent. Degree choice was also an important determinant (see full results in Table A.10). The areas of study that had the highest average starting salaries in Table A.5, such as medicine & dentistry, engineering and maths & physical sciences, had significant positive estimates on the associated dummy variables (relative to studying arts & social sciences). As previously discussed, these results were potentially biased due to the GPA variable capturing the effect of some unobserved variable, and so these results were corrected for endogeneity and sample selection bias.

Table 5.1: **Wage Equation Results**

| | OLS | 2SLS | Heckman | Multinomial |
|---|---|---|---|---|
| GPA | 0.0101*** | 0.0105 | 0.003 | 0.0001 |
| | [-0.0031] | [-0.0077] | [-0.0042] | [0.0048] |
| Agricultural Sciences | -0.0228** | -0.0283** | -0.0264* | -0.0592*** |
| | [-0.0115] | [-0.0121] | [-0.0153] | [0.0206] |
| Architecture | -0.0851*** | -0.0928*** | -0.0418 | -0.1157*** |
| | [-0.0165] | [-0.0233] | [-0.0295] | [0.0369] |
| Business & Economics | -0.0161** | -0.0278*** | -0.0439*** | -0.0483*** |
| | [-0.0079] | [-0.0083] | [-0.0132] | [0.0115] |
| Engineering | 0.0676*** | 0.0691*** | 0.0195 | 0.0361*** |
| | [-0.0084] | [-0.0082] | [-0.0199] | [0.0139] |
| Health Sciences | 0.0163* | 0.0099 | 0.0053 | -0.0088 |
| | [-0.0089] | [-0.0101] | [-0.0116] | [0.0118] |
| Law | 0.0439*** | 0.0240* | 0.0421*** | 0.0341** |
| | [-0.0122] | [-0.0128] | [-0.0113] | [0.0167] |
| Math & Physical Sciences | 0.0381*** | 0.0250*** | 0.0284** | 0.0088 |
| | [-0.0092] | [-0.0092] | [-0.0118] | [0.0156] |
| Medicine & Dentistry | 0.2544*** | 0.2599*** | 0.1885*** | 0.2418*** |
| | [-0.0126] | [-0.0134] | [-0.0279] | [0.0305] |
| Music | 0.0216 | 0.0428* | 0.0417 | 0.0142 |
| | [-0.0271] | [-0.0239] | [-0.0321] | [0.0335] |
| Teaching | 0.0374** | 0.0278 | -0.0201 | 0.0043 |
| | [-0.0145] | [-0.017] | [-0.0261] | [0.0318] |
| $\lambda$ | | | -0.0748*** | |
| | | | [-0.0246] | |
| $\rho_1$ | | | | -0.2003*** |
| | | | | [0.0732] |
| $\rho_2$ | | | | 0.9718*** |
| | | | | [0.3118] |
| $\rho_3$ | | | | 0.8628* |
| | | | | [0.4404] |
| $\rho_4$ | | | | -1.3837** |
| | | | | [0.6198] |
| $\rho_5$ | | | | -0.3954 |
| Statistical significance shown at the 10% (*) 5% (**) and 1% level (***). | | | | |

The instrumental variable model suggested in (3.2) was estimated using the Stata command *ivreg2* [Baum et al., 2007]. The results of the estimation can be seen in Table 5.1 (for full results see Table A.10). In comparison to the least-squares regression, we see that the coefficient on GPA, despite being close to the original estimate, is no longer significant. This was due to larger standard errors, which likely arose due to the less efficient estimator. Looking at the first-stageof the regression, we note that entry score is a significant positive predictor of GPA. There is also a significant positive correlation between the GPA and degree satisfaction variables. These results confirm our beliefs about how our instruments should be related to GPA. We also note that the dummy variable for final year employment is negatively correlated with GPA. This could reflect causation going either way, in that those who are employed may have less time for studying, which could negatively impact grades, or those with low grades may realise a need to gain other experience to compete in the graduate labour market.

Before accepting the results of these regressions, we first must consider the quality of the instruments used in regression. Staiger and Stock [1994] showed that the results of 2SLS regression are biased if the instruments used are weakly related to the endogenous variables. Using the test results in Table A.16, it appears that the instruments are sufficiently correlated with GPA, as the under-identification tests is rejected, and the Cragg-Donald F-statistic is able to reject the null hypothesis of weak IV's under the critical values provided by Stock and Yogo [2005]. As there are more instruments than endogenous regressors, we can test the assumption that the chosen instruments are themselves uncorrelated with the errors of the wage equation using the Sargan [1958] test. From these tests, our instrument choices appear to be valid.

While the tests on the instruments indicate that the instruments are valid, we can also test whether endogeneity was an issue under least-squares estimate of (3.1). Using a Hausman [1978] test for endogeneity, we find that we are unable to reject the null hypothesis that the GPA variable was exogenous in the baseline model. Therefore, the use of 2SLS in this context is unnecessary, and we should rely on the least-squares results. However, this does not rule out the potential for bias in the estimated return to GPA if the unobserved factors affecting wage are common to most of the sample that found employment.

Following the previous discussion about the potential sample selection issues, the model is first corrected using a Tobit II model. These results, presented in Table 5.1 (for full results, see Table A.11) were obtained using the two-step Heckman estimator from the in-built Stata command *Heckman*. The standard errors were bootstrapped 50 times to correct for the biased standard errors that are obtained when the two-step method is used.

The inclusion of the IMR correction term (denoted $\lambda$ in the regression output) can be used to identify whether the least-squares model suffers from sample selection bias. In these results, the negative coefficient on the IMR variable is statistically significant. This suggests that there is a negative correlation between the error terms in the selection stage and the error in the wage equation, meaning that those choosing to work actually have lower expected wages. This could potentially be explained by the high ability individuals in our sample choosing to undertake further study following graduation.

The coefficient on the GPA variable is no longer significant after the correction is applied. We also find that the marginal returns to degrees in which a high proportion of students found full-time employment tended to decrease (see Table A.4). The return to medicine and dentistry decreased, but was still significant, while the returns to studying engineering or teaching became insignificant.

The methods of sample selection and endogeneity were applied together as a sensitivity analysis. This was estimated using a method suggested by Wooldridge [2010], where the Heckman correction term is first calculated using only exogenous regressors, and then this correction term is included in the 2SLS estimation. The results of this can be seen in Table A.12. These results yielded similar results to the individual processes. GPA became significant as a predictor for employment, but was no longer significant for wages, and exogeneity was not rejected for GPA, despite satisfactory instruments. However, when both methods were applied, sample selection bias was only present at the 15 per cent level.

Interestingly, the return to studying honours or advanced degrees, both of which had large proportions of students undertaking further study, increased once the selection criteria was included.

Given that the Heckman model found sample-selection bias, we may be able to better determine the source of this bias by separating the non-working graduates into their true employment statuses.

The multinomial logit sample selection model was fit using the *selmlog* Stata command provided by Bourguignon et al. [2007].[11] As this code also uses two-step methods, the standard errors were corrected using bootstrapped errors with 100 replications.

The results of the multinomial model, presented in Table 5.1 (full results can be found in Table A.14) are similar to those found in the Heckman selection model. The variable for GPA again becomes insignificant as an indicator of wages. The dummies for study areas that have the highest rates of people undertaking full-time work, such as teaching and engineering, had a reduced marginal return. Unlike in the Heckman correction though, the marginal wage returns to study areas where further study was most common decreased in multinomial correction.

Looking as the multinomial error correction terms in Table 5.1, we observe that

[11] This code is available for download from http://www.parisschoolofeconomics.eu/en/gurgand-marc/stata-command/

there is a significant negative correlation between the error terms on both the full-time employment and not participating equations and the wage equation. The negative correlation between the errors in the full-time employment equation and the wage equation suggests that those who found full-time employment are not those who would be expected to earn the highest wages, ceteris paribus. The negative correlation between the not participating error and the wage equation error suggests that the decision not to participate in the labour force may be driven by low expected earnings. There is also a significant positive relationship between the error of the part-time employment equation and the wage equation error, suggesting those in part-time employment would be expected to obtain high-wage jobs if they found full-time employment.

