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School of Economics and Finance

Overeducation in the Australian Graduate Labour Market

Ian W. Li

**This thesis is presented for the Degree of
Doctor of Philosophy
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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made. This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Ian W. Li
4th February 2013

Abstract

The uptake of university education in Australia has increased in recent years. At the same time, studies in Australia and elsewhere have indicated that substantial imbalances exist between the labour demand for, and supply of, highly qualified individuals, and that this may result in unfavourable labour market outcomes. This thesis explores these types of issues in the Australian graduate labour market, using data on Australian university graduates from 1999 to 2009, with a focus on education-job mismatch and its consequences.

In the empirical analyses, the incidence, determinants and labour market outcomes of education-job mismatch are explored. The research also examines the earnings impacts of education-job mismatch on segments of the Australian graduate labour market. Specifically, the gender, institutional and length of job tenure differences in education-job mismatch and earnings effects are explored. The research in these areas will be of help in providing information on issues such as the gender wage gap, and the deregulation of university fees. This thesis makes valuable contributions to the literature in at least two aspects. First, the increase in university education attainment in Australia has been fuelled by policy changes in the higher education sector in recent years. The findings of the thesis will, therefore, be timely in adding to the debate on these changes, at least from a labour market perspective. Second, the methodology used in the examination of education-job mismatch and graduate earnings has not been used in any other studies, as far as the author is aware.

A substantial proportion of Australian graduates are found to be mismatched, in that they possess qualifications higher than that required for their jobs. This has been shown to lead to adverse earnings consequences, particularly for those with large extents of education-job mismatch. Policy implications arising from the findings of the analyses are provided, and directions for future research are given in the concluding chapter.

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Glossary of Terms

ABS	Australia Bureau of Statistics
ANZSCO	Australian and New Zealand Standard Classification of Occupations
AQF	Australian Qualifications Framework
ASCO	Australia Standard Classification of Occupations
ATN	Australian Technology Network
BGS	Beyond Graduation Survey
GCA	Graduate Careers Australia
GDS	Graduate Destination Survey
Go8	Group of Eight
HECS	Higher Education Contribution Scheme
IRU	Innovative Research Universities
NESB	Non-English Speaking Background
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
ORU	Overeducation, Required education and Undereducation

CHAPTER 1

Issues and Trends in the Australian Graduate Sector

1.1 Changes in the Australian Graduate Labour Market

A number of changes have occurred in the composition of the higher education labour market in Australia since the 1970s. For instance, there are now many more Australians attaining a higher education qualification than in earlier decades. Statistics from the Australian Bureau of Statistics (ABS) show that only three percent of Australians aged 20-64 years held a higher education qualification in 1971 (ABS 2004). Over 30 years, this increased five-fold, to 16 percent in 2001 (ABS 2008). In 2006, 24 percent of Australians held a bachelor's degree or above educational qualification (ABS 2008). The rate of growth for higher education does not show any signs of slowing; if anything, the statistics suggest that higher education qualifications are being obtained at an increasing rate. In terms of higher educational attainment, Australia ranks favourably compared to other developed countries. For instance, in 1999, 27 percent of Australians held a tertiary qualification, as compared to the Organisation for Economic Co-operation and Development (OECD) mean of 22 percent. These trends are continuing, as indicated by more recent data from the OECD (2011). Specifically, the following are observed. First, around 45 percent of Australians aged 25 to 34 years old have attained tertiary levels of education compared to the OECD mean of around 38 percent.[1] Second, this is much higher than the corresponding figure of 29 percent for older Australians in the 55 to 64 years old age group. This points to a rapid acceleration in the uptake of higher education within these three decades.[2]

Apart from the sharp increase in higher educational attainment over the years, and the corresponding shift in educational attainment within the younger age groups, there have also been other shifts in the demographic attributes of the higher educated. For instance in 2004, Australian females were more likely to hold higher education qualifications than Australian males, with 17 percent of women holding a higher

[1] Tertiary education refers to post-school education, and includes university and vocational qualifications.
[2] To be precise, the OECD (2011) figures look at individuals born from 1933 to 1975.

education qualification, compared to 15 percent of men (ABS 2004).[3] This is a reversal of the trend up to the 1970s, when the proportion of Australian men holding higher education qualifications was much higher than that of Australian women. Reasons that have been offered for the change in the gender proportion of higher education participation include demographic changes, increased labour market opportunities for women, and even increased divorce rates (Booth and Kee 2011). For example, with divorce rates on the rise, women need to invest more in their own education and training to 'hedge' against the unfavourable circumstance of divorce, so as to insure their own financial stability. These changes in the education and training decisions of Australian women are expected to impact greatly on the Australian labour market, and thus one of the aims of this thesis is to assess the impact of these changes on the labour market, and more specifically, among sub-groups in the graduate labour market.

1.2 The Expansion of Higher Education and Earnings

The rapid increase in higher educational attainment brings forth another issue relating to the returns to higher education. There is widespread support for having a more educated population, as more education is associated with positive economic and social outcomes, and, in particular, with better labour force status. For example, in 2003, individuals aged 20-64 years with a higher qualification had an unemployment rate of three percent, compared with the higher six percent unemployment rate of those without. Additionally, 2001 data from the ABS showed that median earnings for the more educated group was almost 50 percent higher than the median earnings for the less educated group (ABS 2004). However, it is noteworthy that data from the Graduate Destination Surveys show a decline in earnings growth for holders of higher qualifications relative to average earnings for the entire labour market (ABS 2004). That is, the median annual salary of all workers has increased nearly three-fold from 1977 to 2003. In contrast, the median annual salary for university graduates, which was equivalent to average earnings in 1977, was only 82 percent of average earnings in 2003. These statistics point to a fact, albeit crudely, that is not readily obvious; while getting a degree is advantageous in terms of monetary pay-offs, the wage premium might be eroding over time, or might

[3] A higher education qualification is defined by the ABS as a qualification at the bachelor's degree level or above.

not be as high as expected. This has important implications for individuals in their consideration of further education.

It is widely recognised that higher education is integral to economic growth, by increasing productivity and the supply of workers for highly skilled jobs. This is affirmed by the Australian Government's commitment to the Australian higher education and research sectors in the form of its financial support of $5.4 billion over the next four years, with additional funding promised for the next ten years. The Australian Government has also set an ambitious target of having 40 percent of Australians aged 25-34 years attain a bachelor's degree or above by the year 2025. Federal funding has also been committed to uncapping the number of government-funded university places from 2012. These facts highlight the Australian Government's recognition of the importance of education.

However, it is unclear if such a highly educated workforce is required in Australia. As McGuinness (2006) puts it in the UK context, these sorts of governmental push towards more higher education "implicitly assume that there is some unmet demand for graduate labour or that employers hiring graduates will upgrade their production techniques in order to take advantage of a more educated workforce". This might put some graduates in a position where they are overeducated for their jobs, given that the supply of graduates has increased in the labour market while demand for graduates remains unchanged. Another study by Dolton and Silles (2008, pg. 125) argued, "Yet, as the average educational attainment of the workforce has increased, there is an indication that the occupational structure of the labour market does not have the capacity to absorb the increased number of educated workers into traditional graduate occupations". These arguments suggest that the quick expansion of highly skilled workers, given the slower growth of demand for the same, might potentially impact unfavourably on the individual as well as the economy, at least in the short run. Moreover, the detrimental effects of education mismatch have the potential to persist even in the long run (Hartog 2000).

1.3 Policy Implications

There are policy implications for the issues raised above, particularly as they relate to education policy and funding. A paper by Coelli and Wilkins (2008), for example, highlights the differing views of the Australian political parties with regard to education and training. In particular, the current ruling Labor Government promised an ‘education revolution’ before they were elected into office in 2007. One of the rationales for their heavy support in increasing education and training is that these increase employment in Australia without fuelling inflation (Coelli and Wilkins 2008). High inflationary pressures in 2008 were also often attributed to a chronic skills shortage by Treasurer Wayne Swan (Coelli and Wilkins 2008). Conversely, Opposition Member of Parliament Malcolm Turnbull acknowledges the existence of skills shortages in certain sectors, but rejects the idea that these skills shortages are prevalent in all sectors, and in all states and territories. In their study, Coelli and Wilkins (2008) found support for the view of the Labor Government, particularly, that a skills mismatch exists, but questioned if the current policy response of subsidising education and training is cost-effective.

At the same time, a recent landmark change has occurred in the Australian university landscape. Prior to 2012, Commonwealth-supported undergraduate student places in Australian universities were capped and regulated by the federal government. This has now changed, with the introduction of the ‘demand-driven funding’ system (Department of Education, Employment and Workplace Relations 2012d). Under this system of ‘uncapped’ student places, the Commonwealth government guarantees funding to all undergraduate students who have secured a place in an Australian university, with the exception of students studying medicine. Student places are therefore constrained only by student demand and the capacity of the universities. This policy appears to have led to a surge in university enrolments, based on a news article from The Sydney Morning Herald (2012). Drawing on figures from the Department of Industry, Innovation, Science, Research and Tertiary Education, The Sydney Morning Herald (2012) reports enrolment increases of up to 14 percent for some Australian universities.

1.4 Thesis Layout

This thesis will therefore explore the central issue of overeducation in the Australian graduate labour market. Specifically, the study will focus on the incidence and earnings impact of overeducation amongst Australian university graduates. The analysis will also be centred on sub-groups of the graduate population, based on personal and institutional attributes. The thesis is organised in the following manner. Chapter 2 presents a general literature review of the studies on overeducation, with some references to the broader human capital theory literature. A data description is presented in the same chapter. Chapters 3 to 7 are the empirical studies in this thesis. These chapters are 'stand-alone' in the sense that they contain their own literature reviews and methodology sections. A description of these empirical chapters is as follows.

Chapter 3 examines the determinants of overeducation status. This chapter offers a preliminary look at the incidence of overeducation, undereducation, and required education (ORU) amongst Australian university graduates, from 1999 to 2009. The incidence of ORU status analyses are also performed for sub-groups of the graduate population, such as gender and university groups. The latter part of this chapter examines the determinants of overeducation, utilising logit models.

Chapters 4 to 7 look at the earnings impact of ORU. In Chapter 4, an examination of the ORU earnings effects for Australian university graduates is performed using Ordinary Least Squares (OLS) regression. Specifically, a model suggested by Vahey (2000) is used. The analysis in this thesis is, to the best of the author's knowledge, the first study to utilise such a specification.

The gender differences in graduate earnings are explored in Chapter 5. This chapter looks at the gender wage gap amongst Australian university graduates, and whether ORU earnings impacts have widened, or narrowed the gap. The statistical analyses in this chapter also focus on two other gender-related issues of interest. First, the chapter looks at whether the 'job search hypothesis' proposed by Frank (1978) can be validated for the Australian graduate labour market. Second, gender differences in the occupational mobility of Australian graduates are explored.

Chapter 6 explores the ORU earnings effects across groups of graduates with different amounts of work tenure. This analysis accommodates an interesting quirk in the dataset. That is, graduates who report having some work tenure have accumulated this work experience prior to the completion of their most recent qualification. The analysis of ORU earnings effects can therefore provide a unique perspective on how ORU impacts on the earnings of graduates with varying amounts of experience. For instance, it will be interesting to observe whether firm-specific experience is able to offset the earnings disadvantages of ORU.

Chapter 7 shifts the focus from the differences in ORU earnings impacts for graduates with different personal characteristics to graduates with different institutional characteristics. This chapter thus examines the differences in ORU earnings impacts across university groups. This is done from the perspective of differences in quality across institutions.

Chapter 8 provides a summary of the empirical chapters in the thesis and concluding remarks. Some directions for future research are also provided.

CHAPTER 2

Literature Review and Data Description

2.1 Introduction

This chapter consists of two parts. The first part will be devoted to a review of the literature. This literature review will briefly describe the link between education and earnings in section 2, and how the ORU literature fits into this broader literature. This is followed by a discussion of the methodology and theoretical framework in the ORU literature, in the same section. The second part of this chapter describes the data to be used in the empirical analyses in the thesis. Descriptive statistics are also presented and discussed. These take place in section 3. Section 4 provides a summary of the chapter.

2.2 Education and Earnings – What do We Know?

There exists a large body of research in the human capital theory literature.[4] An extensive part of this literature is dedicated to the documentation of the impact of education on an individual's earnings. The early writers in this field recognised that acquiring education entails substantial costs, particularly when the indirect costs of education are taken into account. Thus, individuals were argued to only engage in further education to the extent that the appropriately discounted future income stream is increased by an amount on par or greater than the costs of education. In other words, the education decision was treated as an investment decision. This education decision could be undertaken at the individual or national levels.

Studies in this area have been around for several decades. Friedman and Kuznets (1945), for example, were among the first to formalise human capital theory.[5] Subsequently, both empirical and theoretical developments of the topic have been made by other economists. In this regard, advancements by Gary Becker and Jacob Mincer (see, for example, Becker 1962, Mincer 1974) warrant a mention. For example, Mincer contributed greatly to the research in this area, and is widely

[4] There are alternative theories and bodies of literature which link education to labour market earnings. These include the screening hypothesis (Arrow 1973), and job market signalling (Spence 1973).

[5] Polachek (2007) discusses some of the earliest roots of human capital theory. He argues that the notion dates as far back as the 1700s.

regarded as a groundbreaking pioneer in empirical labour economics.[6] Significant contributions were made with his doctoral dissertation (Mincer 1958a), his seminal article (Mincer 1958b), and his book titled "Schooling, Experience and Earnings" (Mincer 1974), in which he formulated the Mincerian earnings function (alternatively known as the human capital earnings function), which is the dominant 'workhorse' of labour market analyses today.

Empirically, the human capital earnings function has been proven to be sound. In Mincer (1974), more than 50 percent of the variation in earnings could be explained when schooling, experience and weeks worked were taken account of. Polachek (2007) notes that Mincer's human capital earnings function has been applied "…in over 100 countries with the same resounding success…", and has been used to establish a plethora of observations regarding the performance of individuals in the labour market.

The empirical studies in the literature have shown strong links between education and earnings. Psacharopoulos (1981; 1985; 1994) and Psacharopoulos and Patrinos (2004) provide a cross-country overview of studies, and report positive premiums to education. These premiums are high, and can be up to around 38 percent in the case of developing countries. Even OECD countries, which have the lowest returns to education, have reasonably high returns of at least 11 percent, which is higher than most alternative forms of investment. Education thus appears to be an attractive investment option, given its high rate of return.

2.2.1 Education, Job Mismatch and Earnings

In more recent times, however, a further development of, if not a challenge to, human capital theory is provided by the Overeducation, Required education and Undereducation (ORU) literature. This is distinguished from human capital theory by the attempts to introduce demand-side considerations into a model that is formulated with only supply-side perspectives in mind. In other words, the question this area of study seeks to address is: "How does educational mismatch affect the return to

[6] Jacob Mincer is often called the "father of modern labour economics" (see, for example, Grossbard 2006), though he considers himself, if anything, 'a' father and not 'the' father of modern labour economics (pg. 19).

education?”. One of the earliest studies in this field was conducted by Freeman (1976), who found that the increased supply of college graduates was not met by a corresponding increase in demand in the US.[7] Since the seminal study by Freeman (1976), the literature in this area has grown considerably, perhaps also due to the rapid expansion of higher education in the developed countries.

These studies (Freeman 1975; 1976; 1977) observe the same outcome with regard to the earnings of these qualified individuals: the wage premium for college graduates over high school graduates has been eroding over time. For instance, Freeman (1977) observed that the starting salary of bachelor degree graduates decreased sharply in real terms. At the same time, the income of male college graduates relative to male high school graduates also fell.

The expansion of higher education attainment carried on to the 1980s, and continued to be an area of great research interest. Duncan and Hoffman (1981) further developed and influenced the research into educational-job mismatch in the labour market, by changing the way overeducation is defined in Freeman’s (1975; 1976; 1977) approach. Specifically, Duncan and Hoffman (1981) formally defined overeducation as the excess educational attainment beyond that required for the job an individual is in, whereas Freeman’s (1975; 1976; 1977) approach observed only the wage differential of college workers versus other graduates. The latter approach is inferior in that it fails to consider the match or mismatch of educational attainment and job requirements, which arguably would account for the differences in earnings under a human capital framework.

2.2.2 Measurement Issues and Methodological Considerations

The overeducation literature has generally used three approaches to define educational mismatch: i) job analysis; ii) worker self-assessment; and iii) realised matches. The job analysis and realised matches approaches rely on objective measures of overeducation, while the worker self-assessment uses the worker’s subjective assessment of educational (mis)match. Specifically, the job analysis

[7] Freeman (1977) notes that the supply of college graduates in the US changed considerably during the 1950s, 1960s and 1970s, and college enrolments in 1970 had increased three-fold compared with 1950.

approach requires the use of job dictionaries, whereby the level of education required to perform a job is analysed and defined by professional job analysts. This is then compared to the acquired level of education to determine if the individual is overeducated, undereducated or correctly matched.

The worker self-assessment method relies on the individual worker to specify the education required for the job. As Hartog (2000) notes, this self-assessment may be direct or indirect. In the direct case, the worker is required to state the level of education required for the job, such as a ‘high school education’, or a ‘bachelor’s degree’. In the indirect case, the worker simply reports whether a higher or lower level of education is required relative to the actual attained level of education.

The realised matches approach, also known as the ‘empirical’ approach, uses the mean or modal level of education within the data as the benchmark. For instance, where the mean level of education for nurses is observed to be a ‘bachelor’s degree’, a ‘bachelor’s degree’ will be used as the required level of education to be a nurse. Nurses who have a higher level of education will then be classified as overeducated, while those with lower levels of education will be considered undereducated. In cases where education is measured in years rather than levels, an arbitrary cut-off point, such as one standard deviation above or below the mean, is used.[8] There are advantages and disadvantages associated with the use of each approach (see Hartog 2000, pg. 132-133 for a discussion). Nevertheless, Hartog (2000) notes that the adoption of a certain approach is typically determined by data availability.[9]

From an empirical viewpoint, the choice of approach has a small impact on the incidence of educational mismatch, while having no material influence on ORU earnings effects. McGuinness (2006), for instance, reviews a number of studies which assess the incidences of overeducation under different definitions (see, for instance, Battu, Belfield and Sloane 2000; McGoldrick and Robst 1996). Generally, it can be said that the realised matches approach generates lower incidences of

[8] As a result, the realised matches approach typically yields symmetrical incidences of overeducation and undereducation.
[9] Hartog (2000) does argue that the job analysis method is conceptually superior. Due to the high costs involved in employing the job analysis approach, however, the worker self-assessment method may be the best practical measure.

overeducation compared to the other two approaches. This can be reasonably expected due to the requirement for mismatched workers to be one standard deviation away from the reference mean - there is thus, by definition, a two standard deviation 'safety' zone under which workers will not be considered mismatched to their jobs.

In comparison, estimated ORU earnings effects are robust to the choice of approach. Groot and van den Brink (2000), for example, conducted a cross-country meta-analysis of 25 studies, and reported no substantial difference in estimated earnings effects across the various definitions of education-job mismatch. Reviews of the literature by Hartog (2000) and McGuinness (2006) report consistent estimates of ORU earnings effects by various studies, across the various definitions employed.

There are methodological differences in the estimation models used in analyses of ORU earnings effects. Generally speaking, these can be separated into two broad forms, and the methodological frameworks for both are discussed in McGuinness (2006).[10] The first uses continuous measures of education, such as years of schooling. The years of surplus schooling is then distinguished from the years of education that are usual for the worker's occupation, and both schooling concepts are entered into the estimating equation. This permits quantification of the returns to correctly matched and years of surplus education.

The second form relies on dichotomous measures of education-job match or mismatches. For instance, Verdugo and Verdugo (1989) entered both the education level and education-job match status of the workers into the estimating equation as dummy variables. McGuinness and Bennett (2007) utilised a continuous measure of the years of schooling in their estimation model, while using dichotomous variables to represent the overeducated and undereducated. Vahey (2000) proposed the use of vectors of dichotomous variables to examine the earnings effect of vertical extents of education-job mismatch(es). The empirical findings yielded by each of these specifications are consistent. That is, returns to overeducation tend to be positive, but are less than the returns to matched or required levels of education.

[10] Note that where the analysis is focused on the graduate labour market, the concept of undereducation is of limited relevance.

Overeducation has vast implications on both the macroeconomic and microeconomic scales. On a microeconomic basis, overeducation is detrimental to firms in that overeducation has been found to lower productivity (McGuinness 2006). As a result of this lower productivity, overeducated employees may suffer wage losses, diminishing the returns to their education. Alternatively, individuals who are overeducated tend to report lower job satisfaction (for instance, see Battu, Belfield and Sloane 2000) or higher rates of turnover (for example, see Alba-Ramirez 1993). On a macroeconomic level, McGuinness (2006) suggests that tax revenues might be wasted on educating individuals if the level of education does not increase their productivity. This is particularly true for developed countries such as Germany and Australia which have substantial public funding of higher education. Overeducation, therefore, has far-reaching implications on many levels. As such, empirical research on overeducation would be useful in informing individuals making investments on their human capital, and to policy makers in the allocation of national resources.