Although our results appear to suggest that GPA is not a significant determinant of wages, it may be worth investigating whether GPA remains important within certain areas of study. It may be the case that within certain areas of graduate employment where hiring is dominated by a single employer (e.g. public employment for teaching or medicine), there is no room for GPA to strongly dictate wages, and these observations are reducing the observed impact. To test if this was an issue, the multinomial selection model was repeated for the four largest areas of study in terms of graduates: business and economics, arts and social sciences, engineering, and maths and physical sciences. This was done by running separate regressions on subsets of the data rather than including GPA interaction terms in the model since GPA for those with double degrees could not be split between areas of study. The results of these regressions can be found in Table A.15. In most cases, the result emulate those from the entire sample. The effect of GPA was insignificant in most categories at the 5 per cent level, except business and statistics, where a negative effect was observed. Unfortunately, our sample size is too small to investigate this question effectively.

Further studies could use larger dataset to investigate this question.

Overall, our estimates suggest that GPA has a limited impact on graduate starting wages. However, given the strong emphasis on ability in standard wage equations, we may expect this outcome to begin to have an impact over time. These results may be similar to those of Murnane et al. [1995], in which it takes a number of years of employment before the impact of ability begins to affect wage differentials.

## 5.2 Graduate Employment Outcomes

The results of our selection models can also be used to determine how our explanatory variables determine employment status. The multinomial model in particular allows us to consider the outcomes of those not in full-time employment.

The probit model used in the first-stageof the Heckman sample selection model compares those who were in full-time employment against those that were not. The results, in Table A.11, which are measured as marginal effects, show that while GPA may not be a significant predictor of wages, it does have a significant positive effect on the probability of finding full-time employment.

The multinomial logit model provides more information about the factors that affect graduate employment status, as it splits those not employed into multiple categories: working part-time, unemployed, undertaking further study or not participating. The effects of variables in this multinomial logit stage are presented as relative-risk ratios (RRR) in Table 5.2 (for full results, see Table A.13). These RRR's represent the relative increase in the probability of being in a particular category. An RRR coefficient greater than one therefore represents an outcome being more likely as the variable increases, while an RRR less than one indicates that increasing the variable makes that outcome less likely.

Table 5.2: **Multinomial Selection Relative-Risk Ratios**

| | **full-time** | **part-time** | **Participating** | **Study** |
|---|---|---|---|---|
| GPA | 1.5328*** | 1.1327** | 1.0524 | 1.3553*** |
| | [0.0783] | [0.0593] | [0.0636] | [0.0653] |
| Work FY | 5.4759*** | 8.9579*** | 1.7062*** | 2.6338*** |
| | [0.4707] | [0.8395] | [0.1662] | [0.2074] |
| International | 0.127*** | 0.5013*** | 2.3153*** | 1.358*** |
| | [0.0154] | [0.0571] | [0.2831] | [0.1336] |
| Agricultural | 1.9314*** | 1.2022 | 1.4207 | 2.516*** |
| | [0.4076] | [0.2541] | [0.3703] | [0.4958] |
| Architecture | 0.8212 | 1.5754 | 2.501*** | 5.6554*** |
| | [0.2678] | [0.4466] | [0.7702] | [1.4686] |
| Business & Economics | 2.6134*** | 1.039 | 1.2981* | 1.1122 |
| | [0.3495] | [0.136] | [0.201] | [0.1396] |
| Engineering | 2.5534*** | 0.4451*** | 0.5089*** | 0.3777*** |
| | [0.3429] | [0.0632] | [0.0868] | [0.0511] |
| Health Sciences | 2.3413*** | 1.4866** | 1.5529** | 1.9741*** |
| | [0.4178] | [0.2607] | [0.3341] | [0.3315] |
| Law | 1.554** | 1.4324* | 1.1755 | 2.5771*** |
| | [0.3287] | [0.2974] | [0.3119] | [0.5202] |
| Maths & Physical Sciences | 1.2126 | 0.6516*** | 0.8538 | 1.2676* |
| | [0.1696] | [0.0906] | [0.1438] | [0.1615] |
| Medicine & Dentistry | 11.5409*** | 3.9257*** | 1.0065 | 0.31*** |
| | [2.9997] | [1.0608] | [0.3482] | [0.107] |
| Music | 1.6591 | 3.074*** | 2.785** | 3.4722*** |
| | [0.6217] | [1.0805] | [1.1268] | [1.1978] |
| Teaching | 6.3295*** | 1.4402 | 1.8724 | 0.2724*** |
| | [2.3641] | [0.5389] | [0.8474] | [0.1255] |
| Double Degree | 0.561*** | 1.7024*** | 1.0426 | 0.9562 |
| | [0.0971] | [0.2929] | [0.2345] | [0.1594] |
| Honours | 0.5224*** | 0.8857 | 0.9553 | 2.9628*** |
| | [0.074] | [0.1227] | [0.1669] | [0.3691] |
| Advanced | 0.258 | 0.248 | 0 | 4.8469** |
| | [0.3199] | [0.3081] | [0] | [3.568] |
| Age | 1.285*** | 0.8874*** | 0.9903 | 0.9391 |
| | [0.0656] | [0.0381] | [0.0456] | [0.0377] |
| $Age^2$ | 0.9963*** | 1.0013** | 1.0004 | 1.0006 |
| | [0.0007] | [0.0006] | [0.0006] | [0.0005] |
| Low SEB | 1.2826* | 0.9721 | 0.7854 | 1.0537 |
| | [0.1672] | [0.1339] | [0.1477] | [0.1375] |
| High SEB | 1.1753 | 1.3516*** | 1.2499* | 1.1749 |
| | [0.1194] | [0.1401] | [0.1657] | [0.1183] |

Statistical significance shown at the 10% (*) 5% (**) and 1% level (***).

GPA is again found to be a significant indicator or employment status. Table A.15 shows that GPA has a significant relative-risk ratios (RRR) for three categories: working full-time, working part-time, and further study. These results suggests that a unit increase in GPA increases the probability of being in full-time work by 53.28 per cent, part-time work by 13.27 per cent, and further study by 35.53 per cent, relative to the base outcome of unemployment.

These results also show that, as well as being useful indicators of wages, area of study is an important determinant of graduate employment outcomes. These results closely follow the relative proportions of students in each employment category from each area of study seen in Table A.4. Study in areas where full-time employment was high, such as teaching, engineering or medicine, had large significant RRR's for the full-time employment category. Similarly, areas where there were a large proportion of students enrolling in further study (e.g. architecture or agricultural sciences), had large RRR's for further study.

Working during the final years for students has significant RRR that was greater than 1 for all categories, relative to the base outcome of unemployment. These values are particularly strong for either work options, suggesting that for those who do seek employment, final year work experience strongly increases the probability of success.

Age appears to have a concave effect on the likelihood of working full-time, but a convex effect on part-time work. This suggests that the youngest and oldest graduates in the sample are likely to be in part-time work, while those in the middle are more likely to be in full-time employment.[12]

These results suggest that the typical application of the wage equation to the graduate labour market is not the most appropriate predictor of graduate outcomes. The main variation in wages between individuals appears to be most strongly driven

[12]This interpretation of the quadratic age variables RRR estimates followed the work of Hu [2005]

by area of study, which was also found to be an important determinant of whether employment was found. These wage and employment outcomes follow the general ranking that we would expect from the descriptive statistics. Favourable characteristics that we may expect to have a positive impact on wages, such as GPA or work experience, are much better predictors of whether an individual gains employment than of their expected wage.

# 6. Conclusion

This thesis explored the impact of academic success in graduate labour markets using two measures of success; wages and employment status. Least-squares results on wage outcomes confirmed the results of previous literature, where GPA was found to have a significant positive impact on graduate starting wages. Areas of study were also found to be strong predictors of wages.

This paper expanded on the existing literature by re-estimating the model for graduate starting wages while checking for the presence of endogeneity and sample selection bias. Endogeneity was tested through an instrumental variable estimator, using university entrance scores and degree satisfaction as instruments for GPA. The IV method found no presence of endogeneity of the GPA variable in our wage equation. However, entry scores and degree satisfaction were both found to be suitable instruments. Both measures were found to be significant positive predictors of GPA, as expected.

Sample-selection bias was explored using a Heckman two-step estimator and a multinomial logit sample-selection estimator. These results found that sample-selection bias was present in the least squares estimation of our model. Once the corrections were applied, GPA and work experience were not useful predictors of wages. Instead, the majority of the dispersion in starting wages appears to be driven by area of study. Given the requirement of certain degrees for many areas of employment, these differences are likely reflections of the supply and demand conditions in labour markets associated with different areas of education. These results were similar in both models.

The multinomial selection model also allowed use of the data for graduates not in full time employment, which provided information on graduate employment status. Although GPA and work experience were not found to significantly impact wages, they did have a significant effect on employment status. Both had positive impacts on the probability of being in employment or further study after graduation, relative to the base outcome of unemployment.

These results indicate that studies on university graduate short-term outcomes are much more informative *at the individual level* if used for explaining employment status rather than wages. Studies that do wish to use GPA as a predictor of wages should be aware of the sample selection bias that is likely to arise in these type of recent graduate datasets.

There are a number of ways in which the work of this thesis could be extended to further research. Using larger datasets would allow research to better explore how these findings hold within particular areas of study. This issue would also benefit from datasets that involved graduates from a range of locations in order to remove the potential for bias arising from localised labour market conditions. The exploration of other selection processes in which joining the labour force and finding employment were treated as different stages would also be a worthwhile addition to this model. Finally, the use of panel data that includes short-term employment outcomes alongside longer-term data would allow an exploration on whether GPA remains a useful predictor for longer term outcomes.

# A. Appendix

## A.1 Dataset Details

### A.1.1 AGS Survey Questions

1. The staff put a lot of time into commenting on my work
2. The teaching staff normally gave me helpful feedback on how I was going
3. The course helped me develop my ability to work as a team member
4. The teaching staff of this course motivated me to do my best work
5. The course provided me with a broad overview of my field of knowledge
6. The course sharpened my analytic skills
7. My lecturers were extremely good at explaining things
8. The teaching staff worked hard to make their subjects interesting
9. The course developed my confidence to investigate new ideas
10. I felt part of a group of students and staff committed to learning
11. Students ideas and suggestions were used during the course
12. I was able to access information technology resources when I needed them
13. I learned to explore ideas confidently with other people
14. The course developed my problem-solving skills
15. Relevant learning resources were accessible when I needed them

16. Health, welfare and counselling services met my requirements
17. The staff made a real effort to understand difficulties I might be having with my work
18. University stimulated my enthusiasm for further learning
19. I felt I belonged to the university community
20. The course improved my skills in written communication
21. The library services were readily accessible
22. I learned to apply principles from this course to new situations
23. I was satisfied with the course and careers advice provided
24. I Consider what I learned valuable for my future
25. As a result of my course, I feel confident about tackling unfamiliar problems
26. My course helped me to develop the ability to plan my own work
27. I was able to explore academic interests with staff and students
28. My university experience encouraged me to value perspectives other than my own
29. Overall, I was satisfied with the quality of this course

### A.1.2 Degree Classification

Table A.1: **Degree Classifications**

| **Degree** | **Classification** |
|---|---|
| B.Ag Sc (Oenology) | Agricultural Sciences |
| B.Ag Sc (Viticultural Science) | Agricultural Sciences |
| B.Agricultural Sciences | Agricultural Sciences |
| B.Agriculture | Agricultural Sciences |
| B.Architectural Design | Architecture |
| B.Architecture | Architecture |
| B.Arts | Arts & Social Sciences |
| B.Arts - pre 1996 | Arts & Social Sciences |
| B.Arts (Dance) | Arts & Social Sciences |
| B.Business Info Technology | Business & Economics |
| B.Commerce | Business & Economics |
| B.Commerce (Accounting) | Business & Economics |
| B.Commerce (Corporate Finance) | Business & Economics |
| B.Commerce (Int Business) | Business & Economics |
| B.Commerce (Management) | Business & Economics |
| B.Commerce (Marketing) | Business & Economics |
| B.Commerce Plan | Business & Economics |
| B.Comp Sci (Soft Eng) | Maths & Physical Sciences |
| B.Computer Graphics | Maths & Physical Sciences |
| B.Computer Science | Maths & Physical Sciences |
| B.Dental Surgery | Medicine & Dentistry |
| B.E(Civ&St) & B.E(Civ&Env) | Double Engineering |

*Continued on next page*

Table A.1 – *Continued from previous page*

| **Degree** | **Classification** |
|---|---|
| B.E(Petrol Eng) & B.E(Mining) | Double Engineering |
| B.E(Petrol) & B.E(Civ&Env) | Double Engineering |
| B.E(Petrol) & B.E(Civ&Struc) | Double Engineering |
| B.E(Petroleum) & B.E(Chem) | Double Engineering |
| B.E(Petroleum) & B.E(Mech) | Double Engineering |
| B.Ec (International Ag Bus) | Business & Economics |
| B.Economics | Business & Economics |
| B.Environmental Policy & Mgt. | Agricultural Sciences |
| B.Finance | Business & Economics |
| B.Finance (International) | Business & Economics |
| B.Finance (Quantitative) | Business & Economics |
| B.Food & Nutrition Science | Maths & Physical Sciences |
| B.Food Tech & Management | Maths & Physical Sciences |
| B.Health Sciences | Health Sciences |
| B.Innov. & Entrepreneurship | Business & Economics |
| B.International Development | Arts & Social Sciences |
| B.International Studies | Arts & Social Sciences |
| B.Languages | Lanuage |
| B.Laws | Law |
| B.Math & Comp Sci | Maths & Physical Sciences |
| B.Mathematical Sciences | Maths & Physical Sciences |
| B.Media | Arts & Social Sciences |
| B.Medical Science - honours | Medicine & Dentistry |
| B.Medicine & B.Surgery | Medicine & Dentistry |

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Table A.1 – *Continued from previous page*

| **Degree** | **Classification** |
|---|---|
| B.Mus Ed, Prac - Composition | Music |
| B.Mus Perf, Class - Brass | Music |
| B.Mus Perf, Class - Keyboard | Music |
| B.Mus Perf, Class - Percussion | Music |
| B.Mus Perf, Class - Strings | Music |
| B.Mus Perf, Class - Voice | Music |
| B.Mus Perf, Class - Woodwind | Music |
| B.Mus Perf, Jazz | Music |
| B.Mus St Integ Studs Keyboard | Music |
| B.Mus St Integrated Studies | Music |
| B.Mus St Music Technology | Music |
| B.Mus St Perf & Pedagogy | Music |
| B.Mus(Pop Music & Creative Tech) | Music |
| B.Music(Classical Performance) | Music |
| B.Music(Composition) | Music |
| B.Music(Jazz Performance) | Music |
| B.Music(Music Education) | Music |
| B.Music(Performance & Pedagogy) | Music |
| B.Music(Sonic Arts) | Music |
| B.Natural Resource Management | Agricultural Sciences |
| B.Nursing | Health Sciences |
| B.Oenology | Agricultural Sciences |
| B.Oral Health | Health Sciences |
| B.Psychological Science | Health Sciences |

*Continued on next page*

Table A.1 – *Continued from previous page*

| **Degree** | **Classification** |
|---|---|
| B.Psychology - honours | Health Sciences |
| B.Sc (Agricultural Science) | Agricultural Sciences |
| B.Sc (Animal Science) | Agricultural Sciences |
| B.Sc (Biomedical Science) | Maths & Physical Sciences |
| B.Sc (Biotechnology) | Maths & Physical Sciences |
| B.Sc (EcoChemistry) | Maths & Physical Sciences |
| B.Sc (Evolutionary Biology) | Maths & Physical Sciences |
| B.Sc (HighPerfCompPhys) (Hons) | Maths & Physical Sciences |
| B.Sc (Laser Physics & Tech) | Maths & Physical Sciences |
| B.Sc (Marine Biology) | Maths & Physical Sciences |
| B.Sc (Mineral Geoscience) | Maths & Physical Sciences |
| B.Sc (Molecular & Drug Design) | Maths & Physical Sciences |
| B.Sc (Molecular Biology) | Maths & Physical Sciences |
| B.Sc (Nanoscience & Materials) | Maths & Physical Sciences |
| B.Sc (Natural Resources) | Maths & Physical Sciences |
| B.Sc (Petroleum Geoscience) | Maths & Physical Sciences |
| B.Sc (Space Sc & Astrophysics) | Maths & Physical Sciences |
| B.Sc (Sustainable Envir) | Maths & Physical Sciences |
| B.Sc (Veterinary Bioscience) | Agricultural Sciences |
| B.Sc (Viticulture) | Agricultural Sciences |
| B.Science | Maths & Physical Sciences |
| B.Science (Dentistry) - hons | Medicine & Dentistry |
| B.Social Sciences | Arts & Social Sciences |
| B.Viticulture & Oenology | Agricultural Sciences |