Duncan and Hoffman (1981) suggest two different frameworks can be used to account for the decline in higher education returns. In the first scenario, the production techniques and demand for skilled labour is fixed, and does not change in response to changes in the educational attainment of the labour force. Therefore, as the number of better educated workers grows faster than the skill requirements of the jobs, a large number of workers becomes overeducated. As a consequence, some workers will be assigned to jobs below their educational level. At the same time, these overqualified workers do not secure a higher wage relative to those in the same job, but earn the same amount as those who are correctly matched by educational level. Under this situation of inelastic production techniques and fixed wages, skills mismatch has the potential to become a long-term problem.

The alternative scenario allows for change in production techniques and skills requirements. As average educational attainment increases, firms adapt their production technique to take advantage of the highly skilled labour which is relatively abundant and also increasingly cheaper. As a result, workers do not work below their skill levels, and are appropriately matched to their jobs in terms of education level. This explanation treats overeducation as a short-run disequilibrium which arises temporarily due to a lack of (or insufficiently fast) adjustment by firms and individuals. Both frameworks explain the rationale behind the declining returns to higher education, but are at odds in their interpretation of educational mismatch as a long- or short-run problem. Many empirical studies have analysed the ORU labour market outcomes in the context of the various theoretical frameworks (see Hartog 2000 and McGuinness 2006 for a review of the literature). In McGuinness (2006), a description of human capital theory, the job competition model and assignment theory, as well as their consistency with regards to the labour market outcomes in empirical analyses of ORU, is given. McGuinness's (2006) survey of the international literature found that, generally, the empirical evidence supports the assignment theory perspective of the labour market, though it is also conceded that other labour market interpretations, such as human capital theory, could very well remain relevant under certain conditions (see McGuinness 2006, pg. 410).

2.3 Data Description

The data for the analysis are drawn from the Graduate Destination Surveys (GDS) conducted by Graduate Careers Australia (GCA), for the years 1999 to 2009.[11] The GDS is an annual census of Australian university graduates, conducted with the aim of identifying the main destinations of higher education students in Australia post-graduation, and has been conducted annually by GCA since 1974.[12] The target population of the GDS is graduates who have completed the requirements for a higher education award from an Australian institution. All students, including international students, are included in the survey. The graduates are sent a copy of the questionnaire about four months after they have completed the requirements for their course. Hence, two rounds of the survey are conducted every year, in April and October.

The survey is a rich source of information regarding graduates who studied in Australia, as well as their outcomes in the labour market. In particular, the survey contains information about the individual graduate's personal, employment and

[11] This survey has also come to be known as the Australian Graduate Survey, but will be referred to as the Graduate Destination Survey for the remainder of this thesis.
[12] The term 'graduate' technically requires a formal recognition of course completion. For the purpose of this thesis, however, students who have fulfilled the requirements of their course (graduands) will be referred to as graduates.

schooling characteristics, all of which are important determinants of labour market outcomes. One shortcoming of the GDS data is that it contains little or no information on the graduates' marital status, number of children and other socioeconomic indicators. As these are potentially strong predictors of an individual's participation, attachment, and performance in the labour market, more priority could be given to procuring this information. Nevertheless, the GDS contains a wealth of other information which can be used for the analysis of the graduate labour market.

2.3.1 Questionnaire and Collection Methods

The questions asked in the survey have progressively grown over the years. In 1974, the survey comprised of around 25 individual questions. In 2009, the GDS had over 50 questions, including the original 25. Each institution is responsible for the administering of the survey for their own graduates, although the survey format, standard recommended methodology and code of practice are provided by GCA. In the first instance, a copy of the GDS (together with the Course Experience Questionnaire) is mailed out to the graduates. [13] If the questionnaire is not returned to the institution within four weeks, an email reminder is sent. Subsequent methods of follow-up, such as telephone calls or further reminder emails can be made, at the discretion of the respective institution's survey manager. The survey manager at each institution is responsible for the collection, coding and data entry of the survey on top of the administration, in accordance with the coding instructions from GCA. The dataset from each institution is then collected by GCA, who collates and analyses the data, before providing all institutions with a complete dataset. GCA produces two annual publications, namely, GradStats and GradFiles. These may be viewed on the GCA website (Graduate Careers Australia 2011).

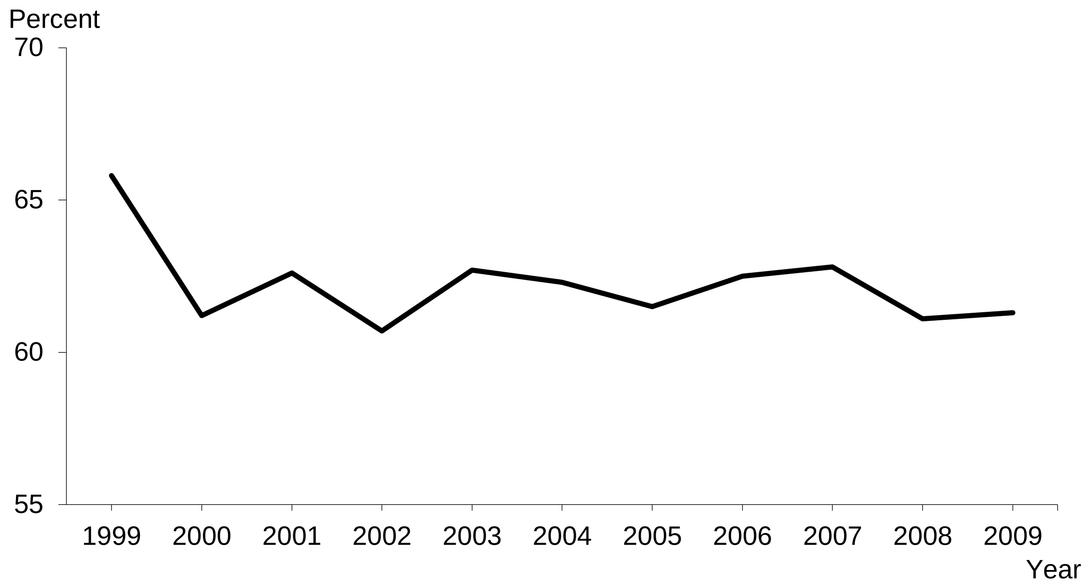
2.3.2 Code of Practice

The use of the GDS data is governed by a Code of Practice set by GCA and the Australian Vice-Chancellors' Committee. The Code of Practice provides guidelines for the use and public disclosure of information from the GDS. In particular,

[13] This Course Experience Questionnaire collects information from undergraduates, primarily with regards to course satisfaction. Students who have completed a postgraduate course receive the Postgraduate Research Experience Questionnaire.

individual respondents may not be identified, and the data cannot be used to knowingly undermine the reputation and standing of institutions.[14] Further, the Code of Practice stipulates that the GDS survey data should not be disclosed publicly where the response rate for that particular year is less than 50 percent, while also stating that a total response rate of 70 percent is desirable. However, this target rate of 70 percent has not been achieved for close to two decades. The response rate over this period was highest in 1999, at about 66 percent, and has remained at around 62 percent since. These response rates are far above the 50 percent required for reliable analysis, as stated by the GDS Code of Practice. The response rates for the years 1999 to 2009 are given in Figure 2.1.

Figure 2.1: GDS Response Rates, 1999 to 2009

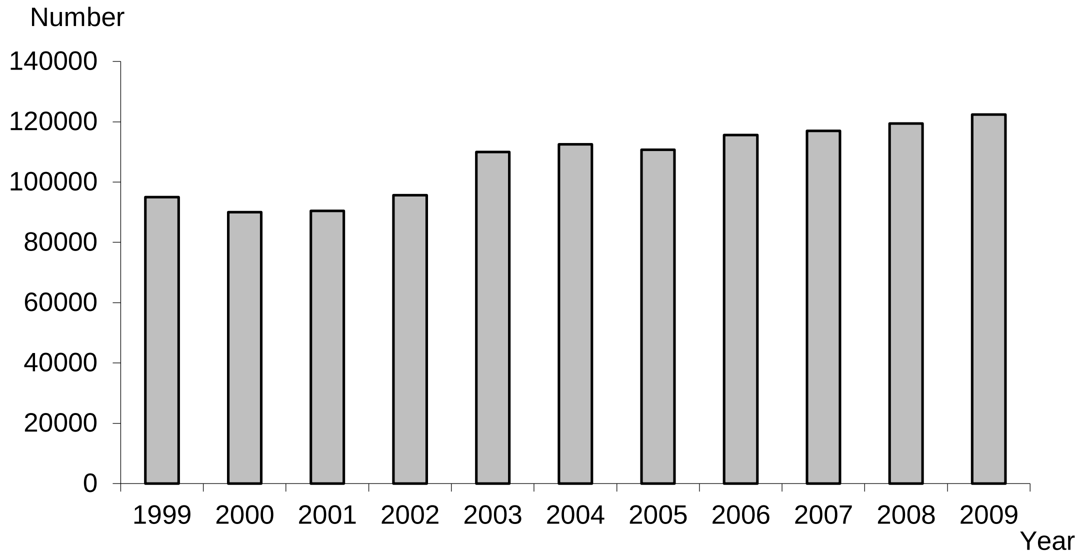


In addition, the sample sizes for the respective years are relatively large. Figure 2.2 sets out the number of observations in each sample year. The lowest number of recorded observations is in the year 2000, with just over 90,000 observations. The year with the highest number of observations is the year 2009, with 122,380 observations. Post 2003, all years had well in excess of 100,000 observations. There is a total number of 1,178,840 observations over this period. The large sample size of

[14] Therefore, the main sets of statistical analyses in the thesis do not distinguish between graduates from individual institutions, but focuses on differences between 'university groups'. The rationale for drawing distinctions between university groups is elaborated in greater detail in Chapters 3 and 7.

the GDS and the reasonable response rates thus provides assurance of quality in the dataset.

Figure 2.2: Number of Observations in the GDS, 1999 - 2009



Guthrie and Johnson (1997) assessed the reliability of the GDS data by analysing the methodology used in data collection, and comparing the GDS data with the corresponding population parameters published by the Department of Employment, Education, Training and Youth Affairs. They report that a high degree of consistency can be found for respondents and non-respondents for full-time workforce related figures. Thus, Guthrie and Johnson (1997) concluded that the GDS data is nationally representative of the graduate labour market in Australia.

The sample used for analysis in subsequent chapters was restricted to graduates who were employed in Australia at the time of the survey. In addition, graduates who had missing values in variables of interest were excluded from the sample. Following these exclusions, a ‘purged’ sample of 569,325 observations remained.

2.3.3 Descriptive Statistics

A description of the variables used in the statistical analyses in the following chapters is presented in Table 2.1. This table also presents the means and standard deviations of the variables.

As the graduates in the sample could be either employed on a full-time or part-time basis, the use of the hourly wage as the dependent variable in examining graduate earnings is appropriate. The mean hourly wage of the graduates, in natural logarithmic form, is 2.824.[15] This represents, in real dollar terms, an hourly wage of around $16.85.

The data contained information about the university where the graduates completed their qualification, and this information was used to categorise the graduates by university groups. Around 28 percent of the graduates were from the Group of Eight universities, while 19 and 13 percent were from the Australian Technological Network and Innovative Research University groups, respectively. The remaining 40 percent were categorised as All Other universities. These proportions appear to be reasonably consistent with statistics from the Department of Education, Employment and Workplace Relations (2010).

The descriptive statistics on the personal characteristics of the graduates are in line with expectations. The average age of the graduates was 29 years. Around 17 percent came from a non-English speaking background, and roughly five percent were not of Australian residency status. The only anomaly here appears to be the high proportion of females in the sample, at 61 percent. While this figure appears to be higher than expected, this can be attributed to two reasons. First, a study of non-respondents by Guthrie and Johnson (1997) found that females were more likely to respond to the GDS survey. Second, the proportion of females engaged in higher education has been increasing steadily over the years (ABS 2004). More recent figures from the Australian Bureau of Statistics indicate that among individuals who obtain an Australian university degree, around 60 percent are females. This would be just slightly less than that indicated by the descriptive statistics of the GDS. Thus, the overrepresentation of females in the sample is unlikely to be a problem.

[15] The mean hourly wage was computed by deflating wage figures in the data by the Australian CPI from 1999 to 2009.

Table 2.1: Summary Statistics and Description of Explanatory Variables

Variable	Mean	Std. Dev.
Dependent Variable		
Log hourly wage = Hourly wage, in real terms, expressed in logarithmic format	2.824	0.616
University Group		
Group of Eight = Go8 university	0.279	0.449
ATN = ATN university	0.190	0.393
IRU = IRU university	0.130	0.336
Other = Other university (omitted category)	0.400	0.490
Personal Characteristics		
Female = Female graduates (omitted category = Male graduates)	0.611	0.488
Age = Age, expressed in years	29.409	9.428
Age squared = Age squared, expressed in years	953.792	673.722
NESB = Non-English speaking background (omitted category = English-speaking backgound)	0.174	0.379
Non-Australian = No Australian residency status (omitted category = Australian residency status)	0.045	0.208
Study Characteristics		
Double degree = Double degree qualification (omitted category = No double degree)	0.091	0.287
Part-time study = Studied on a part-time basis (omitted category = Studied full-time)	0.353	0.478
Further study = Engaged in further study (omitted category = No further study)	0.196	0.397
Broad field of study		
Natural and Physical Sciences	0.062	0.241
Information Technology	0.050	0.217
Engineering	0.054	0.226
Architecture and Building	0.021	0.142
Agriculture and Environment	0.021	0.144
Nursing	0.071	0.258
Medicine	0.100	0.300
Education	0.145	0.353
Society and Culture	0.171	0.376
Creative Arts and Others	0.063	0.242
Management and Commerce (omitted category)	0.242	0.428
Employment Characteristics		
Self-employed = Self-employed (omitted category = Not self-employed)	0.039	0.193
Private sector = Employed in private sector (omitted category = Public sector)	0.597	0.490
Short-term employment = Short-term employment (omitted category = Long-term employment)	0.306	0.461
Tenure = Job tenure, expressed in years	2.371	3.998
Tenure squared = Job tenure squared, expressed in years	21.606	80.220

Table 2.1: Summary Statistics and Description of Explanatory Variables (cont.)

Variable	Mean	Std. Dev.
Industry of Employment		
Accounting	0.034	0.180
Wholesale and retail	0.078	0.268
Accommodation	0.033	0.178
Manufacturing	0.041	0.198
Forestry and mining	0.011	0.105
Legal services	0.024	0.153
Government	0.092	0.289
Education	0.145	0.352
Higher education	0.063	0.243
Health and community services	0.158	0.365
Medicine and dentistry	0.040	0.196
Construction	0.013	0.112
Other services	0.077	0.267
Transport and communication	0.031	0.173
Engineering consulting	0.021	0.143
Financial services (omitted category)	0.139	0.345
Year of Graduation		
1999 = Graduated in 1999 (omitted category)	0.075	0.264
2000 = Graduated in 2000	0.078	0.268
2001 = Graduated in 2001	0.065	0.247
2002 = Graduated in 2002	0.069	0.253
2003 = Graduated in 2003	0.085	0.279
2004 = Graduated in 2004	0.095	0.294
2005 = Graduated in 2005	0.098	0.297
2006 = Graduated in 2006	0.089	0.284
2007 = Graduated in 2007	0.109	0.311
2008 = Graduated in 2008	0.116	0.321
2009 = Graduated in 2009	0.120	0.325

Note: Values of means in some categories may not sum to unity due to rounding.

The statistics for degree characteristics are reasonably representative of a graduate population. While a rather large proportion, of close to 35 percent of graduates, had undertaken their studies on a part-time basis, note that the sample consists of both undergraduates and postgraduates, and it would be expected that a number of postgraduates undertake their studies whilst engaging in employment. Restricting the sample to just undergraduates lowers the proportion of students engaged in studies on a part-time basis to just one-fifth of the sample. A minority, of nine percent, of the graduates were enrolled in a double-degree program, and one-fifth of the graduates reported being engaged in further studies at the time of the survey.

The sample was also categorised by field of study. Management and Commerce was the most popular field of study, with close to a quarter of all graduates having been enrolled in this field. Society and Culture, Education and Medicine also accounted for substantial proportions of the graduates, with ten to 17 percent of the graduates enrolled in each field. The remaining fields each accounted for small proportions of the sample.

Statistics on employment characteristics were also in line with expectations. Close to 60 percent of the sample were employed by the private sector, with the remainder employed in the public sector. The majority of the graduates were employed on permanent bases. The mean length of tenure an average graduate had was around 2.4 years. There is a reasonable spread of graduates across the various industries of employment. A large number of graduates were employed in the Education, Health and Community Services, and Financial Services industries. These industries each accounted for about 15 percent of graduates. The Mining and Construction industries accounted for the lowest share of employment, at about one percent each. These proportions do not seem to depart from the norm.

2.4 Summary

This chapter has provided a general description of the studies in the ORU literature. It has also provided a commentary on some of the methodological frameworks that are used in studies of ORU earnings effects. More in-depth literature reviews will be provided in each of the empirical chapters that follow.

The data that will be used in the subsequent statistical analyses have also been discussed. In particular, background information and collection methods of the GDS have been discussed, and the descriptive statistics of the data sample have been presented.

The following points can be made regarding the data. First, the response rates for each of the years indicate a reasonable level of response, and the data can be considered to be of a standard which makes it reliable for robust analyses. This is further supported by Guthrie and Johnson's (1997) study of non-response, which concluded that the GDS provides a reasonable indication of the graduate labour market. Second, the dataset comprises a large number of observations. This is valuable to the analyses to be conducted in subsequent chapters due to the methodology employed, which requires disaggregation of the sample into very detailed categories.[16] Third, an examination of the descriptive statistics indicated that the traits and characteristics of the sample were consistent with those expected of a graduate population. The dataset can therefore be considered to be reliable for analysis.

[16] This is explained more comprehensively in Chapter 4 in the study of ORU earnings effects.

CHAPTER 3

Which Graduates are more Susceptible to Overeducation?

3.1 Introduction

This chapter examines the incidence and determinants of ORU status in the Australian graduate labour market. The organisation of this chapter is as follows. Section 2 reviews the literature on the determinants of ORU status. Section 3 looks at the incidence of ORU in the labour market, starting with an examination of the entire labour market. This will be followed by an examination of the incidences of ORU status for various disaggregated groups, such as gender and university (group) attended. The analysis will then turn to the use of logit models to uncover the likelihoods of educational-job mismatch that are attributable to various graduate characteristics. In particular, section 4 presents the methodology. Sections 5 and 6 present the results for the binary and multinomial logit models, respectively. Section 7 offers summary comments for the chapter.

3.2 Literature Review on the Determinants of ORU

Studies in the ORU literature which inform on the incidence of ORU tend to do so through the descriptive statistics of their respective data samples. Hartog (2000) provides a summary of the reported incidence of ORU in 14 such studies, while McGuinness (2006) tabulates the incidences reported in 33 studies (some of which are covered in Hartog 2000). As noted earlier in Chapter 2, the incidence of ORU varies across studies, and it is difficult to detect any pattern. However, McGuinness (2006) indicated that the realised matches approach yields lower incidences of education-job mismatch, compared to the job analysis and worker self-assessment approaches. Further, estimates tend to differ by country, with studies on the US labour market yielding the highest incidences of educational mismatch. While studies of the ORU earnings effects have a consensus on the trend and magnitude of estimated effect (see Chapter 2), it appears that the incidence of ORU could be dependent on the features of the labour markets in each country.

A smaller number of studies explore the characteristics (or determinants) of educationally mismatched individuals through the use of probit or logit models. Fleming and Kler (2008), for instance, used a bivariate probit model to examine the characteristics of the overeducated in Australia, as well as the impact of overeducation on job satisfaction. They found that those who were working on a casual basis, were employed in a small sized firm, had union membership or who worked in the manufacturing industry, were more likely to be overeducated. Conversely, migrants from English-speaking backgrounds and who had been in Australia for a substantial period of time, as well as those from the public services industry, were less likely to be overeducated.

Dolton and Silles (2001) also estimated a probit model of the determinants of overeducation, using data on university graduates from the UK. This study found that some degree characteristics were important determinants of overeducation. Specifically, graduates with a higher degree class or postgraduate qualifications were more likely to be correctly matched to their occupation. However, the inclusion of the level of educational attainment in the estimating equation, particularly where the realised matches approach is used to define ORU, has been questioned by Chiswick and Miller (2009). Chiswick and Miller (2009) argue that as the definition of educational mismatch is inherently dependent on the level of educational attainment, the inclusion of the latter introduces a link between the dependent and the explanatory variables "based on this measurement issue, rather than on outcomes of worker behaviour" (Chiswick and Miller 2009, pg. 166). Further, they noted that the actual years of education variables dominated the estimating equation when these were included, and had large estimated coefficients and 't' statistics.

The faculty of degree (and hence field of study) was also found to be important in determining education-job (mis)match (Dolton and Silles 2001). Graduates in arts and humanities, and languages, for example, were found to be more likely to be overeducated.[17] Some employment characteristics were also found to be important determinants of overeducation. Dolton and Silles (2001) reported that those employed on a part-time basis were more likely to be overeducated compared to those employed full-time. Those in the occupation categories of professionals and associate professionals, or who worked in the education sector, were less likely to be

[17] Robst (2007b) reported that graduates from these fields of study were also more likely to be mismatched to their occupations, due to the more generic nature of the skills learnt in these majors.

overeducated. Gender, however, was found to be unimportant in determining whether an individual was overeducated or not.