*Continued on next page*

Table A.1 – *Continued from previous page*

| **Degree** | **Classification** |
|---|---|
| B.Wine Marketing | Business & Economics |
| BE(Honours)(Chem&Pharm) | Engineering |
| BE(Honours)(Chem) | Engineering |
| BE(Honours)(Chem-Energy&Env) | Engineering |
| BE(Honours)(Chem-FoodWine&Bio) | Engineering |
| BE(Honours)(Chem-Process&Prod) | Engineering |
| BE(Honours)(Civil & Arch) | Engineering |
| BE(Honours)(Civil&Env) | Engineering |
| BE(Honours)(Civil&Struct) | Engineering |
| BE(Honours)(Computer Systems) | Engineering |
| BE(Honours)(E&E) | Engineering |
| BE(Honours)(E&E-Avionics) | Engineering |
| BE(Honours)(Mech&Aero) | Engineering |
| BE(Honours)(Mech&Auto) | Engineering |
| BE(Honours)(Mech&Sports) | Engineering |
| BE(Honours)(Mech&SustEnergy) | Engineering |
| BE(Honours)(MechAero) | Engineering |
| BE(Honours)(Mechanical) | Engineering |
| BE(Honours)(Mechatronic) | Engineering |
| BE(Honours)(Mining) | Engineering |
| BE(Honours)(Petroleum) | Engineering |
| BE(Honours)(Software) | Engineering |
| BE(Honours)(Tele) | Engineering |

## A.2 Descriptive Statistics

Table A.2: **GPA by Area of Study (%)**

| | <3 | 3-4 | 4-5 | 5-6 | >6 | Total |
|---|---|---|---|---|---|---|
| Agricultural Sciences | 0.66 | 6.19 | 32.46 | 46.72 | 13.98 | 100.00 |
| Architecture | 0.25 | 4.30 | 49.11 | 42.03 | 4.30 | 100.00 |
| Arts & Social Sciences | 0.69 | 5.84 | 29.98 | 45.31 | 18.19 | 100.00 |
| Business & Economics | 0.67 | 18.55 | 49.95 | 26.02 | 4.82 | 100.00 |
| Engineering | 0.38 | 4.89 | 37.00 | 40.67 | 17.05 | 100.00 |
| Health Sciences | 0.20 | 3.42 | 32.06 | 42.61 | 21.71 | 100.00 |
| Law | 0.00 | 4.82 | 40.84 | 47.59 | 6.75 | 100.00 |
| Maths & Physical Sciences | 0.94 | 8.86 | 32.33 | 34.34 | 23.54 | 100.00 |
| Medicine & Dentistry | 0.00 | 4.17 | 66.32 | 22.92 | 6.60 | 100.00 |
| Music | 0.00 | 1.43 | 23.21 | 54.29 | 21.07 | 100.00 |

Table A.3: **Wage by GPA (%)**

| Wage | GPA | | | | |
|---|---|---|---|---|---|
| | < 3 | 3-4 | 4-5 | 5-6 | >6 |
| < \$30k | 0.00 | 1.99 | 2.43 | 2.01 | 1.55 |
| \$30k-\$40k | 25.00 | 17.91 | 13.41 | 10.16 | 7.06 |
| \$40k-\$50k | 0.00 | 24.38 | 28.67 | 28.48 | 18.54 |
| \$50k-\$60k | 41.67 | 28.86 | 23.47 | 31.32 | 32.01 |
| \$60k-\$70k | 16.67 | 11.94 | 10.06 | 11.17 | 18.76 |
| \$70k-\$80k | 8.33 | 4.98 | 6.47 | 5.59 | 7.06 |
| \$80k-\$90k | 8.33 | 4.48 | 3.82 | 4.40 | 7.73 |
| \$90k-\$100k | 0.00 | 1.00 | 5.66 | 3.11 | 3.09 |
| \$100k-\$200k | 0.00 | 4.48 | 5.90 | 3.48 | 4.19 |
| > \$200k | 0.00 | 0.00 | 0.12 | 0.27 | 0.00 |
| Total | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |

Table A.4: **Graduate Employment Status by Area of Study (%)**

| | **Work Full-Time** | **Work Part-Time** | **Unemployed** | **Not Working or Studying** | **Further Study** | Total |
|---|---|---|---|---|---|---|
| Agricultural Sciences | 25.29 | 22.07 | 7.51 | 7.06 | 38.07 | 100.00 |
| Architecture | 5.88 | 16.91 | 4.66 | 9.80 | 62.75 | 100.00 |
| Arts & Social Sciences | 12.97 | 32.90 | 9.54 | 8.90 | 35.69 | 100.00 |
| Business & Economics | 21.88 | 18.50 | 13.59 | 18.06 | 27.98 | 100.00 |
| Engineering | 45.47 | 14.34 | 18.42 | 8.32 | 13.45 | 100.00 |
| Health Sciences | 24.24 | 24.62 | 5.11 | 6.53 | 39.49 | 100.00 |
| Law | 29.25 | 18.87 | 6.60 | 5.66 | 39.62 | 100.00 |
| Maths & Physical Sciences | 14.48 | 14.61 | 11.69 | 7.44 | 51.79 | 100.00 |
| Medicine & Dentistry | 58.17 | 25.16 | 7.52 | 5.88 | 3.27 | 100.00 |
| Music | 10.93 | 32.12 | 2.65 | 6.62 | 47.68 | 100.00 |
| Teaching | 44.55 | 37.27 | 5.91 | 8.64 | 3.64 | 100.00 |

Table A.5: **Wage Summary by Area of Study**

| **Area of study** | **N** | **Mean** | **Median** | **Standard Deviation** | **Interquartile Range** |
|---|---|---|---|---|---|
| Agricultural Sciences | 283 | 56083.21 | 50000 | 18069.95 | 21000 |
| Architecture | 24 | 42075 | 40500 | 7098.699 | 7000 |
| Arts & Social Sciences | 121 | 47169.03 | 43000 | 13253.7 | 15800 |
| Business & Economics | 441 | 48897.26 | 46000 | 16181.02 | 10000 |
| Engineering | 612 | 63348.34 | 59450 | 19443.78 | 17680 |
| Health Sciences | 256 | 54460.56 | 53500 | 13243.22 | 8000 |
| Law | 93 | 59116.72 | 50000 | 27555.6 | 18000 |
| Maths & Physical Sciences | 218 | 61689.45 | 57000 | 20962.98 | 28000 |
| Medicine & Dentistry | 178 | 93438.93 | 90000 | 27938.83 | 28000 |
| Music | 33 | 60764.76 | 56000 | 43800.92 | 10000 |
| Teaching | 98 | 55983.07 | 57000 | 8937.389 | 8000 |

Table A.6: **Employment Status by GPA (%)**

| GPA | Working Full-Time | Working Part-Time | Unemployed | Not Working or Studying | Further Study | Total |
|---|---|---|---|---|---|---|
| $\leq 3$ | 24.00 | 20.00 | 20.00 | 18.00 | 18.00 | 100.00 |
| 3-4 | 24.88 | 23.77 | 13.92 | 15.64 | 21.80 | 100.00 |
| 4-5 | 22.78 | 23.35 | 12.25 | 10.79 | 30.83 | 100.00 |
| 5-6 | 26.67 | 22.70 | 8.61 | 7.27 | 34.74 | 100.00 |
| $\geq 6$ | 28.33 | 17.43 | 6.10 | 5.92 | 42.22 | 100.00 |

Table A.7: **Degree satisfaction by GPA (%)**

| GPA | Satisfaction | |
|---|---|---|
| | Unsatisfied | Satisfied |
| < 3 | 0.81 | 0.45 |
| 3-4 | 11.23 | 7.14 |
| 4-5 | 44.79 | 35.18 |
| 5-6 | 32.00 | 41.05 |
| > 6 | 11.16 | 16.19 |
| Total | 100.00 | 100.00 |

Table A.8: **Degree satisfaction by graduate starting wage (%)**

| Wage | Satisfaction | |
|---|---|---|
| | Unsastified | Satisfied |
| < $30k | 1.95 | 2.17 |
| $30k-$40k | 15.33 | 10.83 |
| $40k-$50k | 28.71 | 26.22 |
| $50k-$60k | 26.28 | 29.26 |
| $60k-$70k | 10.46 | 12.22 |
| $70k-$80k | 4.38 | 6.22 |
| $80k-$90k | 4.14 | 4.96 |
| $90k-$100k | 3.89 | 3.70 |
| $100k-$200k | 4.14 | 4.39 |
| > $200k | 0.73 | 0.04 |
| Total | 100.00 | 100.00 |

Table A.9: **GPA by Entry Score (%)**

| Entry Score | GPA | | | | | |
|---|---|---|---|---|---|---|
| | <3 | 3-4 | 4-5 | 5-6 | >6 | Total |
| <50 | 0.00 | 15.87 | 41.27 | 31.75 | 11.11 | 100.00 |
| 50-60 | 0.85 | 15.25 | 57.63 | 23.73 | 2.54 | 100.00 |
| 60-70 | 0.23 | 14.55 | 53.64 | 29.09 | 2.50 | 100.00 |
| 70-80 | 0.43 | 10.58 | 49.66 | 35.49 | 3.84 | 100.00 |
| 80-85 | 0.11 | 10.05 | 45.40 | 40.11 | 4.34 | 100.00 |
| 85-90 | 0.33 | 5.79 | 40.03 | 45.33 | 8.52 | 100.00 |
| 90-95 | 0.07 | 3.34 | 30.58 | 51.42 | 14.58 | 100.00 |
| >95 | 0.73 | 7.60 | 31.08 | 36.99 | 23.60 | 100.00 |

## A.3 Regression Output

### A.3.1 2SLS

Table A.10: **Two-Stage Least Squares Results**

| | **OLS Wage** | **2SLS First Stage (GPA)** | **2SLS Second Stage (Wage)** |
|---|---|---|---|
| GPA | 0.0101*** | | 0.0105 |
| | [0.0031] | | [0.0077] |
| Female | -0.0308*** | 0.1250*** | -0.0270*** |
| | [0.0051] | [0.0322] | [0.0055] |
| Work FY | 0.0009 | -0.1298*** | -0.0059 |
| | [0.0058] | [0.0364] | [0.0062] |
| International | -0.0636*** | 0.2955** | -0.0198 |
| | [0.0101] | [0.1344] | [0.0223] |
| 2010s2 | 0.0141 | 0.1018 | 0.0369* |
| | [0.0170] | [0.1253] | [0.0208] |
| 2011s1 | 0.0236 | -0.3827*** | 0.0336 |
| | [0.0212] | [0.1479] | [0.0246] |
| 2011s2 | 0.0356** | 0.0807 | 0.0621*** |
| | [0.0169] | [0.1241] | [0.0206] |
| 2012s1 | 0.0294 | -0.2243 | 0.0565** |
| | [0.0202] | [0.1455] | [0.0242] |
| 2012s2 | 0.0494*** | 0.0981 | 0.0790*** |
| | [0.0170] | [0.1237] | [0.0205] |
| 2013s1 | 0.0464** | -0.2188 | 0.0587** |
| | [0.0224] | [0.1488] | [0.0247] |
| 2013s2 | 0.0716*** | 0.1460 | 0.1031*** |
| | [0.0176] | [0.1253] | [0.0208] |

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Table A.10 – *Continued from previous page*

| | **OLS Wage** | **2SLS First Stage (GPA)** | **2SLS Second Stage (Wage)** |
|---|---|---|---|
| 2014s1 | 0.0198 | -0.0551 | 0.0440* |
| | [0.0200] | [0.1451] | [0.0240] |
| 2014s2 | 0.0538*** | 0.1149 | 0.0877*** |
| | [0.0173] | [0.1247] | [0.0207] |
| 2015s1 | 0.0350* | -0.1375 | 0.0482** |
| | [0.0201] | [0.1427] | [0.0237] |
| 2015s2 | 0.0355** | 0.2587** | 0.0625*** |
| | [0.0176] | [0.1272] | [0.0212] |
| Agricultural Sciences | -0.0228** | 0.0449 | -0.0283** |
| | [0.0115] | [0.0735] | [0.0121] |
| Architecture | -0.0851*** | 0.0669 | -0.0928*** |
| | [0.0165] | [0.1410] | [0.0233] |
| Business & Economics | -0.0161** | -0.3237*** | -0.0278*** |
| | [0.0079] | [0.0483] | [0.0083] |
| Engineering | 0.0676*** | 0.0324 | 0.0691*** |
| | [0.0084] | [0.0492] | [0.0082] |
| Health Sciences | 0.0163* | 0.0546 | 0.0099 |
| | [0.0089] | [0.0610] | [0.0101] |
| Law | 0.0439*** | -0.1214 | 0.0240* |
| | [0.0122] | [0.0783] | [0.0128] |
| Maths & Physical Sciences | 0.0381*** | -0.0919* | 0.0250*** |
| | [0.0092] | [0.0554] | [0.0092] |
| Medicine & Dentistry | 0.2544*** | -0.8990*** | 0.2599*** |
| | [0.0126] | [0.0777] | [0.0134] |
| Music | 0.0216 | 0.0641 | 0.0428* |
| | [0.0271] | [0.1443] | [0.0239] |
| Teaching | 0.0374** | -0.2788*** | 0.0278 |

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Table A.10 – *Continued from previous page*

| | **OLS Wage** | **2SLS First Stage (GPA)** | **2SLS Second Stage (Wage)** |
|---|---|---|---|
| | [0.0145] | [0.1012] | [0.0170] |
| Double Degree | -0.0096 | 0.2698*** | 0.0050 |
| | [0.0091] | [0.0574] | [0.0098] |
| Honours | 0.0193** | 0.4094*** | 0.0089 |
| | [0.0094] | [0.0620] | [0.0108] |
| Advanced | 0.0604*** | 0.3766 | 0.0720 |
| | [0.0102] | [0.6504] | [0.1079] |
| Entry Score | | 0.0325*** | |
| | | [0.0015] | |
| Satisfaction | | 0.2219*** | |
| | | [0.0398] | |
| Constant | 4.6324*** | 2.1689*** | 4.6043*** |
| | [0.0234] | [0.1862] | [0.0443] |
| Statistical significance shown at the 10% (*) 5% (**) and 1% level (***). | | | |

### A.3.2 Heckman Selection

Table A.11: **Heckman Correction Results**

| | **OLS Wage** | **Heckman Wage Correction** | **Heckman Selection Marginal effects** |
|---|---|---|---|
| GPA | 0.0101*** | 0.0030 | 0.0438*** |
| | [0.0031] | [0.0041] | [0.0053] |
| Female | -0.0308*** | -0.0264*** | -0.0137 |
| | [0.0051] | [0.0047] | [0.0088] |
| Work FY | 0.0009 | -0.0180** | 0.0967*** |
| | [0.0058] | [0.0072] | [0.0086] |
| International | -0.0636*** | 0.0068 | -0.2511*** |
| | [0.0101] | [0.0210] | [0.0068] |
| 2010S2 | 0.0141 | 0.0132 | 0.0569* |
| | [0.0170] | [0.0174] | [0.0302] |
| 2011S1 | 0.0236 | 0.0250 | 0.0039 |
| | [0.0212] | [0.0209] | [0.0325] |
| 2011S2 | 0.0356** | 0.0340** | 0.0587** |
| | [0.0169] | [0.0167] | [0.0299] |
| 2012S1 | 0.0294 | 0.0346 | -0.0263 |
| | [0.0202] | [0.0243] | [0.0299] |
| 2012S2 | 0.0494*** | 0.0500*** | 0.0449 |
| | [0.0170] | [0.0170] | [0.0291] |
| 2013S1 | 0.0464** | 0.0558*** | -0.0362 |
| | [0.0224] | [0.0205] | [0.0288] |
| 2013S2 | 0.0716*** | 0.0843*** | -0.0322 |
| | [0.0176] | [0.0175] | [0.0247] |
| 2014S1 | 0.0198 | 0.0359* | -0.0681*** |
| | [0.0200] | [0.0206] | [0.0251] |