McGoldrick and Robst (1996) used a multinomial logit model in their US study, and estimated the likelihood of being overeducated for the three different definitions of 'required schooling'.[18] Females were more likely to be overeducated when the job analysis approach was employed. The reverse was true when the realised matches approach was used. Kiker *et al.* (1997), however, reported that males were more likely to be overeducated and less likely to be undereducated. This difference in the probability of educational mismatch reflects the findings in the ORU literature which reports on the incidence of educational mismatch using descriptive statistics, where there is no consensus on whether members of any gender are more likely to be overeducated or undereducated. As mentioned above, this is likely to be specific to the labour market being studied, and could be a reflection of social norms and culture of the respective labour markets.

McGoldrick and Robst (1996) also found that union membership results in a lower likelihood of overeducation, a finding that is at odds with that of Fleming and Kler (2008). Marital status was found to have no statistically significant impact on the likelihood of being educationally mismatched for males in Mexico (Quinn and Rubb 2006), and likewise, the number of children was not found to have any impact on the likelihood of education-job match (McGoldrick and Robst 1996). There is much more agreement on the role labour market experience plays in determining educational mismatch, as workers with less tenure and experience are typically found to be more likely to be overeducated (Chiswick and Miller 2009; Kiker *et al.* 1997; Quinn and Rubb 2006). Conversely, older workers are usually found to be more likely to be undereducated (Chiswick and Miller 2009).

Miller and Ren (2012) studied the determinants of ORU in the Chinese labour market, and found that while the incidence of ORU is as prevalent in 2006 as it was in 1993, actual educational attainment played a much more important role in the determination of ORU in 2006. Worker characteristics, on the other hand, were

[18] These definitions, namely, the job analysis, self-assessment, and realised matches approaches, are described in Chapter 2.

found to exert less influence in determining the incidence of ORU by 2006. They argued that this was a likely result of the higher education expansion in China. However, in 2006, labour market experience was found to decrease the likelihood of being overeducated while having no effect on undereducation. Females were found to be more likely to be undereducated relative to being correctly matched, but did not differ statistically from males in the probability of being overeducated relative to being correctly matched. Workers who held rural registration were less (more) likely to be overeducated (undereducated), relative to being correctly matched.

One study, by McGuinness (2003), analysed the way in which the quality of Northern Ireland universities, as proxied by research scores, impacted on the overeducation status of their graduates in their first and subsequent jobs two to four years later. This study established that while university quality lowered the probability of overeducation in their first jobs for graduates from higher quality institutions, the impact was much higher for students with third class or pass degrees, and the estimated effects were negligible for graduates with better degree classes. Another way of interpreting this finding is that obtaining a better degree class can be used to compensate for the lower quality of the university attended. However, university quality was reported to have no statistically significant impact in determining overeducation for the graduates in their subsequent job two to four years after graduation.

An earlier US study by Robst (1995) reported findings at odds with McGuinness (2003). While college quality in the US was not found to be an important factor in the determination of undereducation, the three measures of college quality used in Robst (1995) were all associated with large reductions in the probability of overeducation.[19] For instance, a ten percent increase in the average aptitude test scores was associated with a 2.4 percentage point decline in the probability of overeducation. A recent study on Swedish graduates by Berggren (2010) found that graduates from older and more well-established universities were more likely to be matched to their jobs in terms of education levels and field of specialisation.

[19] The three measures used by Robst (1995) were: i) average aptitude test scores (ACT or SAT) for graduates in the freshmen class of the college; ii) expenditure per student; and iii) a prestige ranking.

Therefore, there are mixed findings on the role university quality plays in determining overeducation status in the labour market.

There are, thus, a number of determinants of ORU which have been identified in the literature. Some personal characteristics, such as migrant status and English-speaking background, have been found to increase the likelihood of being overeducated. Those who were employed on a part-time or casual basis are also more likely to be overeducated, as are those employed in small sized firms. The probability of educational mismatch also decreased as the time spent in the labour market increases. The level of educational attainment, occupation, industry of employment and field of study have also been found to influence educational mismatch. However, the first two groups of these characteristics will not be included in the empirical analysis of the present study, for the reasons outlined in Chiswick and Miller (2009). Finally, the limited number of studies which have examined the effects of university quality on overeducation have reported inconsistent impacts. Thus, the focus of the present analysis will contribute to the literature in this area.

3.3 Incidence of Educational Mismatch, 1999-2009

This section examines the incidences of mismatch in the Australian graduate labour market and the sub-markets within. Thus far, the literature has generally found that only 60 percent of workers are appropriately trained for their jobs, leaving around 40 percent of workers either overeducated or undereducated. The *a priori* expectation of the study at hand is that a larger incidence of overeducation than has been generally reported in the literature will be found, as the present study concentrates on the highly educated segment of the labour market. This high incidence of educational mismatch is also expected to be reflected in a lower incidence of undereducation, for the same reason.

It would be valuable to start off with a consideration of the 'vertical' extent of overeducation, that is, "How overqualified are graduates in their jobs?". This is presented in Table 3.1.

Table 3.1: Proportion of Educational Mismatch Across Qualifications

		Required Level				
		Certificate	*Diploma*	*Bach. Pass*	Row total	Relative Frequency
Attained Level of Qualifications	*Diploma*	0.29	0.33	0.39	1.00	0.70
	Assoc. Deg.	0.23	0.48	0.29	1.00	0.62
	Bach. Pass	0.26	0.11	0.63	1.00	58.48
	Bach. Honours	0.21	0.11	0.67	1.00	7.13
	Grad. Cert.	0.10	0.10	0.80	1.00	5.74
	Grad. Dip.	0.10	0.07	0.82	1.00	9.94
	Masters	0.13	0.08	0.79	1.00	14.71
	PhD	0.04	0.06	0.91	1.00	2.68
	Relative Frequency	20.67	10.57	68.76	-	100.00
	N					569,325

Note: Rows may not sum to unity due to rounding.

In Table 3.1, the required level of qualifications for the graduates' occupations are presented in the rows, while the actual attained level of qualifications are set out in the columns. In total, there are 98 occupation categories. These are detailed in Appendix A. The required level of qualifications to perform each occupation is derived from the Australian Standard Classification of Occupations (ASCO), which is managed and updated by the Australian Bureau of Statistics (Australian Bureau of Statistics 2011). The GDS data from 1999 to 2005 had been coded according to the ASCO classification, while the data from 2006 to 2009 were coded based on the Australian and New Zealand Standard Classification of Occupations (ANZSCO), also managed by the ABS. The data from 2006 to 2009 were then recoded into the ASCO classification, using the ANZSCO to ASCO correspondence table published by the ABS. The required level of qualifications, as identified in the ASCO publication, consists of five types: 1) certificate ii, 2) certificate iii, 3) certificate iv, 4) diploma, and 5) bachelor's pass degree. However, the three certificate categories have been collapsed into one 'certificate' category, as the number of observations in each separate required-attained category (such as those who attained a diploma and worked in a job that required a certificate ii) was too small. The classification of occupations, as well as the required level of education for each, are listed in Appendix B.[20]

[20] This is the 'job analysis' approach to defining ORU, as discussed in the literature review in Chapter 2. Unless otherwise stated, this is the approach utilised throughout the rest of the thesis.

In Table 3.1, the number of graduates in each corresponding required and attained field are given, expressed as a proportion of all those with the same attained qualification. The relative frequency in the last column indicates the proportion of the total sample that each level of attained qualification takes up.

Note that there are two ‘matched’ categories and two ‘undereducated categories’, while the remaining 20 categories are for the ‘overeducated’. The ‘matched’ categories are of those who have attained a diploma or a bachelor’s pass degree, and who are working in a job that requires the same. The ‘undereducated’ categories are of those who have attained a diploma or associate degree, and who are working in jobs that require a bachelor’s pass degree.

Looking at the relative frequencies for the columns, it can be observed that about 21 percent of graduates work in jobs that require only a certificate qualification, and about 11 percent of graduates are in jobs that require a diploma. The majority of the graduates were working in bachelor’s pass level occupations.

A large proportion of diploma holders were working in a job that required a bachelor’s pass degree. However, there are substantial numbers of diploma graduates working in jobs that require certificates and diplomas, with close to one-third being in each of the three categories. Diploma holders are therefore rather well-spread across the categories of overeducated, correctly-matched and undereducated. Associate degree graduates, in comparison, are heavily concentrated in diploma level jobs, with close to half of them being overeducated in this category. About one-third of them are undereducated in bachelor’s pass level jobs, and the remaining quarter overeducated in certificate level jobs.

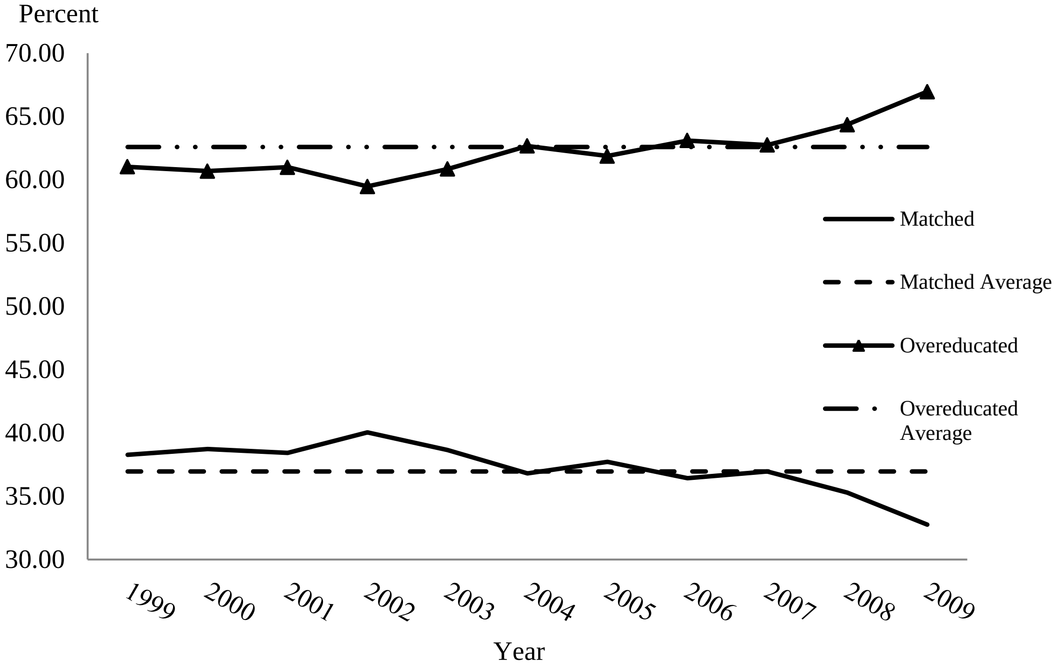
A sizable majority, of 63 percent, of bachelor’s pass degree graduates are correctly matched. However, a substantial 37 percent are overeducated, with 11 percent in diploma level jobs and 26 percent in certificate level jobs. Bachelor’s honours graduates share a similar pattern, as there are 67 percent in bachelor’s level jobs, 11 percent in diploma level and 21 percent in certificate level jobs. Graduate certificate and graduate diploma graduates exhibit similar patterns to each other. Both have about ten percent working in certificate level jobs, and about 80 percent in bachelor's pass degree jobs. The incidences of overeducation are very similar, therefore, between: i) bachelor's pass and honours graduates, and ii) graduate certificate and graduate diploma holders.

Masters graduates mostly find jobs that require a bachelor's pass degree, as there are close to 80 percent in this category. Eight percent procure diploma level jobs, and 13 percent are in employment that requires a certificate. Doctoral graduates fare slightly better, as 91 percent are in employment with a minimum qualification of a bachelor's pass degree. Six percent of the doctorate graduates are in diploma level jobs, and four percent are in certificate level jobs.

Having considered the 'vertical' extent of ORU, an examination of the trend in ORU over the years would add value. This can be observed in Figure 3.1. Figure 3.1 charts the proportion of educational match and mismatch in the Australia graduate labour market, over the time period 1999 to 2009. A number of points can be drawn from this diagram. First, the overeducated and the correctly matched make up the vast majority of the graduate labour market. The undereducated accounted for less than one percent, across all years of the sample, and hence have not been plotted in the diagram. The latter point accords with the expectation that the incidence of undereducation will be quite low in this sample. This is also consistent with Kler (2005), who finds no incidence of undereducation in the Australian graduate labour market, using both job analysis and realised matches methodologies.

Second, as expected, the number of workers who are appropriately qualified for their occupations is lower than the 60 percent that has generally been reported in the literature. Across all years, the average incidence of job-education match stands at around 37 percent. On the flip side, the incidence of overeducation, at around 63 percent across all years, is higher, as expected.

Figure 3.1: ORU in the Australian Graduate Labour Market, 1999-2009

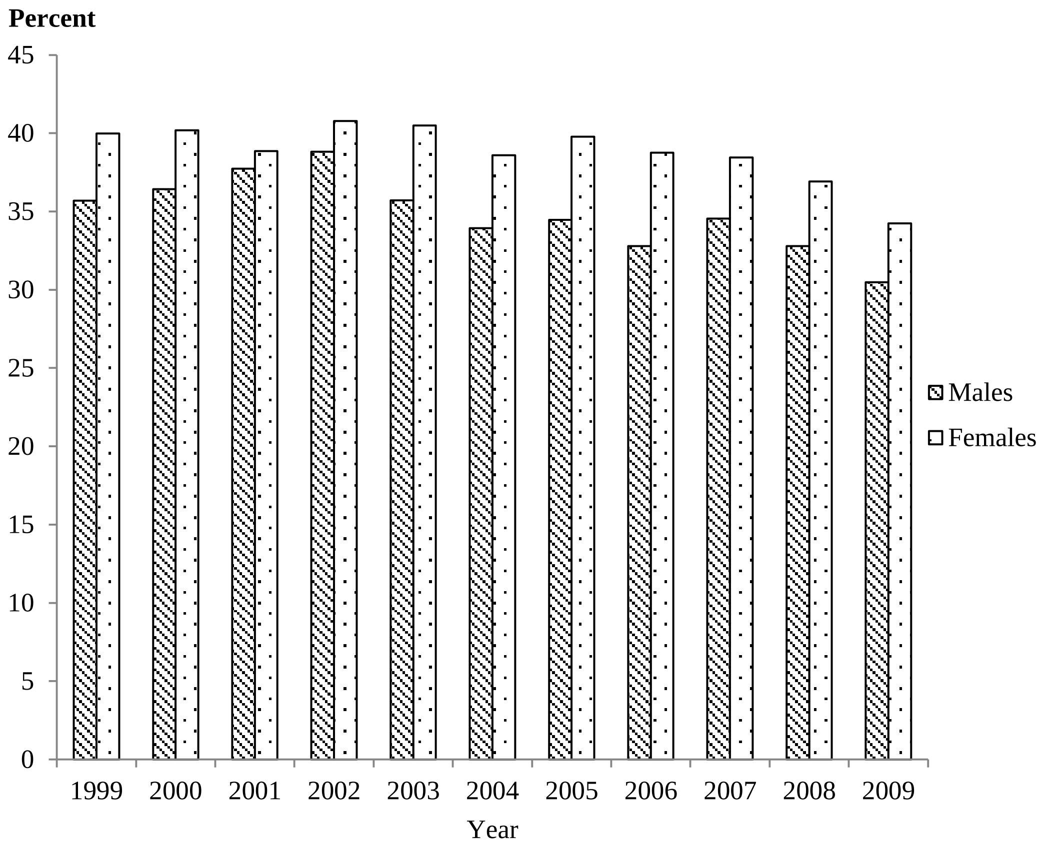


Third, general trends can be observed. Overall, overeducation has risen over the reference time period. From 1999 to 2007, the general trend has been a gradual increase in overeducation, with the exception of a slight dip in 2005, and a modest decrease in 2002. In particular, the rate of increase in overeducation seems especially marked from 2007 to 2009, perhaps as a consequence of declining labour market demand due to the global financial crisis. Graduates could be more adversely affected if firms decide to put hiring on hold and utilise existing human capital, instead of riding out the financial crisis by making existing staff redundant (see, for example, Bloomberg 2008). As a result, fresh graduates could have downgraded their job expectations. In the absence of demand shocks such as the global financial crisis, the steadily increasing incidence of overeducation could likely be attributed to the rapid expansion of higher education, and, therefore, expansion of labour market supply. The upward trend of overeducation is mirrored by the decreasing proportions of appropriately trained workers.

3.3.1 Incidence of Overeducation by Gender

Educational mismatch in the form of overeducation is highly prevalent in the graduate labour market. This can be further examined in terms of gender. The differences by gender in education-occupation match and mismatch can be observed from Figure 3.2, which charts the proportion of workers who are appropriately trained for their professions, across the reference time period. Two items are apparent from this figure. First, females are more appropriately trained in all years, compared to males. Second, the degree of education-job match appears to be gradually decreasing for both males and females. It can thus be concluded that the growth of educational mismatch affects both sexes. Across all years, an average of 34 percent of males are appropriately trained for their jobs, while the corresponding figure for females is 38 percent. There are, therefore, some gender differences in the incidence of overeducation, and further analysis of the ORU earnings effects by gender is warranted.

Figure 3.2: Proportion of Appropriately Trained Workers by Gender, 1999-2009



3.3.2 Incidence of Overeducation by University Grouping

Another interesting question pertaining to overeducation lies in the differences by university grouping. An analysis on university groups is of interest for the following reasons. Universities and university groups typically market themselves to prospective students on the basis of positive labour market outcomes.[21] A cursory search on the World Wide Web on the websites of some Australian universities, for example, found frequent references to the salaries and employment rates of their graduates, which are potentially misleading, as these figures do not account for education-job mismatch, and the adverse earnings effects that accompany this mismatch. Other common references on university websites include statements on university rankings, accreditations or alumni endorsements. The Go8 universities, which are also typically perceived as being the most prestigious universities in Australia, for example, state that they are "consistently the first choice of the majority of highest qualified Australian school leavers" (Group of Eight 2011b). At the same time, it is also on the basis of 'product differentiation' that the Group of Eight universities are making their case for deregulation of student university fees (The Australian 2010c).[22]

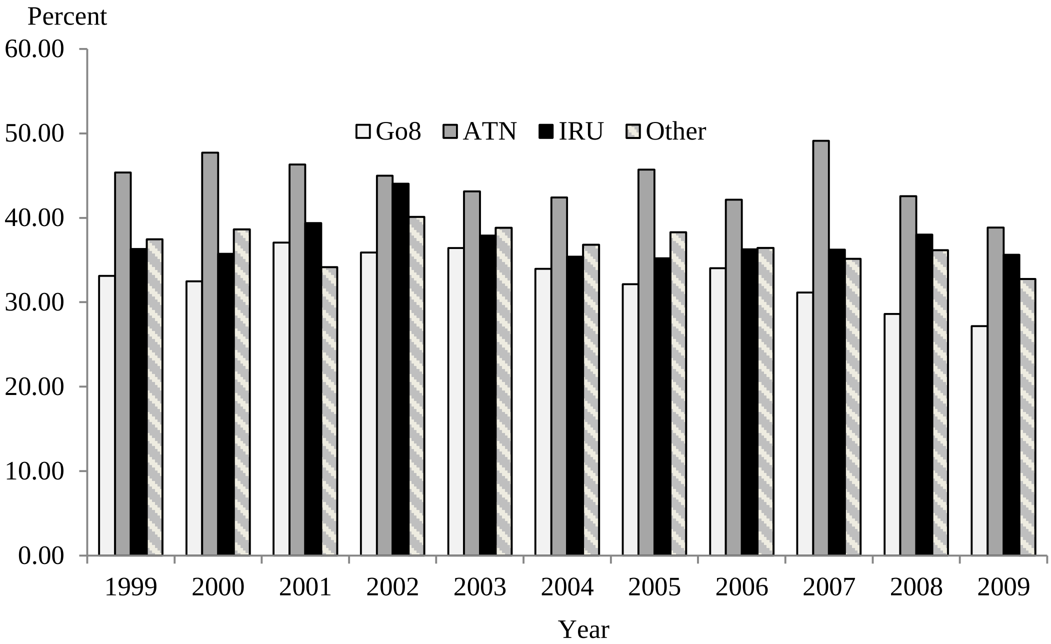
Some Australian universities have also grouped themselves into various alliances or consortiums, each with their own focuses and differences.[23] Thus, given the large amount of federal funding into the higher education sector, an examination of the incidence and effects of overeducation for each institution group will be beneficial. The proportions of appropriately trained graduates, disaggregated by institution type, are presented in Figure 3.3. The university groups examined in the analysis are the Group of Eight (Go8), the Australian Technological Network (ATN), the Innovative Research Universities (IRU) and all other universities (Other).

A cursory examination of Figure 3.3 reveals some interesting facts about the incidence of overeducation amongst the different university groups. The Go8 appear to perform the worst in this regard, having the lowest proportions of appropriately matched graduates in each year. On average, only 33 percent of Go8 graduates are correctly matched to their jobs. Naturally, this may simply be a reflection of the composition of the graduates. Specifically, the Go8 are the most research intensive

[21] The analyses are not disaggregated to individual institutions for two reasons. First, larger numbers are desirable, due to the more detailed specification of the ORU dummy variables used in many of the analyses in this thesis. Second, the GDS Code of Practice stipulates that individual institutions cannot be named in the analysis of the data.
[22] At present, university fees in Australia are strictly regulated and apply to all universities.
[23] A more detailed description of differences across university consortiums is presented in Chapter 7.

universities in Australia, and also account for a larger proportion of doctoral graduates, who by definition are overeducated. This is covered in the next sub-section.