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Table A.11 – *Continued from previous page*

| | **OLS Wage** | **Heckman Wage** | **Heckman Selection** |
|---|---|---|---|
| 2014S2 | 0.0538*** | 0.0700*** | -0.0477** |
| | [0.0173] | [0.0187] | [0.0235] |
| 2015S1 | 0.0350* | 0.0506** | -0.0650*** |
| | [0.0201] | [0.0237] | [0.0246] |
| 2015S2 | 0.0355** | 0.0598*** | -0.0782*** |
| | [0.0176] | [0.0200] | [0.0214] |
| Agricultural Sciences | -0.0228** | -0.0264** | 0.0180 |
| | [0.0115] | [0.0121] | [0.0197] |
| Architecture | -0.0851*** | -0.0418* | -0.1394*** |
| | [0.0165] | [0.0254] | [0.0143] |
| Business & Economics | -0.0161** | -0.0439*** | 0.1819*** |
| | [0.0079] | [0.0101] | [0.0168] |
| Engineering | 0.0676*** | 0.0195 | 0.3396*** |
| | [0.0084] | [0.0137] | [0.0193] |
| Health Sciences | 0.0163* | 0.0053 | 0.0664*** |
| | [0.0089] | [0.0088] | [0.0179] |
| Law | 0.0439*** | 0.0421*** | 0.0023 |
| | [0.0122] | [0.0112] | [0.0191] |
| Maths & Physical Sciences | 0.0381*** | 0.0284*** | 0.0567*** |
| | [0.0092] | [0.0069] | [0.0160] |
| Medicine & Dentistry | 0.2544*** | 0.1885*** | 0.4798*** |
| | [0.0126] | [0.0240] | [0.0308] |
| Music | 0.0216 | 0.0417 | -0.0836*** |
| | [0.0271] | [0.0327] | [0.0203] |
| Teaching | 0.0374** | -0.0201 | 0.4065*** |
| | [0.0145] | [0.0219] | [0.0447] |
| Double Degree | -0.0096 | 0.0149 | -0.1180*** |
| | [0.0091] | [0.0095] | [0.0115] |

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Table A.11 – *Continued from previous page*

| | **OLS Wage** | **Heckman Wage** | **Heckman Selection** |
|---|---|---|---|
| Honours | 0.0193** | 0.0545*** | -0.1580*** |
| | [0.0094] | [0.0151] | [0.0082] |
| Advanced | 0.0604*** | 0.1462*** | -0.1767*** |
| | [0.0102] | [0.0222] | [0.0201] |
| Age | | | 0.0535*** |
| | | | [0.0057] |
| $Age^2$ | | | -0.0007*** |
| | | | [0.0001] |
| Low SEB | | | 0.0453*** |
| | | | [0.0139] |
| High SEB | | | -0.0061 |
| | | | [0.0092] |
| Constant | 4.6324*** | 4.7681*** | |
| | [0.0234] | [0.0464] | |
| lambda | | -0.0748*** | |
| | | [0.0200] | |

Statistical significance shown at the 10% (*) 5% (**) and 1% level (***).

### A.3.3 2SLS with Heckman Correction

Table A.12: **Two-stage Least Squares with Heckman Correction Results**

| | **Heckman First Stage** | **2SLS First Stage (GPA)** | **2SLS Second Stage (Wage)** |
|---|---|---|---|
| Female | -0.0076 | 0.1302*** | -0.0263*** |
| | [0.0088] | [0.0325] | [0.0056] |
| Work FY | 0.0953*** | -0.1779*** | -0.0153 |
| | [0.0086] | [0.0579] | [0.0095] |
| International | -0.2535*** | 0.4832** | 0.0172 |
| | [0.0068] | [0.2212] | [0.0361] |
| 2010s2 | 0.0636** | 0.0889 | 0.0340 |
| | [0.0306] | [0.1259] | [0.0209] |
| 2011s1 | -0.0021 | -0.3835*** | 0.0343 |
| | [0.0320] | [0.1479] | [0.0246] |
| 2011s2 | 0.0631** | 0.0658 | 0.0589*** |
| | [0.0301] | [0.1249] | [0.0207] |
| 2012s1 | -0.0283 | -0.2163 | 0.0586** |
| | [0.0299] | [0.1457] | [0.0242] |
| 2012s2 | 0.0507* | 0.0884 | 0.0768*** |
| | [0.0294] | [0.1240] | [0.0206] |
| 2013s1 | -0.0395 | -0.1988 | 0.0632** |
| | [0.0286] | [0.1500] | [0.0250] |
| 2013s2 | -0.0258 | 0.1674 | 0.1070*** |
| | [0.0252] | [0.1268] | [0.0210] |
| 2014s1 | -0.0691*** | -0.0184 | 0.0514** |
| | [0.0251] | [0.1491] | [0.0247] |
| 2014s2 | -0.0412* | 0.1445 | 0.0933*** |

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Table A.12 – *Continued from previous page*

| | **Heckman First Stage** | **2SLS First Stage (GPA)** | **2SLS Second Stage (Wage)** |
|---|---|---|---|
| | [0.0240] | [0.1277] | [0.0211] |
| 2015s1 | -0.0662*** | -0.1052 | 0.0550** |
| | [0.0246] | [0.1459] | [0.0242] |
| 2015s2 | -0.0672*** | 0.3064** | 0.0714*** |
| | [0.0224] | [0.1348] | [0.0223] |
| Agricultural Sciences | 0.0137 | 0.0430 | -0.0288** |
| | [0.0196] | [0.0735] | [0.0121] |
| Architecture | -0.1417*** | 0.1772 | -0.0707** |
| | [0.0143] | [0.1748] | [0.0288] |
| Business & Economics | 0.1618*** | -0.3900*** | -0.0403*** |
| | [0.0163] | [0.0786] | [0.0127] |
| Engineering | 0.3513*** | -0.1011 | 0.0423* |
| | [0.0191] | [0.1344] | [0.0220] |
| Health Sciences | 0.0639*** | 0.0332 | 0.0054 |
| | [0.0178] | [0.0642] | [0.0106] |
| Law | 0.0069 | -0.1252 | 0.0237* |
| | [0.0194] | [0.0783] | [0.0128] |
| Maths& Physical Sciences | 0.0509*** | -0.1148* | 0.0206** |
| | [0.0158] | [0.0594] | [0.0098] |
| Medicine & Dentistry | 0.4587*** | -1.0690*** | 0.2280*** |
| | [0.0313] | [0.1771] | [0.0280] |
| Music | -0.0814*** | 0.1156 | 0.0530** |
| | [0.0207] | [0.1521] | [0.0251] |
| Teaching | 0.3865*** | -0.4191** | 0.0004 |
| | [0.0449] | [0.1659] | [0.0271] |
| DoubleDeg | -0.1081*** | 0.3228*** | 0.0150 |
| | [0.0119] | [0.0758] | [0.0125] |

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Table A.12 – *Continued from previous page*

| | **Heckman First Stage** | **2SLS First Stage (GPA)** | **2SLS Second Stage (Wage)** |
|---|---|---|---|
| Honours | -0.1412*** | 0.4934*** | 0.0248 |
| | [0.0085] | [0.1002] | [0.0164] |
| Advanced | -0.1702*** | 0.5695 | 0.1098 |
| | [0.0273] | [0.6750] | [0.1117] |
| Age | 0.0489*** | | |
| | [0.0057] | | |
| $Age^2$ | -0.0007*** | | |
| | [0.0001] | | |
| Low SEB | 0.0410*** | | |
| | [0.0138] | | |
| High SEB | -0.0029 | | |
| | [0.0093] | | |
| Entry Score | | 0.0329*** | |
| | | [0.0016] | |
| Satisfaction | | 0.2210*** | |
| | | [0.0398] | |
| $\lambda$ | | -0.1962 | -0.0394 |
| | | [0.1838] | [0.0300] |
| GPA | | | 0.0129* |
| | | | [0.0078] |
| Constant | | 2.4115*** | 4.6479*** |
| | | [0.2938] | [0.0565] |
| Statistical significance shown at the 10% (*) 5% (**) and 1% level (***). | | | |

### A.3.4 Multinomial Logit Selection Model

#### Full Sample Model

Table A.13: **Multinomial selection relative-risk ratios**

| | **Working Full Time** | **Working Part Time** | **Not in Labour Force** | **Further Study** |
|---|---|---|---|---|
| GPA | 1.5458*** | 1.1285** | 1.0513 | 1.3585*** |
| | (0.0799) | (0.0593) | (0.0637) | (0.0664) |
| Female | 1.1118 | 1.2908*** | 1.0864 | 1.2551*** |
| | (0.0951) | (0.1100) | (0.1046) | (0.0995) |
| Work FY | 5.4770*** | 8.9551*** | 1.6928*** | 2.3746*** |
| | (0.4746) | (0.8373) | (0.1643) | (0.1886) |
| International | 0.1048*** | 0.4811*** | 2.3073*** | 1.5294*** |
| | (0.0132) | (0.0552) | (0.2829) | (0.1531) |
| 2010S2 | 1.7024** | 1.0520 | 1.6559 | 1.5961** |
| | (0.4229) | (0.2653) | (0.6055) | (0.3799) |
| 2011S1 | 1.2512 | 1.3765 | 2.4973** | 1.0401 |
| | (0.3618) | (0.3916) | (0.9512) | (0.2846) |
| 2011S2 | 1.7697** | 1.1226 | 2.7643*** | 1.5217* |
| | (0.4333) | (0.2792) | (0.9736) | (0.3581) |
| 2012S1 | 0.8555 | 1.0160 | 2.3794** | 0.8190 |
| | (0.2435) | (0.2846) | (0.8820) | (0.2213) |
| 2012S2 | 1.8932*** | 1.1281 | 2.8112*** | 2.1652*** |
| | (0.4666) | (0.2832) | (0.9971) | (0.5122) |
| 2013S1 | 1.1989 | 1.8404** | 3.7195*** | 1.2893 |
| | (0.3553) | (0.5267) | (1.3963) | (0.3563) |
| 2013S2 | 1.2058 | 1.2032 | 3.1038*** | 2.1637*** |
| | (0.2974) | (0.2992) | (1.0906) | (0.5089) |
| 2014S1 | 0.8427 | 1.2992 | 3.6238*** | 1.3659 |