Figure 3.3: Proportion of Appropriately Trained Workers by Institution Groups, 1999-2009



The ATN had the highest proportion of appropriately qualified graduates, across all years, and often outperformed other university groups by a large margin. Across all years, 45 to 50 percent of ATN graduates have the right amount of training for their work. When compared to the worst performing Go8 universities, the ATN universities had between seven to 18 percent more graduates who were correctly matched to their jobs.

The IRU and Other universities have proportions that fall between the two groups mentioned above, with the IRU universities having a marginally higher proportion of correctly matched graduates. Both groups here have average proportions of matched graduates, at around 37 percent.

3.3.3 A Closer Examination - Bachelor's Degree Graduates

To accommodate the reservation expressed above relating to the graduate composition of the university groups, the Figure 3.3 analyses were repeated with the sample restricted to bachelor's degree graduates. This change in focus improved the educational match for the Go8 universities, who were found to have, on average, about half of graduates who are appropriately trained for their work. However, this improvement was not confined to the Go8 universities. When the sample was restricted to bachelor's degree graduates, the ATN university group had about two-thirds of correctly matched graduates. Similarly, the proportion of appropriately qualified graduates rose to 53 and 56 percent for the IRU and Other university groups, respectively. In this regard, the ATN graduates seem to do well, whereas the performance of the other university groups seem to be similar.

This section has examined the incidence of educational mismatch over 1999 to 2009. Overeducation has been found to gradually increase over the reference time period, and has increased at a faster rate over 2007 to 2009. The examination of samples disaggregated by gender and by university grouping has further uncovered differences within each of these sub-groups. Females were found to be more overeducated than males, and the current trend indicates a widening of this difference in educational mismatch. Amongst the various university groups, the ATN graduates were found to be the most appropriately qualified for their work. Go8 graduates were the least matched to their occupations.

The descriptive analysis on the incidence of education-occupation match and mismatch in the Australian labour market has thus uncovered large incidences of overeducation. Thus, a more in-depth analysis into the characteristics of overeducated workers will be conducted in the next section. Specifically, logit models will be used to identify the characteristics of graduates which influence their education-occupation match or mismatch status. This analysis commences with a binary logit model. Subsequently, a multinomial logit model will be used to examine how graduate characteristics affect the vertical extent of overeducation.

3.4 Logit Models

The empirical analysis of this section will start off with a binary logit model that estimates the determinants of overeducation. This can be expressed as:

(3-1) $ORU_i^* = \beta X_i + \varepsilon_i$, i = 1,…,n

where ORU_i^* is a latent index representing the propensity of the individual i to be overeducated, X_i denotes the set of characteristics hypothesised to have impacts on the propensity to be overeducated, and β is a vector of parameters to be estimated. ORU_i^* is not observed, but rather a binary indicator variable ORU_i is measured, where:

(3-2) $ORU_i = 1 \; where \; ORU_i^* \geq 0$

$ORU_i = 0 \; where \; ORU_i^* < 0.$

The determinants of ORU are then estimated using the binary logit model:

(3-3)$(PrORU_i = 1|X_i) = \frac{e^{\beta X_i}}{1+e^{\beta X_i}}$.

Note that in the current analysis, the undereducated will be excluded. As mentioned in Chapter 2, the concept of undereducation is of limited relevance in analyses of the graduate labour market. This is supported by the descriptive analyses above, which found very low incidences of undereducation for the Australian graduate population in this study, and its various sub-groups.

Further, in order to arrive at more detailed conclusions regarding the determinants of the vertical extent of overeducation, a multinomial logit model is estimated. This model can be written as:

(3-3) $PrORU_{ik}|X_i = \frac{e^{\beta_k X_i}}{\sum_{l=0}^{6} e^{\beta_l X_i}}$, i = 1,…,n; k = 0,…,6 where $PrORU_{ik}$ denotes the probability that worker i is in the kth educational mismatch category, with k = 0 denoting the correctly matched, k = 1 denoting one level of educational attainment over the required level, and k = 2 denoting two levels of educational attainment over the required level, and so on.

The values of k are determined by using 'levels' assigned to each qualification by the Australian Qualifications Framework (AQF), which is the national policy for regulating qualifications in Australian institutions of education and training (AQF 2011). The AQF assigns each qualification a 'level' based on the complexity, depth of achievement, and autonomy required of graduates to demonstrate the achievement. The AQF levels for the qualifications of interest are presented in panel (iv) of Table 3.2, together with the calculated k values for the extent of overeducation in panels (i) to (iii). For example, doctoral graduates working in a diploma level job would be considered to be in the k = 5 category. This is calculated by using the AQF level of 10 for doctoral qualifications, and subtracting the corresponding AQF level of 5 for diplomas, thus yielding five levels of educational attainment over the required level (k = 5).

Table 3.2: Extent of Overeducation and Australian Qualifications Framework Levels

	Required Levels			
Actual Educational Level	Certificate (i)	Diploma (ii)	Bachelor's Pass (iii)	AQF Level (iv)
Certificate	(a)	(a)	(a)	4
Diploma	1	0	(a)	5
Associate Degree	2	1	(a)	6
Bachelor's Pass	3	2	0	7
Bachelor's Honours	4	3	1	8
Graduate Diploma	4	3	1	8
Graduate Certificate	4	3	1	8
Masters	5	4	2	9
PhD	6	5	3	10
AQF Level	4	5	7	

Notes: (a) denotes not applicable. k values are given in panels (i), (ii) and (iii), while AQF levels are presented in panel (iv).

3.5 Results of the Binary Logit Model

The results of the estimation of the binary logistic regression model, as expressed in equation (3-1), are presented in Table 3.3. This table lists both the log of the odds ratio and the marginal effects of being overeducated relative to being correctly matched. Specifically, the log odds ratios are obtained from:

(3-4) $\widehat{\ln\left[\frac{O_i}{C_i}\right]} = \hat{\beta}X_i$

where O denotes the overeducated, and C denotes the correctly matched.

All of the estimated log odds ratios in Table 3.3 are statistically significant, except for two of the year variables (2000 and 2001) and two of the variables for industry of employment (government and construction). This indicates that apart from the level of higher educational attainment and occupation, which are used to formulate the dependent variable, overeducation is determined by a number of other factors relating to the graduates' themselves, or to their choices in the labour market. Females, for example, are slightly more likely to be overeducated in comparison to their male peers. This is different from the finding in the earlier section looking at the incidence of overeducation by gender, where the summary statistics for the data sample suggested that females were more appropriately trained. Hence, the finding here implies that, after taking account of other factors, such as field of study, females are more likely to be educationally mismatched. However, the marginal effect in panel (ii) on females has a very small value, of less than one percentage point. Therefore, while the log odds ratio indicates that females are more likely to be overeducated rather than appropriately trained, the increased probability is negligible.

Table 3.3: Estimates from the Logit Model of the Determinants of Overeducation

Variable	Log Odds	Marginal Effect
Constant	-2.662***	(a)
	(57.500)	(a)
Female	0.046***	0.008***
	(6.484)	(6.486)
Age	0.141***	0.025***
	(53.922)	(54.462)
Age squared/100	-0.145***	-0.026***
	(39.992)	(40.218)
Tenure	0.152***	0.027***
	(63.960)	(65.040)
Tenure squared/100	-0.499***	-0.090***
	(44.187)	(44.529)
NESB	0.181***	0.033***
	(20.257)	(20.282)
Non-Australian	0.706***	0.127***
	(38.814)	(38.971)
Double degree	-0.616***	-0.111***
	(56.424)	(57.030)
Go8	0.430***	0.077***
	(52.409)	(52.755)
ATN	-0.241***	-0.043***
	(27.876)	(27.956)
IRU	0.262***	0.047***
	(25.869)	(25.918)
Natural and Physical Science	0.446***	0.080***
	(27.553)	(27.628)
Information Technology	-0.571***	-0.103***
	(37.249)	(37.449)
Engineering	-0.397***	-0.071***
	(25.096)	(25.161)
Architecture	-0.504***	-0.091***
	(22.593)	(22.640)
Agriculture and Environment	0.130***	0.023***
	(5.262)	(5.263)
Nursing	-1.270***	-0.228***
	(76.698)	(77.993)
Medicine	-0.542***	-0.097***
	(39.018)	(39.229)
Education	-0.240***	-0.043***
	(16.165)	(16.182)
Society and Culture	0.259***	0.047***
	(21.717)	(21.769)
Creative Arts and Others	-0.035**	-0.006**
	(2.373)	(2.374)
Self-employed	-0.242***	-0.044***
	(13.615)	(13.620)
Private Sector	0.136***	0.024***
	(16.526)	(16.543)
Short-term employment	0.256***	0.046***
	(35.412)	(35.511)
Further study	0.183***	0.033***
	(21.446)	(21.469)

Table 3.3: Estimates from the Logit Model of the Determinants of Overeducation (cont.)

Variable	Log Odds	Marginal Effect
Part-time study	0.532***	0.096***
	(61.554))	(62.424)
Accounting	-1.926***	-0.346***
	(96.391)	(99.413)
Retail and Wholesale	1.154***	0.207***
	(66.783)	(67.528)
Accommodation	2.096***	0.377***
	(61.403)	(61.902)
Manufacturing	-0.170***	-0.031***
	(9.731)	(9.734)
Mining	-0.369***	-0.066***
	(12.414)	(12.421)
Legal services	-0.169***	-0.030***
	(7.527)	(7.528)
Government	0.012	0.002
	(0.808)	(0.808)
Education	-0.694***	-0.125***
	(44.963)	(45.276)
Higher education	0.366***	0.066***
	(20.298)	(20.326)
Health and Community services	-0.480***	-0.086***
	(33.342)	(33.470)
Medicine and Dentistry	-0.127***	-0.023***
	(6.855)	(6.857)
Construction	0.039	0.007
	(1.362)	(1.362)
Other services	0.109***	0.020***
	(7.363)	(7.365)
Transport and Communications	0.097***	0.017***
	(4.930)	(4.931)
Engineering and Consulting	-0.344***	-0.062***
	(15.167)	(15.180)
2000	0.000	0.000
	(0.019)	(0.019)
2001	0.008	0.001
	(0.485)	(0.485)
2002	-0.073***	-0.013***
	(4.349)	(4.349)
2003	-0.035**	-0.006**
	(2.183)	(2.183)
2004	0.028*	0.005*
	(1.798)	(1.798)
2005	0.043***	0.008***
	(2.773)	(2.773)
2006	0.121***	0.022***
	(7.688)	(7.688)
2007	0.037**	0.007**
	(2.467)	(2.467)
2008	0.117***	0.021***
	(7.777)	(7.777)
2009	0.208***	0.037***
	(13.798)	(13.800)
Pseudo R-squared		0.188
Observations		566,758

Notes: Absolute values of robust ‘t’-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively. (a) denotes ‘not applicable’.

The estimates on the proxies for labour market experience, age and tenure, indicate that the odds of being overeducated, compared to being correctly matched, increase at a decreasing rate with increasing levels of labour market experience. These results differ from the typical finding in the literature that the incidence of educational mismatch falls as an individual accumulates labour market experience (see, for example, Chiswick and Miller 2009). The finding in the current analysis might be an indication that mature-aged graduates are not as successful as their younger peers, and are seen by the labour market as having some negative, but unobservable, characteristic. However, the observed higher log odds of being overeducated as labour market experience increases could also be due to our focus on recent graduates. Most of the younger graduates would hold a bachelor’s pass or honours degree, while a larger proportion of the older graduates would have obtained a postgraduate qualification, and hence be overeducated by definition as age increases. This can be tested by estimating equation (3-1) on a sample restricted to bachelor’s degree graduates in the following section.

In the case of tenure, the graduates with positive tenure would have entered their jobs on the basis of any previous qualifications, and have now obtained a higher qualification. Thus, it is more likely than not that the most recent qualification would place them in the overeducated category, even if they were correctly matched previously. However, the estimates on tenure and its squared term indicate that the higher log odds associated with increasing tenure is positive up to 15 years of accumulated tenure. This points to an extremely inflexible labour market, where even workers who have been with their employers for long periods of time do not get moved into jobs more appropriate for their level of education.

Graduates who did not have Australian residency status or citizenship have higher log odds of being overeducated relative to being correctly matched, as do those from a non-English speaking background.[24] The latter finding is consistent with that in Fleming and Kler (2008), although they also found that migrants who have been in the country for a substantial period of time were more likely to be appropriately

[24] Australia has strict policies relating to the employment of foreign workers. Graduates who are not of Australian residency status are likely to be those who have just completed their degrees and are in the midst of their residency application.

matched to their jobs. The current analysis does not control for the year of arrival in Australia, as information on this is not available from 1999 to 2005, and was also not reported by about half of the non-Australian respondents from 2006 to 2009. It is easy, however, to envisage that educational match is one channel through which immigrant labour market adjustment takes place. The marginal impacts on the incidence of overeducation for the two abovementioned groups, however, are rather substantial. Thus, a graduate who is from a non-English speaking background, and does not possess Australian residency status, has a cumulative 16 percentage points higher probability of being overeducated, compared to an Australian and English speaking peer.

Graduates with a double degree qualification have lower log odds of being overqualified for their jobs relative to being correctly matched, compared to graduates from a single degree program. That is, a double degree affords graduates some protection against being overeducated, by 11 percentage points. This indicates that the double degree program can be a good investment choice to insure against being overeducated in the labour market. Being self-employed decreases the likelihood of being overeducated, while working in the private sector brings the opposite effect of increasing the likelihood of overeducation. The latter finding is similar to that found in Fleming and Kler (2008), who reported that those in the public services industry were less likely to be overeducated relative to those in the private services industry. The marginal impacts for the latter two groups are modest.

The field of study also plays an important role in determining the educational match status. There are a total of eleven fields of study defined for the analysis, with the field of Management and Commerce being the reference category. Relative to the base category, graduates in three fields of study are estimated to have higher log odds of being overeducated compared to being correctly matched, while those in the remaining eight are estimated to have lower log odds. Specifically, graduates who majored in the Natural and Physical Sciences, Agriculture and Environment, and Society and Culture studies are more likely to be overeducated relative to the benchmark group. This is consistent with the findings of Dolton and Silles (2001), who find that graduates majoring in languages or the arts were more likely to be overeducated. However, it is interesting to note that amongst these fields of study which are associated with higher log odds of being overeducated, the graduates who majored in the Natural and Physical Sciences are estimated to have the strongest marginal effect, whereas the majors in languages and arts, most of which would be captured in the field of Society and Culture, have a relatively low estimated marginal effect.

Graduates in the remaining seven fields of study have lower log odds of being overeducated in comparison to being correctly matched. However, one field of study that stands out is the field of Nursing, which has a very large, and negative estimated marginal impact, of almost 23 percentage points. This might be attributed to the high degree to specialisation in this field, which requires a bachelor’s pass degree as the minimum requirement for entry and accreditation (Australian Nursing and Midwifery Council 2009). At the same time, Nursing graduates are in high demand, and will therefore be able to secure employment in the health workforce with considerable ease.

The empirical findings pertaining to the probability of overeducation for the respective fields of study are of importance due to their policy relevance. In Australia, a substantial amount of higher education funding is allocated through the Higher Education Contribution Scheme (HECS). In particular, university fees are subsidised, and the amount of funding allocated varies according to the course of study undertaken (Department of Education, Employment and Workplace Relations 2011a). Courses such as law, accounting, economics and commerce, for example, are allocated a total of $1,793 by the Commonwealth for each Equivalent Full-Time Student Load. Other courses, such as nursing, attract a higher subsidy of $12,093 per Equivalent Full-Time Student Load due in part to the expected lower earnings for graduates (Department of Education, Employment and Workplace Relations 2011b). In 2011, additional subsidies were allocated to the fields of mathematics, statistics, and science. These three fields form the Natural and Physical Sciences category in the empirical analysis, which was the field of study where graduates had the highest likelihood of being overeducated. Thus, as the probability of overeducation reflects, at least in part, the labour market demand in each field of study, the higher subsidies to these courses do not appear to be efficient. On a related note, agriculture is amongst the courses which attract the highest Commonwealth funding, at $19,542 per Equivalent Full-Time Student Load. At the same time, the marginal effect estimated for the Agriculture and Environment graduates indicates that they are more likely to be overeducated, albeit to a lesser extent compared to the Natural and Physical Sciences. The estimated likelihoods of overeducation could guide policy makers in the allocation of funding to university students.

The estimated coefficients for industry of employment are all statistically significant at the one percent level, except for the government and construction industries, which do not differ statistically from the benchmark category of financial services. A striking feature of the estimated coefficients for the industries of employment lies in the size of the estimates for industries such as accounting, retail and wholesale and accommodation and hospitality. Graduates working in the accounting industry have much lower log odds of being overeducated, compared to being correctly matched. Specifically, graduates employed in the accounting industry are associated with a 35 percentage points decrease in probability of being overeducated, relative to their counterparts in the financial services industry. The reverse holds true for graduates working in the retail and wholesale, or accommodation and hospitality industries, as they are more likely to be overeducated, by 21 and 38 percentage points, relative to the reference group. The industries where graduates have lower log odds of being overeducated appear to be those which are profession-based, whereas graduates employed in more general-type industries are associated with higher log odds of being overeducated. Therefore, the logit regression was estimated on a restricted sample of the Society and Culture graduates, whose field of study would not be expected to lead to employment in any particular industry, except for the legal industry. The results of the logit estimates for Society and Culture graduates are presented in Table 3.4.

Table 3.4: Estimates from the Logit Model, Society and Culture Graduates

Variables	Log Odds	Marginal Effect
Constant	0.365***	(a)
	(3.342)	(a)
Female	0.006	0.001
	(0.322)	(0.322)
Age	0.013**	0.002**
	(2.242)	(2.242)
Age squared/100	-0.000	-0.000
	(1.532)	(1.532)
Tenure	0.089***	0.015***
	(17.680)	(17.778)
Tenure squared/100	-0.003***	-0.000***
	(12.292)	(12.324)
NESB	0.073***	0.012***
	(2.882)	(2.882)
Non-Australian	0.476***	0.081***
	(5.669)	(5.672)
Double degree	-0.910***	-0.154***
	(40.069)	(41.340)
Go8	0.172***	0.029***
	(8.940)	(8.945)
ATN	-0.267***	-0.045***
	(11.289)	(11.318)
IRU	-0.040	-0.007
	(1.604)	(1.604)
Accounting	-0.773***	-0.131***
	(12.796)	(12.840)
Retail and Wholesale	1.839***	0.311***
	(31.626)	(31.852)
Accommodation	2.337***	0.395***
	(22.496)	(22.559)
Manufacturing	-0.345***	-0.058***
	(6.274)	(6.279)
Mining	-0.442***	-0.075***
	(3.372)	(3.373)
Legal services	-0.129***	-0.022***
	(4.011)	(4.012)
Government	0.074**	0.012**
	(2.140)	(2.141)
Education	-0.434***	-0.074***
	(12.136)	(12.175)
Higher education	0.576***	0.098***
	(12.964)	(12.999)
Health and Community services	-0.407***	-0.069***
	(13.442)	(13.484)
Medicine and Dentistry	0.081	0.014
	(1.478)	(1.478)
Construction	0.271**	0.046**
	(2.230)	(2.230)
Other services	-0.020	-0.003
	(0.585)	(0.585)
Transport and Communications	0.140**	0.024**
	(2.417)	(2.417)
Engineering and Consulting	0.008	0.001
	(0.066)	(0.066)

Table 3.4: Estimates from the Logit Model, Society and Culture Graduates (cont.)

Variables	Log Odds	Marginal Effect
Part-time study	0.259***	0.044***
	(12.963)	(13.009)
Further study	0.113***	0.019***
	(6.018)	(6.025)
Self-employed	-0.128***	-0.022***
	(3.022)	(3.021)
Private Sector	0.066***	0.011***
	(3.176)	(3.177)
Short-term employment	0.267***	0.045***
	(14.303)	(14.344)
2000	0.022	0.004
	(0.590)	(0.590)
2001	-0.094**	-0.016**
	(2.451)	(2.451)
2002	-0.056	-0.009
	(1.454)	(1.454)
2003	0.001	0.000
	(0.015)	(0.015)
2004	0.124***	0.021***
	(3.336)	(3.336)
2005	0.281***	0.048***
	(7.513)	(7.518)
2006	0.189***	0.032***
	(4.969)	(4.970)
2007	0.212***	0.036***
	(5.827)	(5.828)
2008	0.242***	0.041***
	(6.698)	(6.701)
2009	0.332***	0.056***
	(9.118)	(9.127)
Pseudo R-Squared		0.0930
Observations		96,936

Notes: Absolute values of robust 't'-statistics are presented in parentheses. ** and *** indicate significance at the five and one percent levels, respectively. (a) denotes 'not applicable'.

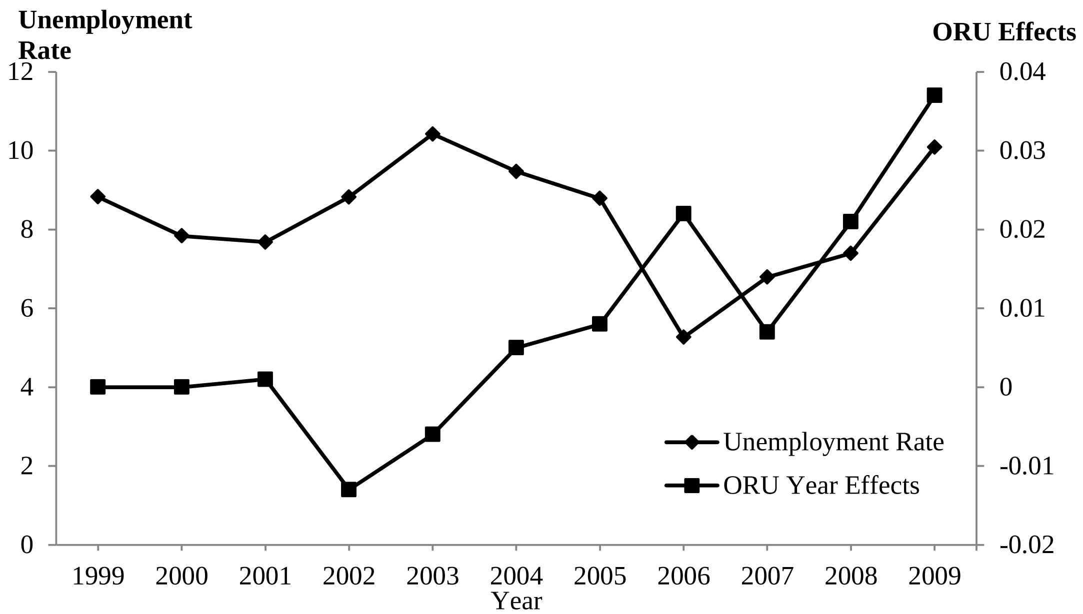
The estimates listed in Table 3.4 are qualitatively similar to their corresponding estimates in Table 3.3, including those on the industry of employment. The estimated log odds ratios and marginal effects for the industries of employment were largely significant, with the exception of medicine and dentistry, other services and engineering consulting. These suggest that the industry of employment is an important determinant of overeducation in the labour market. Regardless of the field of study undertaken while in university, entering a 'professional' industry is associated with large and negative effects on the chances of being overeducated. The reverse is true for employment in industries which require generic skills, such as retail and wholesale or accommodation, as graduates employed in these industries have large and positive impacts on the probability of being overeducated. These reinforce the findings in Table 3.3.

Moving back to a discussion of the full sample in Table 3.3, the estimates on the years of graduation indicate that, relative to the reference category of graduates from 1999, graduates from 2002 to 2009 have higher likelihoods of being overeducated, relative to being correctly matched. These estimates suggest that the increase in labour market demand for graduates is not keeping up with the greater supply of graduates generated by the relatively recent higher education expansion in Australia. However, the estimated marginal impacts were very small, reaching a high of only 3.7 percentage points for graduates in the year 2009. The small estimated impacts are to be expected, since labour market demand and supply shifts are expected to adjust gradually. It would be useful to know though, whether the probability of overeducation across years is related to other trends in the labour market, such as unemployment rates. It would have been expected that as the unemployment rate increases, the probability of overeducation would increase in tandem due to the former being a sign of a tightening labour market. Graduates would therefore have to accept a job that might not be commensurate with their qualifications, as the climate in the labour market does not afford choice.

Figure 3.4 charts the estimated impacts on years from 1999 to 2009, together with the unemployment rates for the graduates, taken from the GDS. The shapes of the curves do not seem to move together, although there are indications of a weak inverse relationship from 1999 to 2006. The pattern identified between unemployment rates and the probabilities of overeducation is rather strenuous, however, and there does not seem to be any influence from the unemployment rate onto the likelihood of overeducation, on the whole.[25]

[25] The data for those who went overseas for work, and those who went for further studies were also examined in comparison with the estimated year effects. Again, there are no discernible patterns detected.

Figure 3.4: Unemployment Rates and ORU Year Estimates, 1999 to 2009



The estimated log odds ratios for the various institutional groups are all statistically significant at the one percent level. Graduates from the Go8 or IRU universities have higher log odds of being overeducated, compared to being correctly matched, in comparison with the omitted category of graduates from Other universities. Graduates from the ATN, in contrast, are estimated to have lower log odds of being overeducated. Therefore, it appears that graduates from the ATN are afforded some modest protection from being educationally mismatched in the labour market, with an estimated four percentage points less chance of being overeducated in comparison to graduates from Other universities. While IRU graduates are associated with a five percentage points increase in the probability of overeducation, Go8 graduates have the largest estimated effect, at almost eight percentage points. However, the caveat from the earlier section on the incidence of ORU by university groups bears repeating. Universities in the research intensive Go8 group account for a large proportion of higher degree completions, such as doctorates, for instance, and thus should also account for a large proportion of the overeducated. This is examined in greater detail below.

3.5.1 Analysis of Bachelor's Pass Degree Graduates

As mentioned above, the empirical findings from Table 3.3 have revealed a couple of anomalies or questions that warrant closer examination. First, the finding that graduates with relatively higher amounts of labour market experience are more likely to be overeducated rather than correctly matched is at odds with the literature, although an explanation that this could be due to the nature of the dataset was offered above. Second, it was argued that the finding that Go8 graduates are more likely to be overeducated could be attributable to a larger number of higher degree completions by these research intensive universities. Thus, the binary logit model was estimated on a restricted sample of bachelor's pass degree holders.

The results of this estimation are presented in Table 3.5. Two empirical findings from this table are highlighted here. First, the estimate for Go8 graduates has changed in sign, from being positive in Table 3.3 to being negative in Table 3.5. This indicates that, relative to the reference group of graduates from Other universities, Go8 graduates have lower log odds of being overeducated, with equally pronounced marginal effects as graduates from the ATN. Further, the estimate on IRU graduates is now statistically insignificant. Thus, it can be concluded that graduates from Go8 and ATN universities are afforded some protection from being allocated to a job that does not utilise the level of educational attainment possessed, in comparison to their counterparts from the IRU and Other universities.

Second, the estimated coefficients on age and its square now exhibit the signs consistent with expectations and the findings in the broader literature. When looking only at bachelor's degree graduates, labour market experience is found to be associated with lower log odds of overeducation, relative to being correctly matched. This is consistent with the findings of the literature (see for example, Chiswick and Miller 2009; Kiker *et al.* 1997; Miller and Ren 2012; Quinn and Rubb 2006). At the same time, this finding bodes well for mature-aged students in higher education, as it indicates that these older students will not be disadvantaged in the graduate labour market.

Table 3.5: Estimates from the Logit Model, Bachelor's Degree Graduates

Variable	Log Odds	Marginal Effect
Constant	1.515***	(a)
	(19.150)	(a)
Female	0.119***	0.018***
	(11.608)	(11.615)
Age	-0.124***	-0.018***
	(25.863)	(25.983)
Age squared/100	0.140***	0.021***
	(20.354)	(20.409)
Tenure	0.218***	0.032***
	(49.844)	(50.611)
Tenure squared/100	-0.792***	-0.118***
	(27.654)	(27.812)
NESB	0.104***	0.015***
	(8.050)	(8.054)
Non-Australian	0.283***	0.042***
	(10.492)	(10.499)
Double degree	-0.291***	-0.043***
	(20.057)	(20.103)
Go8	-0.476***	-0.071***
	(38.664)	(39.009)
ATN	-0.548***	-0.082***
	(41.839)	(42.415)
IRU	-0.003	-0.000
	(0.192)	(0.192)
Natural and Physical Science	0.343***	0.051***
	(17.006)	(17.021)
Information Technology	-0.821***	-0.122***
	(38.946)	(39.451)
Engineering	-0.994***	-0.148***
	(41.174)	(41.665)
Architecture	-0.632***	-0.094***
	(21.284)	(21.362)
Agriculture and Environment	0.138***	0.021***
	(4.500)	(4.500)
Nursing	-2.769***	-0.412***
	(71.708)	(72.874)
Medicine	-1.011***	-0.150***
	(47.578)	(48.298)
Education	-0.983***	-0.146***
	(34.908)	(34.905)
Society and Culture	0.441***	0.066***
	(28.889)	(28.994)
Creative Arts and Others	0.029	0.004
	(1.523)	(1.523)
Self-employed	-0.699***	-0.104***
	(24.292)	(24.396)
Private Sector	0.300***	0.045***
	(21.727)	(21.761)
Short-term employment	0.797***	0.119***
	(75.447)	(78.230)
Further study	0.354***	0.053***
	(29.993)	(30.102)

Table 3.5: Estimates from the Logit Model, Bachelor's Degree Graduates (cont.)

Variable	Log Odds	Marginal Effect
Part-time study	-0.108***	-0.016***
	(7.973)	(7.976)
Accounting	-2.475***	-0.368***
	(73.397)	(75.685)
Retail and Wholesale	1.312***	0.195***
	(69.376)	(70.971)
Accommodation	2.243***	0.334***
	(62.092)	(63.235)
Manufacturing	-0.208***	-0.031***
	(9.328)	(9.334)
Mining	-1.060***	-0.158***
	(20.010)	(20.065)
Legal services	-0.375***	-0.056***
	(13.649)	(13.664)
Government	-0.043**	-0.006**
	(1.968)	(1.968)
Education	-1.888***	-0.281***
	(61.743)	(63.084)
Higher education	-0.596***	-0.089***
	(20.415)	(20.499)
Health and Community services	-0.588***	-0.087***
	(27.708)	(27.798)
Medicine and Dentistry	-0.120***	-0.018***
	(4.315)	(4.315)
Construction	0.429***	0.064***
	(11.990)	(12.000)
Other services	0.277***	0.041***
	(15.112)	(15.139)
Transport and Communications	0.187***	0.028***
	(7.694)	(7.697)
Engineering and Consulting	-0.908***	-0.135***
	(23.224)	(23.283)
2000	0.014	0.002
	(0.614)	(0.614)
2001	-0.021	-0.003
	(0.843)	(0.843)
2002	-0.021	-0.003
	(0.859)	(0.859)
2003	0.031	0.005
	(1.359)	(1.359)
2004	0.023	0.003
	(1.035)	(1.035)
2005	0.088***	0.013***
	(3.961)	(3.961)
2006	0.049**	0.007**
	(2.084)	(2.084)
2007	-0.023	-0.003
	(1.025)	(1.025)
2008	-0.020	-0.003
	(0.919)	(0.919)
2009	0.118***	0.018***
	(5.359)	(5.359)
Pseudo R-squared	0.317	0.317
Observations	316,069	316,069

Notes: Absolute values of robust 't'-statistics are presented in parentheses. ** and *** indicate significance at the five and one percent levels, respectively. (a) denotes 'not applicable'.

Note, however, that the signs on tenure and its square remain unchanged. However, it should also be noted that the present dataset consists of fresh graduates, and those with tenure would have obtained their jobs on the basis of previous qualifications. Thus, obtaining a new and higher qualification would be extremely likely to place these graduates in the ‘overeducated’ category. The remainder of the estimated coefficients for other characteristics are qualitatively similar to those in Table 3.3. Thus, the observations made above relating to those other characteristics stand, and will not be discussed again here.

3.6 Summary of Findings for the Binary Logit Model

The binary logit model has identified some important determinants of overeducation in the Australian graduate labour market. In particular, some fields of study and industries of employment have been found to have relatively large impacts in determining overeducation. Graduates working in profession-based industries, such as accounting, were much less likely to be overeducated (by 35 percentage points).

Other important findings relate to the role of age and having a double degree qualification. Older graduates were more likely to be overeducated, as they were more likely to have completed a postgraduate qualification, which makes them overeducated by construction. Restricting the sample to only undergraduates reverses this finding. This is potentially important for policy, particularly with regards to the re-skilling of mature-aged individuals, as the estimated effects of age indicate that older graduates are well-absorbed into the labour market, and are better matched to their jobs compared to their younger peers.

Lastly, graduates who have a double degree qualification, while being found to have no earnings premium to their relatively wider breadth of skills in later analyses or in the literature, do have a decreased probability, by 11 percentage points, of being overeducated. Therefore, there is some advantage, in terms of labour market outcomes, to obtaining a double degree qualification.

3.7 Results of the Multinomial Logit Model

A multinomial logit model of the determinants of overeducation was also estimated. This model permits assessment of the role that graduates' characteristics play in determining the extent of overeducation. The log odds ratio estimates from this model are presented in Table 3.6. Marginal effects were also calculated, and are listed in Table 3.7. As a discussion of both the log odds ratio and the marginal effects is repetitive and would not add much value, the following discussion will focus on the marginal effects. A note at this point will assist in the interpretation of results. First, the estimated marginal effects in Table 3.7 have column headings ranging from k = 0, to k = 6. Recall that k = 0 indicates the correctly matched, k = 1 denotes the categorical outcome of 'overeducated by one level', and so on for the remaining categories. The highest overeducated category is where k = 6, or where graduates are 'overeducated by six levels'.

A quick examination of Table 3.7 indicates that most estimates are statistically significant at the one percent level. However, going across the rows of marginal effects reveals that the magnitude of the estimated impacts tend to get smaller at the higher overeducated outcomes. Thus, the graduate characteristics used in the analysis only have economically meaningful impacts up to around three levels of overeducation. In the case of the most overeducated category of k = 6, all of the marginal effects are negligible.[26] Thus, likelihood ratio tests, as proposed by Cramer and Ridder (1991), were conducted to examine the possibility of pooling subsets of outcomes into one single category. The results from these tests are presented in Table 3.8. These tests are all statistically significant at the one percent level, and thus reject the null hypotheses that outcomes can be combined. Therefore, the model with the most detailed specification of outcomes is retained.

[26] This could be reasonably expected, as mismatched graduates would most likely be employed in jobs that are not too far removed from their actual level of education.

Table 3.6: Multinomial Logit Estimates of the Determinants of Overeducation

Variable	$\ln(\frac{k=1}{k=0})$	$\ln(\frac{k=2}{k=0})$	$\ln(\frac{k=3}{k=0})$	$\ln(\frac{k=4}{k=0})$	$\ln(\frac{k=5}{k=0})$	$\ln(\frac{k=6}{k=0})$
Constant	-5.100***	-4.777***	-0.961***	-7.456***	-12.435***	-20.212***
	(86.100)	(78.365)	(15.196)	(67.432)	(61.505)	(28.868)
Female	0.007	-0.057***	0.161***	0.145***	0.079***	0.180*
	(0.713)	(6.178)	(17.060)	(9.505)	(3.622)	(1.927)
Age	0.194***	0.188***	-0.013***	0.246***	0.457***	0.604***
	(58.801)	(56.137)	(3.727)	(39.507)	(37.906)	(16.611)
Age squared/100	-0.214***	-0.198***	0.039***	-0.279***	-0.526***	-0.636***
	(47.107)	(43.399)	(8.134)	(31.765)	(29.476)	(12.633)
Tenure	0.086***	0.162***	0.210***	0.187***	0.131***	0.031
	(32.732)	(55.217)	(62.244)	(38.772)	(16.780)	(0.895)
Tenure squared/100	-0.279***	-0.545***	-0.684***	-0.613***	-0.467***	-0.125
	(24.036)	(38.089)	(37.487)	(24.137)	(10.360)	(0.716)
NESB	-0.010	0.290***	0.162***	0.255***	1.155***	0.260**
	(0.786)	(25.319)	(13.592)	(13.323)	(47.089)	(2.277)
Non-Australian	-0.006	0.855***	0.464***	1.125***	2.021***	1.029***
	(0.206)	(38.407)	(19.949)	(36.900)	(62.867)	(6.161)
Double degree	-0.530***	-0.807***	-0.513***	-0.676***	-0.902***	-1.709***
	(33.930)	(45.731)	(35.358)	(24.960)	(20.923)	(4.969)
Part-time study	0.737***	0.745***	-0.002	0.422***	0.177***	-0.374***
	(72.043)	(69.408)	(0.143)	(23.715)	(6.260)	(3.357)
Further study	0.371***	-0.066***	0.158***	0.302***	-0.338***	-0.957***
	(34.986)	(5.726)	(14.524)	(17.726)	(11.954)	(6.265)
Go8	0.679***	0.471***	0.074***	0.455***	0.532***	0.935***
	(63.989)	(43.288)	(6.770)	(26.149)	(20.986)	(8.840)
ATN	-0.093***	-0.170***	-0.435***	-0.425***	-0.406***	-0.083
	(8.034)	(14.642)	(35.351)	(19.759)	(13.958)	(0.592)
IRU	0.408***	0.031**	0.253***	0.355***	-0.096**	0.311**
	(31.964)	(2.136)	(18.530)	(15.610)	(2.327)	(2.106)

Table 3.6: Multinomial Logit Estimates of the Determinants of Overeducation (cont.)

Variable	$\ln(\frac{k=1}{k=0})$	$\ln(\frac{k=2}{k=0})$	$\ln(\frac{k=3}{k=0})$	$\ln(\frac{k=4}{k=0})$	$\ln(\frac{k=5}{k=0})$	$\ln(\frac{k=6}{k=0})$
Natural and Physical Science	0.548***	0.123***	0.619***	0.503***	-0.355***	2.550***
	(25.501)	(5.751)	(32.639)	(16.528)	(6.907)	(12.328)
Information Technology	-0.228***	-0.574***	-0.828***	-0.587***	-0.697***	-0.034
	(10.290)	(29.108)	(39.733)	(17.392)	(19.368)	(0.108)
Engineering	0.210***	-0.726***	-0.594***	-0.492***	-0.798***	1.817***
	(10.136)	(33.034)	(26.951)	(12.913)	(16.943)	(8.382)
Architecture	-0.041	-0.389***	-0.857***	-0.685***	-1.661***	-1.023
	(1.334)	(13.455)	(27.697)	(12.295)	(16.496)	(1.391)
Agriculture and Environment	0.206***	-0.140***	0.306***	0.164***	-0.412***	2.132***
	(6.175)	(4.360)	(10.690)	(3.481)	(5.415)	(9.108)
Nursing	-0.291***	-1.950***	-2.589***	-3.135***	-4.032***	-1.933***
	(14.397)	(77.846)	(62.210)	(31.619)	(21.471)	(3.404)
Medicine	-0.162***	-0.619***	-0.701***	-0.927***	-1.675***	0.195
	(8.828)	(34.437)	(35.062)	(25.201)	(27.406)	(0.758)
Education	0.280***	-0.552***	-0.789***	-0.100***	-1.210***	-0.341
	(15.832)	(29.817)	(32.996)	(2.711)	(18.377)	(1.173)
Society and Culture	0.292***	0.012	0.437***	0.595***	-0.329***	1.558***
	(18.441)	(0.789)	(30.436)	(27.127)	(9.292)	(7.986)
Creative Arts and Others	-0.057**	-0.394***	0.157***	0.199***	-0.729***	1.574***
	(2.566)	(19.373)	(8.788)	(6.942)	(15.172)	(7.381)
Self-employed	-0.017	-0.106***	-0.529***	-0.501***	-0.355***	-0.086
	(0.780)	(5.001)	(20.933)	(13.261)	(7.117)	(0.479)
Private Sector	-0.057***	0.266***	0.229***	0.309***	0.248***	0.243**
	(5.441)	(23.771)	(18.611)	(14.362)	(7.730)	(2.142)
Short-term employment	-0.095***	0.050***	0.662***	0.731***	0.864***	0.749***
	(9.670)	(4.863)	(68.160)	(45.204)	(36.181)	(7.622)

Table 3.6: Multinomial Logit Estimates of the Determinants of Overeducation (cont.)

Variable	$\ln(\frac{k=1}{k=0})$	$\ln(\frac{k=2}{k=0})$	$\ln(\frac{k=3}{k=0})$	$\ln(\frac{k=4}{k=0})$	$\ln(\frac{k=5}{k=0})$	$\ln(\frac{k=6}{k=0})$
Accounting	-1.563***	-1.641***	-2.386***	-2.527***	-2.626***	-2.557**
	(46.424)	(61.608)	(66.183)	(33.141)	(26.385)	(2.505)
Retail and Wholesale	-0.150***	0.421***	1.461***	1.273***	1.500***	1.444***
	(4.945)	(18.193)	(78.468)	(45.876)	(41.734)	(6.687)
Accommodation	0.012	2.122***	2.168***	2.034***	1.983***	1.977***
	(0.179)	(55.468)	(61.108)	(45.700)	(36.618)	(6.049)
Manufacturing	0.066***	-0.267***	-0.219***	-0.357***	-0.152***	-0.700**
	(2.762)	(11.828)	(9.892)	(9.319)	(3.139)	(2.174)
Mining	0.315***	-0.562***	-0.973***	-0.518***	-1.011***	-1.702**
	(8.763)	(13.969)	(19.848)	(7.290)	(7.600)	(2.368)
Legal services	0.190***	-0.759***	-0.099***	-0.191***	-0.507***	-0.426
	(6.261)	(22.571)	(3.776)	(4.355)	(5.731)	(1.131)
Government	0.217***	0.106***	-0.124***	0.121***	0.126**	0.411**
	(10.681)	(5.387)	(5.975)	(3.698)	(2.573)	(2.105)
Education	0.118***	-0.529***	-1.786***	-2.308***	-1.968***	-1.215***
	(6.114)	(26.757)	(64.784)	(44.190)	(23.473)	(4.355)
Higher education	0.549***	0.231***	0.547***	-0.178***	0.038	1.373***
	(23.668)	(10.032)	(24.465)	(4.607)	(0.724)	(8.025)
Health and Community services	-0.072***	-0.183***	-1.026***	-0.985***	-1.216***	-1.161***
	(3.789)	(9.800)	(47.968)	(27.547)	(18.869)	(4.513)
Medicine and Dentistry	0.188***	0.111***	-0.459***	-0.520***	-0.649***	-0.272
	(7.683)	(4.606)	(16.855)	(10.505)	(8.026)	(0.956)
Construction	-0.045	-0.179***	0.331***	0.030	-0.129	-0.308
	(1.093)	(4.643)	(9.417)	(0.480)	(1.384)	(0.588)
Other services	0.123***	0.081***	0.113***	0.113***	0.178***	0.424**
	(5.976)	(4.272)	(6.259)	(3.871)	(4.076)	(2.219)
Transport and Communications	-0.044	-0.078***	0.220***	0.201***	0.352***	0.461*
	(1.521)	(3.016)	(9.260)	(5.302)	(7.497)	(1.768)
Engineering and Consulting	0.190***	-0.340***	-0.872***	-0.916***	-1.038***	-0.244
	(6.419)	(11.202)	(23.446)	(13.397)	(10.812)	(0.803)

Table 3.6: Multinomial Logit Estimates of the Determinants of Overeducation (cont.)