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Table A.13 – *Continued from previous page*

| | **Working Full Time** | **Working Part Time** | **Not in Labour Force** | **Further Study** |
|---|---|---|---|---|
| | (0.2411) | (0.3668) | (1.3458) | (0.3652) |
| 2014S2 | 0.8660 | 1.0345 | 2.4153** | 1.5027* |
| | (0.2092) | (0.2512) | (0.8423) | (0.3467) |
| 2015S1 | 0.8060 | 1.2095 | 3.5811*** | 1.1884 |
| | (0.2229) | (0.3309) | (1.3051) | (0.3120) |
| 2015S2 | 0.8397 | 1.1789 | 4.6282*** | 2.0481*** |
| | (0.2107) | (0.2967) | (1.6249) | (0.4889) |
| Agricultural Sciences | 1.8651*** | 1.1706 | 1.4142 | 2.6252*** |
| | (0.3968) | (0.2474) | (0.3686) | (0.5195) |
| Architecture | 0.7872 | 1.4885 | 2.5032*** | 5.8771*** |
| | (0.2588) | (0.4219) | (0.7707) | (1.5285) |
| Business & Economics | 2.8585*** | 1.0681 | 1.2913 | 0.9792 |
| | (0.3881) | (0.1408) | (0.2008) | (0.1253) |
| Engineering | 2.6999*** | 0.4501*** | 0.5040*** | 0.3628*** |
| | (0.3664) | (0.0641) | (0.0861) | (0.0500) |
| Health Sciences | 2.3777*** | 1.4736** | 1.5561** | 1.9602*** |
| | (0.4266) | (0.2587) | (0.3349) | (0.3313) |
| Law | 1.5998** | 1.4660* | 1.1888 | 2.0361*** |
| | (0.3427) | (0.3061) | (0.3161) | (0.4208) |
| Maths & Physical Sciences | 1.2318 | 0.6393*** | 0.8545 | 1.2605* |
| | (0.1736) | (0.0889) | (0.1439) | (0.1620) |
| Medicine & Dentistry | 12.2013*** | 3.9200*** | 0.9761 | 0.2186*** |
| | (3.2029) | (1.0633) | (0.3381) | (0.0841) |
| Music | 1.5646 | 3.0590*** | 2.7651** | 3.7380*** |
| | (0.5931) | (1.0755) | (1.1188) | (1.2927) |
| Teaching | 7.1843*** | 1.4880 | 1.8511 | 0.1968*** |
| | (2.6972) | (0.5582) | (0.8388) | (0.0979) |

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Table A.13 – *Continued from previous page*

| | **Working Full Time** | **Working Part Time** | **Not in Labour Force** | **Further Study** |
|---|---|---|---|---|
| Double Degree | 0.5258*** | 1.6632*** | 1.0451 | 1.0468 |
| | (0.0920) | (0.2878) | (0.2359) | (0.1775) |
| Honours | 0.5051*** | 0.8720 | 0.9547 | 3.1740*** |
| | (0.0722) | (0.1208) | (0.1667) | (0.3971) |
| Advanced | 0.2567 | 0.2364 | 0.0000 | 5.0287** |
| | (0.3183) | (0.2936) | (0.0009) | (3.6991) |
| Age | 1.2983*** | 0.8968** | 0.9931 | 0.9184** |
| | (0.0668) | (0.0383) | (0.0454) | (0.0374) |
| $Age^2$ | 0.9962*** | 1.0012** | 1.0004 | 1.0009 |
| | (0.0007) | (0.0006) | (0.0006) | (0.0005) |
| Low SEB | 1.2748* | 0.9732 | 0.7853 | 1.0191 |
| | (0.1673) | (0.1344) | (0.1478) | (0.1351) |
| High SEB | 1.1557 | 1.3454*** | 1.2403 | 1.1612 |
| | (0.1181) | (0.1397) | (0.1644) | (0.1185) |
| Constant | 0.0009*** | 1.6303 | 0.1118** | 0.6693 |
| | (0.0009) | (1.3800) | (0.1070) | (0.5355) |

Statistical significance shown at the 10% (*) 5% (**) and 1% level (***).

Table A.14: **Wage Equation: Multinomial Correction**

| | **OLS** | **Multinomial Correction** |
|---|---|---|
| GPA | 0.0115*** | 0.0001 |
| | [-0.0035] | [0.0048] |
| Female | -0.0328*** | -0.026*** |
| | [-0.0057] | [0.0082] |
| Work FY | -0.002 | 0.0128 |
| | [-0.0065] | [0.0221] |
| International | -0.1072*** | -0.0789*** |
| | [-0.0135] | [0.0291] |
| 2010S2 | 0.0212 | -0.0057 |
| | [-0.0202] | [0.013] |
| 2011S1 | 0.0223 | 0.0192 |
| | [-0.0246] | [0.021] |
| 2011S2 | 0.0455** | 0.0088 |
| | [-0.02] | [0.0125] |
| 2012S1 | 0.0364 | 0.0227 |
| | [-0.0237] | [0.0151] |
| 2012S2 | 0.0651*** | 0.0172 |
| | [-0.0199] | [0.0157] |
| 2013S1 | 0.0426 | 0.0414* |
| | [-0.0266] | [0.0247] |
| 2013S2 | 0.0833*** | 0.0505*** |
| | [-0.0206] | [0.0134] |
| 2014S1 | 0.0317 | 0.0069 |
| | [-0.0228] | [0.0203] |
| 2014S2 | 0.0608*** | 0.0451*** |
| | [-0.0204] | [0.0144] |
| 2015S1 | 0.0391* | 0.0246 |

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Table A.14 – *Continued from previous page*

| | **OLS** | **Multinomial Correction** |
|---|---|---|
| | [-0.0235] | [0.0206] |
| 2015S2 | 0.0491** | 0.013 |
| | [-0.0205] | [0.0202] |
| Agricultural Sciences | -0.0308** | -0.0592*** |
| | [-0.0135] | [0.0206] |
| Architecture | -0.0793*** | -0.1157*** |
| | [-0.0184] | [0.0369] |
| Business & Economics | -0.008 | -0.0483*** |
| | [-0.0087] | [0.0115] |
| Engineering | 0.0735*** | 0.0361*** |
| | [-0.0093] | [0.0139] |
| Health Sciences | 0.0191* | -0.0088 |
| | [-0.0104] | [0.0118] |
| Law | 0.0358** | 0.0341** |
| | [-0.0141] | [0.0167] |
| Maths& Physical Sciences | 0.0475*** | 0.0088 |
| | [-0.0101] | [0.0156] |
| Medicine & Dentistry | 0.2572*** | 0.2418*** |
| | [-0.0147] | [0.0305] |
| Music | 0.0003 | 0.0142 |
| | [-0.0302] | [0.0335] |
| Teaching | 0.0518*** | 0.0043 |
| | [-0.0161] | [0.0318] |
| DoubleDeg | -0.015 | 0.0291*** |
| | [-0.01] | [0.0097] |
| Honours | 0.0149 | 0.0075 |
| | [-0.0107] | [0.0246] |
| Advanced | 0.0659*** | 0 |