Variable	$\ln(\frac{k=1}{k=0})$	$\ln(\frac{k=2}{k=0})$	$\ln(\frac{k=3}{k=0})$	$\ln(\frac{k=4}{k=0})$	$\ln(\frac{k=5}{k=0})$	$\ln(\frac{k=6}{k=0})$
2000	-0.011	0.029	-0.011	-0.011	-0.097	0.278
	(0.541)	(1.342)	(0.488)	(0.299)	(1.250)	(1.008)
2001	-0.010	0.074***	-0.037	-0.051	0.166**	0.083
	(0.454)	(3.266)	(1.628)	(1.289)	(2.183)	(0.277)
2002	-0.079***	-0.047**	-0.075***	-0.160***	0.029	0.427
	(3.732)	(2.070)	(3.338)	(4.056)	(0.379)	(1.592)
2003	-0.088***	0.020	-0.027	-0.047	0.288***	0.625**
	(4.330)	(0.950)	(1.282)	(1.285)	(4.271)	(2.471)
2004	0.020	0.064***	0.005	-0.005	0.453***	0.358
	(1.016)	(3.076)	(0.221)	(0.147)	(7.057)	(1.366)
2005	-0.023	0.129***	0.040*	0.056	0.540***	0.205
	(1.179)	(6.311)	(1.950)	(1.594)	(8.355)	(0.776)
2006	0.049**	0.251***	0.087***	0.216***	0.842***	0.359
	(2.435)	(12.031)	(4.051)	(6.045)	(13.387)	(1.370)
2007	-0.044**	0.111***	0.041**	0.081**	0.989***	0.615**
	(2.225)	(5.477)	(2.047)	(2.343)	(16.388)	(2.496)
2008	0.064***	0.323***	-0.037*	0.170***	0.972***	1.058***
	(3.275)	(16.351)	(1.819)	(5.017)	(16.096)	(4.520)
2009	0.099***	0.423***	0.079***	0.346***	1.132***	1.197***
	(5.116)	(21.431)	(3.861)	(10.417)	(18.917)	(5.143)

Notes: Absolute values of robust ‘t’-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively.

Table 3.7: Marginal Effects of Variables from the Multinomial Logit Model

Variable	*k* = 0	*k* = 1	*k* = 2	*k* = 3	*k* = 4	*k* = 5	*k* = 6
Female	-0.009***	-0.003***	-0.016***	0.023***	0.004***	0.000***	0.000***
	(5.120)	(2.270)	(12.360)	(20.230)	(9.010)	(2.750)	(1.690)
Age	-0.034***	0.020***	0.021***	-0.017***	0.006***	0.003***	0.000***
	(54.790)	(45.140)	(44.790)	(37.690)	(28.190)	(29.270)	(9.640)
Age squared/100	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(41.330)	(38.130)	(35.320)	(36.230)	(23.700)	(24.060)	(8.370)
Tenure	-0.036***	-0.001***	0.014***	0.020***	0.003***	0.000***	0.000**
	(64.100)	(3.540)	(36.750)	(48.980)	(22.150)	(5.200)	(1.710)
Tenure squared/100	0.001***	0.000***	0.000***	-0.001***	0.000***	0.000***	0.000
	(43.470)	(3.130)	(25.540)	(28.440)	(13.540)	(3.720)	(1.030)
NESB	-0.043***	-0.022***	0.038***	0.008***	0.005***	0.013***	0.000
	(20.650)	(13.950)	(21.950)	(5.600)	(7.880)	(29.370)	(1.240)
Non-Australian	-0.132***	-0.064***	0.115***	0.011***	0.037***	0.032***	0.000***
	(35.420)	(21.000)	(30.260)	(4.120)	(21.150)	(25.990)	(2.820)
Double degree	0.154***	-0.033***	-0.079***	-0.027***	-0.011***	-0.004***	0.000***
	(56.350)	(16.660)	(39.680)	(16.000)	(15.000)	(15.780)	(6.650)
Part-time study	-0.122***	0.082***	0.090***	-0.052***	0.003***	-0.001***	0.000***
	(63.490)	(54.670)	(56.070)	(37.580)	(5.850)	(5.650)	(5.920)
Further study	-0.038***	0.056***	-0.032***	0.010***	0.008***	-0.003***	0.000***
	(19.160)	(34.800)	(21.640)	(7.490)	(12.560)	(17.490)	(7.460)
Go8	-0.102***	0.083***	0.041***	-0.032***	0.007***	0.002***	0.000***
	(54.910)	(50.810)	(25.650)	(25.620)	(11.000)	(9.830)	(5.050)
ATN	0.056***	0.008***	-0.007***	-0.046***	-0.010***	-0.002***	0.000
	(26.480)	(4.940)	(4.160)	(34.000)	(15.690)	(10.280)	(0.370)
IRU	-0.055***	0.054***	-0.023***	0.018***	0.008***	-0.002***	0.000
	(23.850)	(26.860)	(11.960)	(10.100)	(9.340)	(6.640)	(1.020)

Table 3.7: Marginal Effects of Variables from the Multinomial Logit Model (cont.)

Variable	*k* = 0	*k* = 1	*k* = 2	*k* = 3	*k* = 4	*k* = 5	*k* = 6
Natural and Physical Science	-0.099***	0.057***	-0.030***	0.065***	0.009	-0.004***	0.002***
	(28.210)	(17.170)	(11.820)	(23.940)	(7.600)	(16.480)	(4.620)
Information Technology	0.126***	0.010***	-0.052***	-0.072***	-0.010***	-0.003***	0.000
	(32.230)	(3.180)	(22.460)	(41.030)	(11.110)	(14.130)	(0.700)
Engineering	0.074***	0.086***	-0.089***	-0.058***	-0.010***	-0.004***	0.002***
	(18.460)	(23.440)	(40.850)	(28.030)	(10.280)	(17.210)	(4.220)
Architecture	0.096***	0.036***	-0.032***	-0.080***	-0.014***	-0.007***	0.000
	(16.750)	(7.370)	(8.650)	(33.510)	(11.110)	(26.500)	(1.630)
Agriculture and Environment	-0.030***	0.026***	-0.040***	0.042***	0.003***	-0.003***	0.002***
	(5.150)	(5.360)	(10.960)	(10.790)	(1.990)	(8.420)	(3.840)
Nursing	0.304***	0.066***	-0.161***	-0.160***	-0.039***	-0.010***	0.000***
	(78.250)	(18.630)	(108.200)	(122.780)	(75.750)	(50.860)	(4.100)
Medicine	0.123***	0.023***	-0.061***	-0.060***	-0.018***	-0.007***	0.000
	(35.760)	(8.330)	(28.590)	(30.750)	(23.910)	(33.050)	(1.530)
Education	0.064***	0.096***	-0.070***	-0.085***	0.002	-0.006***	0.000
	(17.660)	(32.100)	(33.560)	(40.020)	(1.590)	(20.820)	(0.680)
Society and Culture	-0.061***	0.025***	-0.029***	0.050***	0.018***	-0.004***	0.001***
	(22.410)	(11.470)	(16.250)	(26.340)	(19.540)	(16.150)	(4.520)
Creative Arts and Others	0.019***	-0.002	-0.061***	0.037***	0.010***	-0.004***	0.001***
	(5.180)	(0.580)	(26.780)	(15.150)	(8.710)	(18.690)	(4.030)
Self-employed	0.049***	0.020***	0.002	-0.057***	-0.012***	-0.002***	0.000
	(11.260)	(6.300)	(0.750)	(25.310)	(13.380)	(5.550)	(0.170)
Private Sector	-0.037***	-0.029***	0.035***	0.022***	0.008***	0.001***	0.000
	(18.660)	(19.240)	(21.830)	(14.500)	(10.980)	(5.010)	(1.340)
Short-term employment	-0.059***	-0.045***	-0.021***	0.093***	0.023***	0.007***	0.000***
	(34.520)	(35.140)	(14.450)	(66.840)	(34.600)	(25.270)	(5.010)

Table 3.7: Marginal Effects of Variables from the Multinomial Logit Model (cont.)

Variable	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5	k = 6
Accounting	0.412***	-0.108***	-0.124***	-0.140***	-0.032***	-0.008***	0.000***
	(116.860)	(41.280)	(59.270)	(106.340)	(53.190)	(35.950)	(4.500)
Retail and Wholesale	-0.167***	-0.097***	-0.021***	0.235***	0.037***	0.013***	0.000***
	(51.660)	(38.170)	(7.560)	(71.780)	(23.990)	(19.080)	(2.890)
Accommodation	-0.304***	-0.145***	0.217***	0.193***	0.032***	0.007***	0.000
	(91.980)	(50.990)	(40.610)	(43.250)	(16.480)	(10.550)	(1.400)
Manufacturing	0.035***	0.030***	-0.034***	-0.021***	-0.009***	-0.001	0.000***
	(8.000)	(8.460)	(12.280)	(8.690)	(8.770)	(1.510)	(2.520)
Mining	0.066***	0.113***	-0.069***	-0.094***	-0.011***	-0.005***	0.000***
	(8.870)	(16.660)	(15.960)	(29.290)	(6.500)	(10.020)	(4.510)
Legal services	0.042***	0.064***	-0.100***	0.000	-0.003***	-0.003***	0.000
	(7.530)	(12.500)	(33.310)	(0.120)	(2.370)	(5.680)	(1.010)
Government	-0.020***	0.033***	0.011***	-0.027***	0.003***	0.001	0.000
	(5.590)	(11.010)	(3.940)	(12.100)	(2.250)	(1.510)	(1.580)
Education	0.142***	0.097***	-0.037***	-0.154***	-0.040***	-0.008***	0.000***
	(36.700)	(29.280)	(14.610)	(97.810)	(65.850)	(29.740)	(4.070)
Higher education	-0.093***	0.061***	-0.007***	0.053***	-0.013***	-0.002***	0.001***
	(23.970)	(16.900)	(2.220)	(16.620)	(15.460)	(5.010)	(3.810)
Health and Community services	0.094***	0.030***	0.008***	-0.104***	-0.022***	-0.006***	0.000***
	(26.130)	(10.440)	(2.920)	(58.490)	(28.240)	(20.090)	(4.620)
Medicine and Dentistry	0.008	0.043***	0.028***	-0.060***	-0.015***	-0.004***	0.000
	(1.680)	(11.060)	(7.430)	(24.190)	(13.450)	(10.440)	(0.990)
Construction	-0.009	-0.012***	-0.037***	0.060***	0.000	-0.001**	0.000
	(1.310)	(2.310)	(7.980)	(11.200)	(0.130)	(1.820)	(0.740)
Other services	-0.025***	0.011***	0.003	0.008***	0.002***	0.001***	0.000
	(7.240)	(3.870)	(1.210)	(3.610)	(1.780)	(2.560)	(1.610)

Table 3.7: Marginal Effects of Variables from the Multinomial Logit Model (cont.)

Variable	*k* = 0	*k* = 1	*k* = 2	*k* = 3	*k* = 4	*k* = 5	*k* = 6
Transport and Communications	-0.011***	-0.013***	-0.021***	0.035***	0.007***	0.003***	0.000
	(2.360)	(3.510)	(6.210)	(10.810)	(4.720)	(6.250)	(1.360)
Engineering and Consulting	0.067***	0.078***	-0.034***	-0.086***	-0.019***	-0.005***	0.000
	(11.720)	(14.840)	(8.650)	(31.430)	(16.750)	(14.060)	(0.300)
2000	0.000	-0.002	0.006**	-0.002	0.000	-0.001	0.000
	(0.110)	(0.820)	(1.850)	(0.730)	(0.360)	(1.350)	(0.890)
2001	-0.003	-0.003	0.014***	-0.007***	-0.002**	0.001***	0.000
	(0.710)	(1.100)	(4.160)	(2.650)	(1.650)	(2.000)	(0.240)
2002	0.017***	-0.007***	-0.001	-0.005	-0.004***	0.001	0.000
	(4.150)	(2.460)	(0.310)	(2.010)	(3.430)	(0.920)	(1.420)
2003	0.006	-0.013***	0.007***	-0.002	-0.001	0.003***	0.000**
	(1.580)	(5.030)	(2.370)	(0.770)	(0.970)	(4.080)	(1.920)
2004	-0.009***	0.000	0.009***	-0.003	-0.001	0.004***	0.000
	(2.370)	(0.150)	(2.860)	(1.170)	(0.870)	(5.820)	(1.110)
2005	-0.015***	-0.011***	0.019***	0.000	0.001	0.005***	0.000
	(4.010)	(4.300)	(6.330)	(0.170)	(0.570)	(6.560)	(0.590)
2006	-0.037***	-0.009***	0.034***	-0.002	0.005***	0.009***	0.000
	(9.960)	(3.250)	(10.400)	(0.630)	(3.530)	(9.110)	(0.900)
2007	-0.015***	-0.015***	0.015***	0.001	0.002	0.012***	0.000
	(4.100)	(5.830)	(5.120)	(0.220)	(1.340)	(11.340)	(1.850)
2008	-0.037***	-0.006***	0.050***	-0.021***	0.003***	0.011***	0.000
	(10.450)	(2.390)	(15.990)	(9.170)	(2.320)	(10.760)	(2.800)
2009	-0.058***	-0.010***	0.061***	-0.012***	0.007***	0.012***	0.000
	(16.740)	(4.090)	(18.960)	(5.270)	(5.950)	(11.710)	(2.950)

Notes: Absolute values of robust ‘t’-statistics are presented in parentheses. ** and *** indicate significance at the five and one percent levels, respectively.

Table 3.8: Results of Likelihood Ratio Tests for Pooling Outcomes

Categories to be combined (k)		χ^2	$P > \chi^2$
1	2	29039.420	0.000
1	3	100000.000	0.000
1	4	31345.936	0.000
1	5	37560.093	0.000
1	6	1862.529	0.000
1	0	61198.752	0.000
2	3	63017.048	0.000
2	4	13907.596	0.000
2	5	19044.200	0.000
2	6	1635.299	0.000
2	0	92497.313	0.000
3	4	8417.134	0.000
3	5	21511.874	0.000
3	6	1759.378	0.000
3	0	132000.000	0.000
4	5	9307.534	0.000
4	6	1395.523	0.000
4	0	48958.396	0.000
5	6	1471.619	0.000
5	0	44555.342	0.000
6	0	2803.036	0.000

The estimated effects for females reinforce the finding in the earlier binary logit model. There do not appear to be large differences between males and females across the different extents of overeducation. The largest estimated marginal effect for females is the 2.3 percentage points increased probability of being overeducated by three extents. This effect arose largely from females being slightly less likely to be correctly matched, or overeducated by one or two extents. The estimates on age and its quadratic term indicate a propensity for older graduates to be overeducated, particularly by one or two extents. Nevertheless, the magnitudes of these 'age effects' are minimal, of around two percentage points for both categories. These effects are accompanied by a 3.4 percentage points decline in the probability of being correctly matched to their jobs, and a 1.7 percentage points decline in the probability of being overeducated by three extents. Thus, while older graduates are more likely to be overeducated, the extents of overeducation for them are typically 'mild'.[27]

[27] Recall that the earlier binary logit analysis suggested that older graduates are more likely to be overeducated due to their increased likelihood to complete postgraduate qualifications.

Completion of a double degree is associated with a 15 percentage points increased probability of being correctly matched. This is due to the estimated reductions in the probability of being overeducated by up to five levels. The largest reduction in the probability of being overeducated, by eight percentage points, is observed at the second extent of overeducation. Graduates who were employed on a short-term or casual basis are associated with reduced probabilities of being correctly matched or overeducated at the lower extents, but are more likely to be overeducated by three or four levels. In particular, graduates employed on a short-term or casual basis are more likely, by nine percentage points, to be overeducated by three levels.

Residency status appears to be associated with large and unfavourable impacts on the likelihood of overeducation. Being of non-Australian residency is associated with a 13.2 percentage points lower chance of being correctly matched, and a 6.4 percentage points lower chance of being overeducated by one extent. These effects are linked to a 11 percentage points higher probability of being overeducated by two extents, and smaller increased probabilities of being overeducated by three to five extents. These might, at least in part, be attributed to Australia's immigration policies. One pathway for foreigners to gain permanent residency in Australia is through the acquisition of skills. While the visa requirements and rules are dynamic in nature, one feature that has largely remained unchanged lies in the additional 'points' given to higher qualifications. Graduates with advanced qualifications, such as a masters degree or PhD, are awarded more bonus 'points' in applications for skilled migration (see, for instance, The Australian 2010b). Thus, on the one hand, foreign students might have added incentives to pursue advanced qualifications in order to bolster their chances at applying for Australian residency.[28] On the other hand, it could be that the advanced qualifications of these graduates have allowed them to stay in Australia for work or residency purposes.

There are mixed patterns for the three institutional groups identified in the analysis. Relative to the benchmark category of Other graduates, being a Go8 graduate is associated with increased probabilities of being overeducated by one or two extents.

[28] The figures in the dataset support this view. The proportion of non-Australian graduates who completed a masters or doctoral degree was much higher, at 43.5 percent, compared to just 16.6 percent of Australian graduates who completed the same levels of qualification.

These are linked to a ten percentage points reduced likelihood of being correctly matched, and a smaller, by three percentage points, likelihood of being overeducated by three extents. Go8 graduates are moderately more likely to be overeducated by one or two extents, by around eight and four percentage points, respectively. IRU graduates are six percentage points less likely to be correctly matched, and two percentage points less likely to be two extents overeducated. The IRU graduates also have a five percentage points higher probability of being overeducated by one extent, and a minute two percentage points increased likelihood of being overeducated by three extents. The last group, of ATN graduates, differ from their peers in the other two university groups, as the estimated marginal effect in the $k = 0$ category indicates a 5.6 percentage points higher chance of being correctly matched. This is largely associated with a decreased likelihood of being overeducated by three levels. Note, however, that these results could be a reflection of the findings in the earlier discussion of the binary logit model. That is, the difference in proportions of postgraduate students across the various university groups could account for these findings.

Among the various fields of study, seven are associated with increased probabilities of being correctly matched. These are the fields of Information Technology, Engineering, Architecture, Nursing, Medicine, Education and Creative Arts and Others, which have increased likelihoods of being correctly matched, ranging from two percentage points (Creative Arts and Others) to 30 percentage points (Nursing). However, the decreased probabilities of overeducation for graduates among these fields differ. Information Technology graduates are more likely to be correctly matched, by 13 percentage points, and less likely to be overeducated by two or three extents, by five and seven percentage points, respectively. Engineering graduates, while being associated with an increased likelihood of being correctly matched by seven percentage points, are also more likely to be overeducated by one level, with the marginal effects for the latter estimated at nine percentage points. At the same time, Engineering graduates are nine and six percentage points less likely to be overeducated by two or three levels, respectively. Thus, for Engineering graduates, increased probabilities of being overeducated are present only at the lowest extent.

Architecture graduates are ten percentage points more likely to be correctly matched. They are also four percentage points more likely to be overeducated by one level. While they are less likely to be overeducated in the remaining categories, they were much less likely to be overeducated by three levels, as the largest marginal effect for this field was estimated in the k = 3 category, at eight percentage points. Nursing graduates are much more likely to be correctly matched, by an increased probability of around 30 percentage points. They are also more likely to be overeducated by seven percentage points. These higher probabilities are associated with 16 percentage points lower representation in each of the overeducated by two and three extents categories, and a reduced probability of being overeducated by four extents. The same trend, on a smaller scale, is observed for graduates in the fields of Medicine and Education.

The fields of Natural and Physical Sciences, together with Society and Culture, are associated with the largest reduced marginal effects of being correctly matched, by 13 and six percentage points, respectively. Natural and Physical Sciences graduates are six percentage points more likely to be overeducated by one level, three percentage points less likely to be two extents overeducated, and seven percentage points more likely to be three extents overeducated. Estimates for Society and Culture graduates followed the same pattern, but with smaller magnitudes. Thus, the fields of study are associated with large estimated impacts in determining overeducation, and its extent. One pattern observed in the estimated marginal effects is that those fields of study which are associated with increased likelihoods of being correctly matched also tend to be associated with increased chances of being overeducated by one extent of overeducation. These tend to be linked to decreased probabilities of being overeducated by two or more levels. The exceptions are graduates in the fields of Natural and Physical Sciences, Agriculture and Environment, Society and Culture and Creative Arts and Others. These fields are all associated with moderate increased probabilities of overeducation in the k = 3 category.

The industries of employment appear to be associated with large estimated impacts on the probability of being overeducated. For instance, graduates who were employed in the accounting industry are more likely to be appropriately matched to their jobs relative to their peers in the financial services industry, by 41 percentage points. This is accompanied by reductions, ranging from 11 to 14 percentage points, in the probabilities of being overeducated by one to three levels. Graduates who worked in the accommodation industry are 30 percentage points less likely to be correctly matched, and 15 percentage points less likely to be slightly overeducated at one level. These were linked to large increased probabilities of being overeducated, by two or three levels, at 22 and 20 percentage points, respectively. Graduates in retail are observed to share similar estimated effects of being overeducated to their peers in the accommodation industry, although the marginal effects calculated for them are of a smaller size. However, they are still very likely, by 24 percentage points, to be overeducated by three levels.

Lastly, estimates on the year of graduation also appear to uncover a trend in the likelihood of being overeducated. Relative to the benchmark category of graduates from the 1999 cohort, graduates from 2000, 2001 and 2003 are not statistically different from the reference group in terms of the likelihood of being correctly matched. Graduates of 2002 were slightly more likely to be correctly matched, by two percentage points. The estimates on being correctly matched for those in later cohorts from the year 2004 onwards, however, were negative. While the estimate for the graduates of 2004 is negligible, at less than one percentage point, modest decreased probabilities of being correctly matched are observed for some of the remaining years. Specifically, graduates of 2006 and 2008 are less likely to be correctly matched, by around four percentage points. The largest decreased probability of being correctly matched is observed for the graduates of 2009, who were six percentage points less likely to be matched to their jobs. The corresponding increased probabilities of being overeducated for these years appear to be concentrated in the k = 2 category. The overall trend here appears to be one of an increasing likelihood of being overeducated, across years.

3.8 Summary of Findings for the Multinomial Logit Model

The multinomial logit model of overeducation has revealed some further insights into the influences on overeducation in the Australian graduate labour market. First, the factors identified in the analysis impact on overeducation status only at the lower levels, and have negligible impacts at the most overeducated categories. Second, gender does not play a large role in determining the extent of overeducation. Third, age, while associated with an increased probability of being overeducated, has only very modest impacts on being overeducated. Fourth, residency status, field of study and industry of employment are all significant factors in determining the extent of overeducation.

3.9 Summary

This chapter has examined the incidences of ORU for the Australian graduate labour market and its sub-populations. While the incidence of undereducation is low, at less than one percent, the incidence of overeducation is relatively high, at around 63 percent. Male graduates were also found to have a higher incidence of overeducation, compared to females. The incidence of overeducation was found to vary across university groups. The ATN university group was found to have more correctly matched graduates, while the Go8 university group had the lowest. This was found, however, to have been influenced by the larger proportion of postgraduates in the Go8. Where only undergraduates were considered, the incidence of overeducation was found to be lower for the ATN and Go8 graduates, while similar proportions of the graduates from the two remaining university groups were found to be overeducated.

The logit models of overeducation have also identified many important determinants of overeducation. The field of study, for example, played an enormous role in determining whether a graduate was overeducated. Graduates in Natural and Physical Sciences, Agriculture and the Environment, and Society and Culture were found to be much more likely to be overeducated compared to Management and Commerce graduates. Graduates who were employed in profession-based industries, such as accounting, were less likely to be overeducated. The completion of a double degree program was also found to be useful in increasing the chances of an education-job match. Older graduates were found to be less likely to be overeducated where only undergraduates were considered.

The extended multinomial logit model added further value to the examination of the determinants of ORU status. First, the characteristics used in the multinomial logit model were found to have impacts only at lower levels of overeducation. That is, impacts were minimal where higher levels of overeducation were considered. Second, gender appeared to play no substantive role in determining ORU status. Lastly, the fields of study and industries of employment were found to be important determinants of overeducation.

CHAPTER 4

Earnings Impact of ORU - The Vahey Model

4.1 Introduction

Education is one of the main forms under which an individual invests in his or her own human capital. A large empirical literature has also been devoted to the study of the earnings premium or returns to investments in education. While there are competing theories on how educational attainment affects earnings, such as human capital theory (Becker 1962) or screening (Arrow 1973), the positive impact that education has on earnings is undisputed. However, a more recent literature on overeducation examines the earnings effects of education-job mismatch. Given the rapid higher education expansion in Australia, and the large incidences of overeducation observed in the preceding Chapter 3, an examination of how graduate earnings are affected by educational mismatch would be useful.

Thus, this chapter will examine the wage effects of overeducation in the Australian graduate labour market. Further, the study adopts a specification of the ORU model proposed by Vahey (2000). This under-utilised approach is based on a detailed dummy variable specification, and appears to offer valuable insights into the labour market performance of educationally mismatched individuals. The empirical relevance of the Vahey (2000) model is assessed using F-tests on various sets of the education-occupation mismatch variables that are the distinguishing feature of the approach. The remainder of this chapter is organised in the following manner. Section 2 reviews the ORU literature, with particular attention focused on the dummy variable specification, and particularly the Vahey (2000) specification. Section 3 describes the methodology and data used. Section 4 discusses the results. A conclusion is presented in section 5.

4.2 Literature Review

Educational mismatch is a feature of contemporary labour markets, and is prevalent at rather high rates. Overviews of the overeducation literature report that the average incidence of mismatch is around 40 percent (for instance, see Hartog 2000, pg. 133; McGuinness 2006, pg. 397). The methodological framework used in the examination of ORU earnings effects has also evolved from early studies such as Freeman (1976), starting with Duncan and Hoffman's (1981) variation on the standard Mincerian earnings equation. Nevertheless, the numerous empirical studies on the effects of overeducation, with very few exceptions, offer the same conclusion.

Educational mismatch has been found to be associated with pronounced impacts on earnings. There are three main findings in this literature. First, the returns to required levels of skills are higher than the returns to actual skill levels. This difference arises because the returns to required levels of skills capture both the payoff to the acquisition of the skills and mobility to an occupation where the skills can be used effectively. Second, while returns to surplus schooling are positive, they are less than the returns to required schooling, and are typically only one-half to two-thirds of the returns to required schooling (Hartog 2000; McGuinness 2006). Groot and Maasen van den Brink (2000), for example, conducted a cross country meta-analysis of 25 studies, and reported that the return to a year of required schooling was around 7.9 percent, while the return to surplus schooling was much smaller, at 2.6 percent.

Third, undereducated workers earn more than their counterparts with the same amount of schooling and who are correctly matched to their jobs (Hartog 2000). This might be attributed to the presence of unobserved factors that influence earnings, such as ability or performance (see, for example, Chiswick and Miller 2008; Hartog 2000).

Further, while different methods of defining education-occupation mismatch exist (see Hartog 2000, pg. 132), the empirical findings with regards to earnings impacts are held to be robust to the approach used (Chiswick and Miller 2010; McGuinness 2006; Rumberger 1987). As Hartog (2000, pg. 135) notes, the three main empirical findings highlighted above "hold independent of the type of measurement".[29]

The empirical frameworks used in the estimation of ORU earnings effects are described in McGuinness (2006). In comparison to the conventional Mincer human capital model which is based on the worker's actual years of schooling, most of the

[29] Measurement issues due to different definitions of education-job mismatch have been discussed in Chapter 2. As highlighted earlier, only the incidence of education-job mismatch varies across definitions, while ORU earnings effects have been found to be consistent regardless of the approach used.

ORU models are based on a decomposition of the actual years of schooling into years of required, surplus or deficit schooling. Comparison of the returns on the actual years of schooling from the Mincer estimating equation and the returns on required, surplus and deficit schooling from the latter equation is then used to inform on the earnings effects of ORU.

An alternative method uses dichotomous variables to represent overeducated and undereducated individuals. Verdugo and Verdugo's (1989) specification included dummy variables for the overeducated and the undereducated, while including the actual level of education in the estimating model.[30] In still other studies (for example, McGuinness and Bennett 2007), dummy variables for overeducated and undereducated status are combined with a continuous measure of the years of required education.

An extension to the dummy variable model was proposed by Vahey (2000). In this specification, vectors of dummy variables for the required education level, as well as for overeducation and undereducation, were entered into the estimating equation. Specifically, in Vahey's (2000) study, five levels of schooling were distinguished, with the occupational categories categorised as requiring the same five different levels of schooling. A total of 25 dichotomous variables reflecting these education-job match statuses could then be formed, and except for one reference group, entered into the estimating equation.

As such, this flexible specification permits an assessment of the earnings effects associated with deeper extents of educational mismatch. It also enables assessment of whether there are non-linearities in the return to years of required education. However, one challenge that exists in using this approach lies in its detailed and fine specification of educational mismatch. As Vahey (2000) points out, "required education is rarely more than one education level from attained education". Thus, only small proportions of individuals can be found in the extremely mismatched categories (see, for instance, Vahey 2000, pg. 221). Vahey's (2000) study therefore used a broader and more 'collapsed' specification, with 15 dummy variable

[30] This specification yielded negative and positive coefficients on the variables for overeducation and undereducation, respectively.

categories which indicated the level of education required for the job, and if individuals with each attained level of education were either overeducated or undereducated. In the current study, the larger sample size permits the use of multiple dummy variables to capture the extent of overeducation and undereducation at each attained level of education.

4.3 Estimation Model

The model used in the estimation of the ORU earnings effects of Australian graduates can be written as:

(4-1) $logw_i = \beta_1 Z_i + \beta_2 D_i^o + \beta_3 D_i^r + \beta_4 D_i^u + \epsilon_i$

where w represents the hourly wage, used in the analysis in natural logarithmic format, Z represents a vector of characteristics correlated with earnings, and D^o, D^u and D^r are vectors of dummy variables indicating if the individual is overeducated (D^o), undereducated (D^u), or correctly matched to an occupation in terms of education (D^r). The variables included in Z indicate the graduates' gender, English speaking background, residency status, mode of enrolment, further study status, university group, broad field of study, self-employment status, length of employment, industry of employment, sector of employment, year of graduation and labour market experience. Two proxies for experience are used, namely, the age of the graduate and the years of tenure in the present job, with both proxies entered into the estimating equation in quadratic form.

Attention is placed in the estimations on assessing the empirical relevance of the Vahey specification. According, a number of F-tests are conducted. The variables in the D^o vector can be categorised in two main ways:

i) by the extent of overeducation at each level of actual educational attainment. For example, the earnings of workers with a masters degree working in certificate level jobs (the most overeducated with this level of qualification), diploma level jobs (an intermediate level of overeducation) and bachelor's pass degree level jobs (the least overeducated among the workers who possess a masters degree) can be compared. F-tests, labelled ‘F-tests by Degree Type’, are conducted to ascertain if it is possible to replace the separate dummy variables for each degree type by a single dummy

ii) by the extent of overeducation at each level of required education. For example, the earnings of workers with PhDs, masters degrees, graduate diplomas, graduate certificates and bachelor’s honours degrees who are employed in jobs that require only a bachelor’s pass degree can be compared. F-tests, labelled ‘F-tests by Job Types’, can be conducted to see if it would be possible to replace the multiple overeducation dummy variables associated with a particular required level of education by a single dummy variable.

The summary statistics for the ORU variables are presented in Table 4.1. The middle portion of the variable name denotes the attained qualification, while the end portion denotes the required qualification associated with the graduates’ occupations. Among these, there were two correctly matched (*oru_dip_dip* and *oru_bach_bach*) and two undereducated (*oru_dip_bach* and *oru_ascdeg_bach*) categories. The remaining 20 categories consist of overeducated graduates. As covered in Chapter 3, the majority of graduates were overeducated, with around 63 percent of them having an educational qualification which is higher than required for their jobs. 37 percent of graduates were correctly matched, and less than one percent were undereducated.[31] The relatively high incidence of overeducation observed here can likely be attributed to the fact that the focus is on university graduates. Nonetheless, the fact that less than 40 percent of graduates are employed in an occupation appropriate for their level of education, even 4 months after graduation, is a cause for concern.

[31] The low incidence of undereducation is consistent with that found in another Australian study by Kler (2005).

Table 4.1: Summary Statistics of ORU Variables

Variable	Mean	Std. Dev.
Undereducated		
oru_dip_bach	0.003	0.052
oru_ascdeg_bach	0.002	0.043
Total	0.005	
Correctly Matched		
oru_dip_dip	0.002	0.048
oru_bach_bach	0.367	0.482
Total	0.369	
Overeducated		
oru_dip_cert	0.002	0.044
oru_ascdeg_cert	0.001	0.037
oru_ascdeg_dip	0.003	0.055
oru_bach_cert	0.152	0.359
oru_bach_dip	0.066	0.248
oru_hons_cert	0.015	0.122
oru_hons_dip	0.008	0.090
oru_hons_bach	0.048	0.214
oru_gcert_cert	0.006	0.076
oru_gcert_dip	0.006	0.075
oru_gcert_bach	0.046	0.210
oru_gdip_cert	0.010	0.101
oru_gdip_dip	0.007	0.084
oru_gdip_bach	0.082	0.274
oru_mast_cert	0.019	0.137
oru_mast_dip	0.012	0.110
oru_mast_bach	0.116	0.320
oru_phd_cert	0.001	0.032
oru_phd_dip	0.002	0.039
oru_phd_bach	0.024	0.154
Total	0.626	

Note: The ORU variable names have the attained level of qualification in the middle portion, and the required level of education in the end portion. *cert* = certificate, *dip* = diploma, *ascdeg* = associate degree, *bach* = bachelor's pass degree, *hons* = bachelor's honours degree, *gdip* = graduate diploma, *gcert* = graduate certificate, *mast* = masters degree, *phd* = doctorate degree

4.4 Results

The results from the estimation of the ORU model of earnings are presented in Table 4.2. The model also included controls for the industry of employment and year of graduation, although these estimated coefficients will not be presented here, for brevity. The adjusted R-squared for this model is 0.188, indicating that the model accounts for 18.8 percent of the variation of graduates' earnings around the mean. As can be seen from Table 4.2, most estimated coefficients are significant at the one percent level, and the signs of the estimated coefficients are consistent with expectations.

In order to determine the contribution of variable sets to the explanatory power of the model, F-tests were conducted, and the partial R-squared values for them were also computed. The results of the F-tests and the partial R-squared values are presented in Table 4.3. The F-statistics for all the variable groups are highly significant. Further, the partial R-squared values indicate that of all these variable sets, the year and personal characteristics effects are the greatest contributors to explaining the variation in graduate earnings.[32] ORU effects come third in importance, while the broad fields of study and other study characteristics account for the least explanatory power. Apart from personal endowments, it seems that wages are determined according to the graduates' labour market choices, and the contribution of schooling choices or characteristics do not play a substantial role in determining earnings.

[32] Separate regressions were run with the real wage as the dependent variable, which was calculated by deflating the nominal hourly wage by the Australian CPI for the corresponding years. The F-tests conducted for this series of regressions indicate that ORU effects are the second most important group of variables in determining graduates' earnings, and the partial R-squared of 0.022 for the ORU variables is only slightly lower than the partial R-squared of 0.023 for personal characteristics. The corresponding partial R-squared values for study characteristics, industry, broad fields of study and years of graduation are 0.004, 0.011, 0.004 and 0.002, respectively.

Table 4.2: OLS Estimates of the Vahey Model of Graduates' Earnings

Variable	Coefficient	Variable	Coefficient
Constant	2.305***	*oru_dip_cert*	-0.216***
	(175.708)		(10.674)
Female	-0.048***	*oru_dip_dip*	-0.018
	(29.159)		(1.561)
Age	0.035***	*oru_dip_bach*	0.031**
	(45.334)		(2.564)
Age squared/1000	-0.397***	*oru_ascdeg_cert*	-0.185***
	(36.847)		(9.440)
NESB	-0.039***	*oru_ascdeg_dip*	-0.068***
	(17.352)		(6.195)
Non-Australian	-0.202***	*oru_ascdeg_bach*	-0.019
	(33.694)		(1.155)
Tenure	0.015***	*oru_bach_cert*	-0.156***
	(30.517)		(55.637)
Tenure squared/1000	-0.404***	*oru_bach_dip*	-0.092***
	(17.551)		(27.292)
Double degree	0.008***	*oru_hons_cert*	-0.101***
	(3.016)		(14.606)
Part-time study	0.086***	*oru_hons_dip*	-0.037***
	(43.574)		(4.350)
Further study	0.007***	*oru_hons_bach*	0.027***
	(3.330)		(7.719)
Go8	0.026***	*oru_gcert_cert*	-0.082***
	(13.210)		(7.423)
ATN	0.031***	*oru_gcert_dip*	0.015
	(13.777)		(1.563)
IRU	0.004*	*oru_gcert_bach*	0.118***
	(1.952)		(32.361)
Natural and Physical Science	-0.076***	*oru_gdip_cert*	-0.117***
	(20.422)		(12.961)
Information Technology	-0.031***	*oru_gdip_dip*	-0.008
	(7.643)		(0.901)
Engineering	-0.008**	*oru_gdip_bach*	0.089***
	(2.006)		(31.084)
Architecture	-0.098***	*oru_mast_cert*	-0.122***
	(17.467)		(14.613)
Agriculture and Environment	-0.138***	*oru_mast_dip*	0.066***
	(27.394)		(8.391)
Nursing	-0.113***	*oru_mast_bach*	0.183***
	(28.156)		(63.714)
Medicine	-0.028***	*oru_phd_cert*	0.076***
	(8.149)		(3.249)
Education	-0.062***	*oru_phd_dip*	0.084***
	(16.597)		(4.066)
Society and Culture	-0.058***	*oru_phd_bach*	0.199***
	(21.762)		(39.303)
Creative Arts and Others	-0.117***	Industry	Included
	(28.527)		
Self-employed	0.015***	Year of Graduation	Included
	(2.679)		
Private Sector	-0.054***		
	(25.817)	Observations	569,325
Short-term employment	-0.095***	Adjusted R-squared	0.188
	(49.105)	F-statistic	1720.73

Notes: Absolute values of heteroscedasticity consistent 't'-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively.

Table 4.3: F-Statistics and Partial R-squared Values for Variable Groups

Set of Variables	F-Statistic	Partial R-squared
Personal Characteristics	1653.79	0.024
Study Characteristics	273.23	0.004
Industry of Employment	374.51	0.011
Broad Fields of Study	233.65	0.004
Year of Graduation	112.64	0.024
ORU	516.40	0.022

Note: P-values were highly significant for all sets of variables.

Graduates from a non-English speaking background earn 3.9 percent less than their English speaking counterparts. Further, those who are not of Australian residency status earn a substantial 20.2 percent less. Thus, foreign workers who come from non-English speaking backgrounds could earn up to a quarter less than their peers. Evidence of such substantial wage differences had been uncovered in earlier studies on Australian graduates. Chia and Miller (2008), for example, found that graduates who were born in non-English speaking countries earned 14 percent less than the native born. A similar estimate, of 16 percent, was reported in Li and Miller (2009), although they also found favourable earnings effects for those born in non-English speaking countries who arrived in Australia as a child.

Age has a small, positive effect on graduate earnings for the overwhelming majority of the sample. When evaluated at 20 years of age, there is a very modest 1.9 percent increase in earnings with an extra year of age. The positive impact on earnings continues until the graduates are 45 years old, thereafter age is associated with small, negative impacts. This pattern is typical in studies of earnings determination in Australia (see, for example, Borland and Suen 1994). The other measure of experience in the model, tenure, shares the same pattern with age, but with even smaller impacts. After ten years of tenure, earnings increase by a negligible 0.7 percent.

The coefficients on broad fields of study indicate that there is a large variation in graduate earnings across fields of study. The field of study that yields the largest premium in graduate earnings is the omitted category of Management and Commerce. Agriculture and Environment graduates earn the least, at 13.8 percent less than Management and Commerce graduates. Science graduates earn 7.6 percent less than the reference group, and graduates from the Architecture, Nursing, and

Other fields of study earn around ten percent less. In this regard, there are some differences between the Australian graduate labour market and that of the United States. In particular, a comprehensive study by Carnevale, Strohl and Melton (2011) examined the earnings of all graduates who have bachelor's degrees in the United States. Their study found a wide disparity in earnings by major. The top earners in the United States majored in Engineering, and had a median salary 314 percent higher than the lowest earners, who majored in Counselling Psychology. Computers and Mathematics graduates were the second highest earners, while Business graduates were the third highest earners in the study by Carnevale, Strohl and Melton (2011). Education and Arts majors were the least financially rewarded.

4.4.1 The Earnings Impacts of ORU

The results of the F-tests conducted to determine if the estimated ORU coefficients were statistically different from each other are presented in Table 4.4. The first set consists of seven separate tests, and examines whether the estimated coefficients on the overeducated were equal within each degree type. Each of these seven F-tests was statistically significant at the one percent level. This indicates that the earnings effects of overeducation for a specific qualification vary according to the level of overeducation. From the methodological perspective, with the large number of observations available for this study, it would be inappropriate to follow Vahey (2000) and represent the overeducated at each level of education by a single dummy variable.[33]

The second set consists of three tests, and looks at whether the estimates were statistically the same across job types. For example, for certificate level jobs the F-test looks at whether *oru_dip_cert* = *oru_ascdeg_cert* = … = *oru_phd_cert*. Again, each of these F-tests was statistically significant at the one percent level, further attesting to the heterogeneity of the wage effects associated with overeducation in the graduate labour market in Australia.

[33] Vahey's (2000) approach, however, was a practical way of analysing the smaller sample in his study.