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Table A.14 – *Continued from previous page*

| | **OLS** | **Multinomial Correction** |
|---|---|---|
| | [-0.0113] | [0.0266] |
| $m_1$ | | -0.0396** |
| | | [0.017] |
| $m_2$ | | 0.1923** |
| | | [0.0848] |
| $m_3$ | | 0.1707* |
| | | [0.0958] |
| $m_4$ | | -0.2738* |
| | | [0.1548] |
| $m_5$ | | -0.0782 |
| | | [0.0963] |
| Constant | 4.6054*** | 4.7812*** |
| | [-0.026] | [0.0317] |
| $\sigma^2$ | | 0.0392** |
| | | [0.0172] |
| $\rho_1$ | | -0.2003*** |
| | | [0.0732] |
| $\rho_2$ | | 0.9718*** |
| | | [0.3118] |
| $\rho_3$ | | 0.8628* |
| | | [0.4404] |
| $\rho_4$ | | -1.3837** |
| | | [0.6198] |
| $\rho_5$ | | -0.3954 |
| | | [0.4812] |
| Statistical significance shown at the 10% (*) 5% (**) and 1% level (***). | | |

## By Individual Study Areas

Table A.15: **Multinomial Selection Wage Correction**

**By Degree**

| | **Business & Economics** | **Maths & Physical Sciences** | **Engineering** | **Arts & Social Sciences** |
|---|---|---|---|---|
| GPA | -0.0770** | -0.0021 | 0.0289 | -0.0235 |
| | [0.0245] | [0.0214] | [0.0166] | [0.0343] |
| Female | -0.0315 | -0.0603* | 0.0038 | -0.0061 |
| | [0.0246] | [0.0241] | [0.0146] | [0.0656] |
| Work FY | 0.0030 | 0.0099 | -0.0175 | 0.2571 |
| | [0.1050] | [0.0662] | [0.0229] | [0.4979] |
| International | 0.0794 | -0.1269 | -0.0455 | -0.2180 |
| | [0.1474] | [0.0714] | [0.0711] | [0.1834] |
| 2010S2 | 0.0219 | 0.0747 | 0.0133 | 0.0514 |
| | [0.0475] | [0.0807] | [0.0445] | [0.2427] |
| 2011S1 | 0.2357** | 0.0096 | 0.0359 | 0.2239 |
| | [0.0814] | [0.0772] | [0.0580] | [0.2075] |
| 2011S2 | 0.1512* | 0.0900 | 0.0823* | -0.0289 |
| | [0.0680] | [0.0834] | [0.0393] | [0.2074] |
| 2012S1 | 0.1814* | 0.0703 | 0.1109 | 0.0568 |
| | [0.0746] | [0.1027] | [0.0599] | [0.2165] |
| 2012S2 | 0.0358 | 0.1493 | 0.0933* | -0.1242 |
| | [0.0571] | [0.0950] | [0.0391] | [0.1984] |
| 2013S1 | 0.1719* | 0.0739 | 0.1695 | 0.1509 |
| | [0.0807] | [0.0933] | [0.0942] | [0.2578] |
| 2013S2 | 0.1090 | 0.0764 | 0.1340*** | 0.0301 |
| | [0.0686] | [0.0788] | [0.0399] | [0.2697] |
| 2014S1 | 0.0756 | 0.0953 | 0.0604 | -0.0310 |

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Table A.15 – *Continued from previous page*

| | **Business & Economics** | **Maths & Physical Sciences** | **Engineering** | **Arts & Social Sciences** |
|---|---|---|---|---|
| | [0.0744] | [0.0750] | [0.0525] | [0.2326] |
| 2014S2 | 0.1595* | 0.1148 | 0.0490 | 0.0020 |
| | [0.0643] | [0.0697] | [0.0458] | [0.2063] |
| 2015S1 | 0.1168 | 0.1375 | 0.0605 | 0.0830 |
| | [0.0608] | [0.0831] | [0.0555] | [0.2671] |
| 2015S2 | 0.2238** | 0.0791 | 0.0539 | 0.1117 |
| | [0.0796] | [0.0836] | [0.0451] | [0.2260] |
| Honours | -0.0515 | 0.0954 | 0.1014 | 0.0198 |
| | [0.0658] | [0.0514] | [0.0595] | [0.2300] |
| Advanced | | 0.0559 | | |
| | | [0.0328] | | |
| $m_1$ | -0.1898* | 0.0674 | 0.0049 | -0.2904 |
| | [0.0804] | [0.1044] | [0.0792] | [0.1686] |
| $m_2$ | 0.4840* | 0.1347 | -0.1371 | -0.1176 |
| | [0.2212] | [0.3377] | [0.1602] | [0.4054] |
| $m_3$ | 0.4163* | 0.0510 | -0.0475 | -0.7949 |
| | [0.2059] | [0.2971] | [0.1152] | [1.2168] |
| $m_4$ | 0.4243 | -0.0899 | 0.1920 | -1.6742* |
| | [0.2842] | [0.4250] | [0.2901] | [0.8490] |
| $m_5$ | -0.5310 | 0.2274 | 0.0892 | -0.8532 |
| | [0.2902] | [0.2235] | [0.1780] | [0.5418] |
| Constant | 5.2604*** | 4.7351*** | 4.5557*** | 4.2666*** |
| | [0.1879] | [0.2838] | [0.1308] | [0.7540] |
| $\sigma^2$ | 0.1937** | 0.0341 | 0.0221 | 0.6812 |
| | [0.0592] | [0.0867] | [0.0237] | [0.5893] |
| $\rho_1$ | -0.4312 | 0.3647 | 0.0328 | -0.3519 |
| | [0.2683] | [0.3159] | [0.3892] | [0.2159] |

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Table A.15 – *Continued from previous page*

| | **Business & Economics** | **Maths & Physical Sciences** | **Engineering** | **Arts & Social Sciences** |
|---|---|---|---|---|
| $\rho_2$ | 1.0996 | 0.7290 | -0.9211 | -0.1424 |
| | [0.6005] | [0.9197] | [0.6954] | [0.5485] |
| $\rho_3$ | 0.9457 | 0.2761 | -0.3190 | -0.9631 |
| | [0.5862] | [0.9726] | [0.5509] | [1.3780] |
| $\rho_4$ | 0.9639 | -0.4867 | 1.2905 | -2.0285* |
| | [0.7971] | [1.2817] | [1.3111] | [0.9926] |
| $\rho_5$ | -1.2063 | 1.2306 | 0.5992 | -1.0337 |
| | [0.8353] | [0.7021] | [0.7860] | [0.7187] |
| Statistical significance shown at the 10% (*) 5% (**) and 1% level (***). | | | | |

## A.4 Test Statistics

Table A.16: **IV Regression Post-estimation Testing**

| Test | Test Statistic | Distribution | P-value |
|---|---|---|---|
| **Underidentification test** | | | |
| Anderson canon. corr. LM statistic | 391.586 | Chi-sq(2) | 0 |
| **Weak identification test** | | | |
| Cragg-Donald Wald F statistic | 235.203 | F(2, 2158) | |
| Stock-Yogo weak ID test critical values | | | |
| 10% maximal IV size | 19.93 | | |
| 15% maximal IV size | 11.59 | | |
| 20% maximal IV size | 8.75 | | |
| 25% maximal IV size | 7.25 | | |
| **Overidentification test of all instruments** | | | |
| Sargan statistic | 0.001 | Chi-sq(1) | 0.9734 |
| **Tests of endogeneity of GPA** | | | |
| Wu-Hausman F test: | 0.17766 | F(1,2158) | 0.67343 |
| Durbin-Wu-Hausman chi-sq test: | 0.18012 | Chi-sq(1) | 0.67127 |

Table A.17: **IV Regression with Sample-Selection Correction Post-estimation Testing**

| Test | Test Statistic | Distribution | P-value |
|---|---|---|---|
| **Underidentification test** | | | |
| Anderson canon. corr. LM statistic | 381.226 | Chi-sq(2) | 0 |
| **Weak identification test** | | | |
| Cragg-Donald Wald F statistic | 227.562 | F(2, 2157) | |
| Stock-Yogo weak ID test critical values | | | |
| 10% maximal IV size | 19.93 | | |
| 15% maximal IV size | 11.59 | | |
| 20% maximal IV size | 8.75 | | |
| 25% maximal IV size | 7.25 | | |
| **Overidentification test of all instruments** | | | |
| Sargan statistic | 0.022 | Chi-sq(1) | 0.8825 |
| **Tests of endogeneity of GPA** | | | |
| Wu-Hausman F test: | 0.00886 | F(1,2157) | 0.92501 |
| Durbin-Wu-Hausman chi-sq test: | 0.00899 | Chi-sq(1) | 0.92446 |

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