Table 4.4: F-Tests for Equality of ORU Coefficients

	Set	Description	F-Stat	Prob > F
(i)	F-tests by Degree Type	Associate Degree***	27.80	0.0000
		Bachelor's Pass Degree***	273.94	0.0000
		Bachelor's Honours Degree***	156.13	0.0000
		Graduate Certificate***	191.90	0.0000
		Graduate Diploma***	289.01	0.0000
		Masters Degree***	706.55	0.0000
		PhD***	27.53	0.0000
(ii)	F-tests by Job Type	Certificate Level Job***	31.81	0.0000
		Diploma Level Job***	86.50	0.0000
		Bachelor's Pass Degree Level Job***	468.28	0.0000
(iii)		F-test for Coefficients on the Undereducated**	6.36	0.0117
(iv)		F-Test for all ORU Coefficients***	657.54	0.0000

Notes: ** and *** denote significance at the five and one percent levels, respectively.

Third, an F-test of the equality of all of the 20 estimated coefficients for the overeducated was conducted. This null hypothesis was also rejected. Finally, an F-test was undertaken to see if the two estimated coefficients on the undereducated are equal. This null hypothesis could not be rejected. These tests thus suggest that there is 'value-added' in a more detailed specification of the overeducation dummy variables in the present study, as compared to the simple approach utilised in typical studies. In other words, a detailed dummy variable specification of the ORU model of earnings, where the data permits, is attractive for the purposes of uncovering more of the ORU earnings effects by the extent of mismatch. This is illustrated below.

As there are a number of ORU dummy variables, the discussion of results will be on groups of dummy variables, based on the attained level of qualification. Following this description of the findings according to the attained level of qualifications, comparisons are provided based around a graphical exposition. The benchmark category for the ORU dummy variables is graduates who have attained a bachelor's pass degree qualification, who are correctly matched to jobs which require a bachelor's pass degree.

4.4.2 Diploma Graduates

The estimated coefficients for diploma graduates capture all three effects of being overeducated, being undereducated, and being appropriately matched to their jobs.[34] Interestingly, graduates from this only other 'matched' category, who work in a job that requires a diploma, have hourly earnings which do not differ statistically from those of the reference group, indicating that they earn similar wages to those appropriately trained who have a bachelor's pass degree. The undereducated graduates here, who work in a job that requires a bachelor's pass degree, have a modest earnings premium of 3.1 percent compared to the reference group. This stands slightly contrary to the literature, whereby undereducated graduates are expected to earn less, due to both the lower level of educational attainment and their job mismatch. This issue is addressed below.

The overeducated diploma graduates have the largest earnings penalty amongst all the other overeducated groups, and earn 21.6 percent less than the correctly matched bachelor's pass graduates. Thus, for diploma graduates, a large variance in earnings exists depending on the type of jobs they are in. The undereducated in this category earn up to 25 percentage points more than the overeducated. This range of findings could be a reflection on atypical job assignments that have leverage due to the relatively small sample size, as each of the job-education mismatch categories for the diploma graduates accounts for less than 0.3 percent of the total sample.

Alternatively, the findings could also be a reflection of the graduates' previous qualifications. As the dataset contains information on the level of the graduates' previous qualification, this was examined. It was revealed that around one-fifth of the diploma graduates reported that they held an undergraduate or postgraduate qualification before their current diploma qualification. Another 12 percent have another qualification at the diploma level. Hence, equation (4-1) was re-estimated, excluding these graduates. The estimated coefficient on the overeducated diploma graduates retained the same level of impact and statistical significance. The estimated coefficient for correctly matched diploma graduates, however, indicated that this group earned 3.4 percent less than the benchmark group of correctly

[34] Typical fields of study for these diploma graduates include Paramedical Studies, Police Studies, Business Management and also Languages.

matched bachelor's pass graduates, significant at the one percent level. Undereducated diploma graduates now have earnings that are not statistically different from the benchmark group, unlike the modest premium observed previously. These results are in line with expectations, and the literature.[35]

4.4.3 Associate Degree Graduates

The undereducated associate degree graduates have earnings that do not differ significantly from those of the benchmark group. However, the overeducated associate degree holders are penalised substantially for their overeducation, or are unable to utilise their surplus educational attainment efficiently in their jobs. These earnings penalties enlarge the more they are overeducated, that is, those who work in diploma level jobs earn 6.8 percent less, while those who work in a certificate level job have an earnings penalty almost three times more, at 18.5 percent. Graduates with this level of education, therefore, also experience large disparities in earnings depending on their jobs, albeit on a smaller scale compared to the diploma graduates.

4.4.4 Bachelor's Pass Degree Graduates

Overeducated graduates in this group also experience substantial earnings penalties. Graduates who work in a job that requires a diploma earn 9.2 percent less than their correctly matched counterparts. However, their peers who worked in even lower level occupations that require only a certificate earn up to 15.6 percent less. Employment in a job that requires lesser qualifications is, therefore, of great detriment to bachelor's pass degree graduates. With respect to the findings thus far, the importance of the level of educational attainment pales in comparison to the requirements of the actual job itself. Clearly, it is the latter that dictates wages.

4.4.5 Bachelor's Honours Degree Graduates

Honours degree graduates who are overeducated in a diploma or certificate level job earn less than the reference group, with the earnings gap ranging from 3.7 percent less for those in a diploma level job, and up to 10.1 percent less for those in a certificate level job. Those who work in a job that still requires an undergraduate

[35] Examination of the other estimated ORU effects discussed below indicated that these were not impacted by the inclusion of graduates with prior qualifications.

degree have a very modest earnings premium of 2.7 percent. Given that an honours degree generally requires an additional year of study, the very small earnings premium suggests that an honours degree is an investment that does not offer very good returns.

4.4.6 Graduates with Graduate Certificates or Graduate Diplomas

The graduates in these two categories have similar impacts on their earnings from being overeducated. Graduate certificate holders in a certificate level job earn 8.2 percent less than the benchmark group, while their similarly overeducated peers holding a graduate diploma earned 11.7 percent less. These graduates, however, earn more than the benchmark category if they are in a bachelor's pass level job. Specifically, graduate certificate holders earn 11.8 percent more while graduate diploma graduates earn 8.9 percent more.

The estimated coefficients on working in a diploma level job were both insignificant, for both types of educational attainment. In this regard, there appears to be a pattern. Being overeducated in a job that requires a vocational or training qualification (certificate) has rather adverse earnings consequences. Conversely, having surplus qualifications in jobs that require an undergraduate qualification is associated with more modest disadvantages in the labour market. As mentioned above, the pattern of the returns to overeducation is very similar for both levels of education.

4.4.7 Masters Graduates

The general trend observed so far for overeducation extends to the graduates who have a masters degree. That is, masters graduates who are overeducated in a certificate level job have much lower earnings, by 12.2 percentage points, than the appropriately trained bachelor's pass graduates. Those in a diploma level job have a relatively small earnings premium of 6.6 percent. Finally, the graduates in a bachelor's degree level job experience a rather substantial 18.3 percent earnings advantage. This pattern follows on from the observed trend for graduate certificate and graduate diploma holders. Specifically, graduates with postgraduate degrees who work in a vocational qualification based job have extremely detrimental earnings effects, while the pay-off to working in a job requiring a bachelor's pass degree qualification is rather substantial. Masters graduates in jobs requiring diplomas have earnings in between those in jobs in the other two categories.

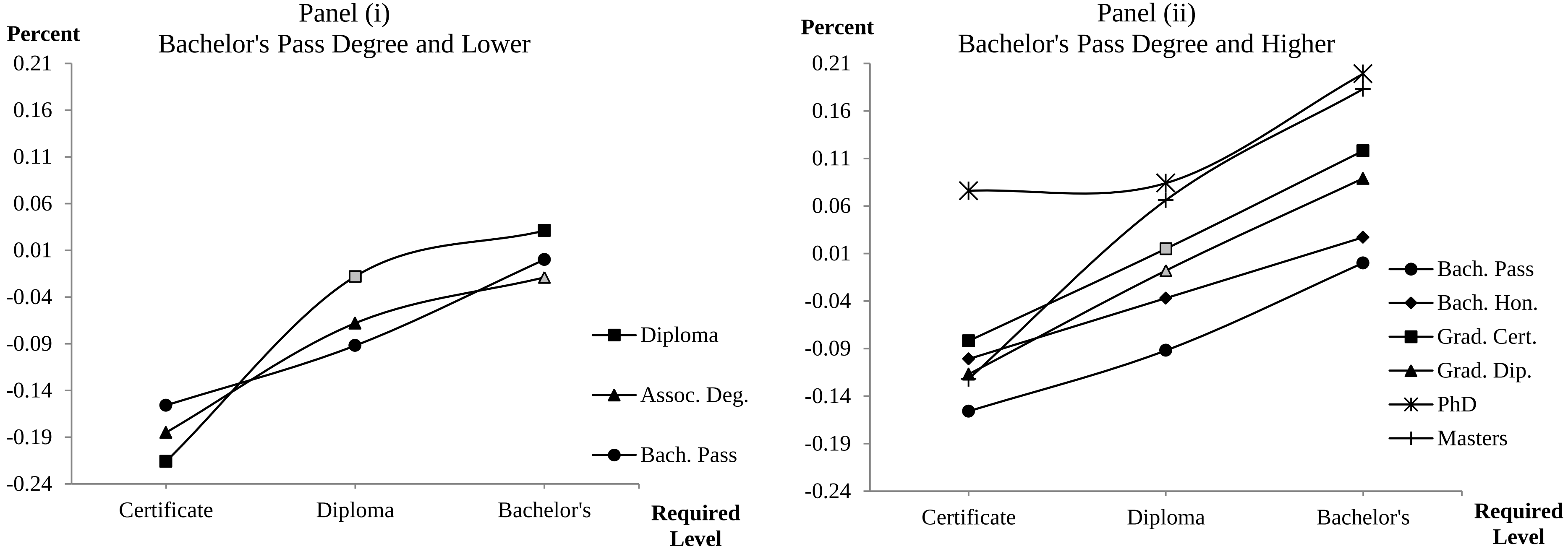
4.4.8 PhD Graduates

Doctoral graduates who are, by definition, the most overeducated category, have positive estimated coefficients for all categories. Doctoral graduates in a certificate level job earn 7.6 percent more than the reference group, while those in a diploma level job do slightly better, at 8.4 percent more. A substantial earnings premium of around 20 percent was estimated for those in a bachelor's level job. Further comments on these earnings returns will be made in comparison with the corresponding returns from other attained levels of education in the next section.

4.4.9 Comparison across Attained Levels

It is generally observed that the more extensive the overeducation, the greater the earnings penalty. The estimated returns to selected attained levels of education are graphed in Figure 4.1, which consists of two panels. Panel (i) on the left presents the estimated ORU coefficients for those who have attained a bachelor's pass degree or lower qualification. These groups consist of a mix of the overeducated, correctly matched, and undereducated. Panel (ii) charts the ORU coefficients for those with a bachelor's pass degree or higher qualification, who, with the exception of the benchmark group of correctly-matched bachelor's pass graduates, are all overeducated. Recall that the F-tests presented earlier, namely the 'F-tests by Degree Type', indicate that the overeducation earnings effects within a degree type are characterised by statistically significant variations.

Figure 4.1: OLS Estimates of the Returns to Education by Level Attained



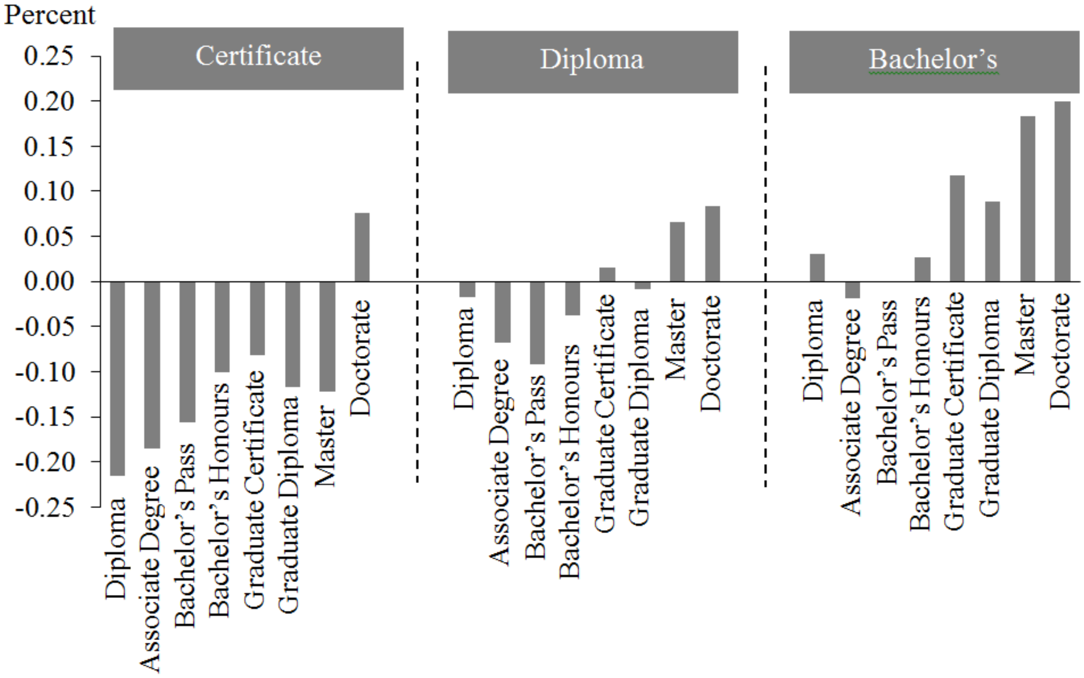
Looking at panel (i) of Figure 4.1, it can be seen that the overeducated for all three education groups working in certificate level jobs earn substantially less than the reference group of correctly-trained bachelor's pass graduates, experiencing lower earnings ranging from 15.6 to 21.6 percent less. The correctly matched diploma graduates actually earn more in comparison to the other two higher but overeducated groups of associate degree and bachelor's pass degree graduates. In particular, bachelor's pass degree graduates, who have the highest educational attainment amongst these graduates, earn the least in this job category. Note, however, that it was shown earlier that the diploma graduates have higher levels of previous qualifications. The exclusion of these 'highly qualified' diploma graduates led to a decline in the earnings premiums previously observed for the correctly matched and undereducated groups. Furthermore, those in bachelor's degree level jobs have very similar levels of earnings, regardless of educational attainment. This similarity in earnings is even more pronounced when the diploma and associate degree graduates who have previous higher educational qualifications are excluded. The pattern in panel (i) of Figure 4.1 thus indicates strongly that a worker's earnings are determined by the nature and requirements of the work that is done, and not primarily by the formal education that is brought to the job.

The coefficients presented in panel (ii) of Figure 4.1 are for the overeducated, except for the appropriately trained bachelor's pass degree graduates (i.e., the reference category). All of the curves, except for those for PhD graduates, have reasonably similar shapes. The predicted earnings effects for jobs requiring a bachelor's pass degree indicate that earnings increase with the level of qualification within that job type. That is, over-qualified workers in occupations that require a bachelor's pass degree earn more than the correctly matched bachelor's pass degree graduates, with the extent of the earnings advantage rising with the level of qualifications. Gaining a higher qualification thus appears to attract a financial reward, even if it results in being overeducated.

A similar description applies to jobs that require a diploma, where the earnings effects follow the same order as the level of qualification, although in each instance workers in jobs that require a diploma earn less than workers in jobs that require a bachelor's pass degree.

In the case of jobs that require a certificate, there are two exceptions to the general pattern documented for the other two job types. First, the relatively small number of PhD graduates employed in jobs that require a certificate (see Table 4.1) do quite well. A PhD offers some protection from the disadvantage associated with being overeducated, though the small numbers involved suggests caution be exercised in making this assessment. Second, the masters graduates employed in certificate level jobs earn about the same as those with lower level qualifications in the same type of jobs. This suggests - as do the data in panel (i) - that any advantage associated with a higher level qualification gets eroded when there is an extensive level of overeducation.

Figure 4.2: Comparisons of Estimated Earnings by Educational Attainment



This point could be made evident with the help of a further illustration. Thus, Figure 4.2 plots the estimated coefficients for all the different educational attainments, by job category. It is obvious that for jobs requiring a certificate, graduates from most levels of qualifications earn less than the benchmark group of adequately trained bachelor's pass graduates, with the earnings penalties declining as the level of qualification increases. Graduates working in bachelor's pass degree jobs all have positive earnings premiums, which increase with the level of qualification. The F-tests of Table 4.4, ‘F-tests by Job Type’, indicate that these variations across the overeducation effects within a job category are statistically significant.

4.5 Conclusion

This chapter has investigated the earnings effects of ORU in the Australian graduate labour market. Educational mismatch is very prevalent in this market, with over 60 percent of graduates being incorrectly matched to their jobs, even four months after graduation.

Several general patterns have emerged in the analysis of ORU in graduates’ earnings, using the Vahey (2000) specification. First, being undereducated produced either statistically insignificant, or very small positive earnings effects. Second, substantial earnings penalties arise for those overeducated in certificate or diploma level jobs. Third, those overeducated in a diploma level job fare slightly better, but most experience a modest detriment in the form of reduced earnings. Only masters or doctoral graduates employed in diploma level jobs obtain positive earnings impacts, relative to the benchmark group of correctly matched bachelor’s pass degree graduates. Last, being overeducated in a job requiring a bachelor’s degree brings modest to large earnings premiums, from 2.7 percent for bachelor’s honours graduates, to 19.9 percent for doctoral graduates. This result is similar to that in Vahey (2000), who observed that male graduates had positive returns to overeducation if the job required at least a bachelor’s degree. However, the marginal returns to earnings decrease quickly with extensive amounts of overeducation.

From the methodological perspective, it has been shown that the Vahey (2000) specification is a better fit to the data than a more parsimonious model where the overeducated categories are grouped, either across all overeducated categories, or across the overeducation groups within a given level of educational attainment, or across those for a particular job type. Moreover, adopting the more detailed description of education-occupation mismatch proposed by Vahey (2000) generates results which are characterised by a high degree of regularity, as illustrated in Figure 4.1 and Figure 4.2. This regularity strengthens the main empirical conclusions of the study, that the estimates from the model of earnings in the analysis indicate the strong tendency for earnings to follow jobs, and for the distinction among types of qualifications to lessen, the more extensive the overeducation.

There are, thus, several points which might be made with regards to the findings of this chapter and the preceding one. Recall that the preceding chapter uncovered a large incidence of overeducation, of around 60 percent, in the Australian graduate labour market. The findings in this chapter have revealed that those who are overeducated experience reduced returns to their education, or even negative earnings effects, in the case of the majority of those who are in a certificate or diploma level job. This suggests that the rate of higher education expansion is exceeding the demand for graduates in the labour market.

Further, the incidence of overeducation across the years of study indicates that this is not a recent phenomenon, and that high rates of overeducation have been prevalent throughout the past decade. In addition, there can be severe earnings penalties associated with being overeducated. The focus, therefore, should not be on a blanket expansion of higher education. Instead, a targeted approach would be more favourable to both individuals and the economy. There is a well-publicised shortage of skilled workers in Australia. The Sydney Morning Herald (2012b), for example, reported on a recent change in Australia's migration policy to expedite work visas for tradesmen, such as electricians and plumbers, from the US. The rationale for this policy change according to Australian Skills Minister, Chris Evans, was to "…address skills shortages in Australia by filling shortfalls in particular areas with qualified candidates from the US…".

Apart from the media, the skills shortage in Australia has also been studied and analysed by governmental agencies. For instance, the Department of Education, Employment and Workplace Relations regularly studies, surveys and monitors the labour market to identify areas of shortages on a state-by-state or national level (Department of Education, Employment and Workplace Relations 2012c). A look at the national skills shortages list for 2011 indicates that the main areas of shortages appear to be for education professionals, trades workers, and certain health professionals or specialised engineers.[36] It would, therefore, be more value-added to use this information to inform education policy and attract funding into areas of need, perhaps in other sectors of tertiary education. The analyses in the preceding chapter have also identified differences in the probability of overeducation across various fields of study. These findings may be used to inform policy makers on the areas of demand in the graduate labour market, where greater priority and resources might be diverted to.

[36] These are generalisations. The actual list is much more detailed, and follows a six digit occupational classification code in the Australian and New Zealand Standard Classification of Occupations.

CHAPTER 5

The Impact of Overeducation on the Gender Wage Gap

5.1 Introduction

In a meta-analysis of 263 international empirical studies spanning from the 1960s to the late 1990s, Weichselbaumer and Winter-Ebmer (2005) reported a halving of the gender wage gap, from 65 percent to 30 percent. This decline was attributed by these authors to the equalisation of human capital endowments. The typical Blinder-Oaxaca wage residual, or the gender wage gap usually attributed to labour market discrimination, was reported to have been unchanged over time.

The gender wage gap in Australia has also fallen considerably since the 1960s (see, for instance, Borland 1999; Gregory 1999). In contrast to the situation overseas, however, the change in Australia appears in large part to be due to a decrease in the size of the Blinder-Oaxaca wage residual, following the Equal Pay decisions of 1969 and 1972, and the Sex Discrimination Act of 1984 (Miller 1994). Nevertheless, a standardised gender pay gap of up to 15 percent remains (Borland 1999).

Recent studies of this gender pay gap have documented a number of striking patterns. First, it has been established that the gender pay gap is quite modest among 15-19 year olds, and increases with age (ABS 2004). The minor gender wage gap among 15-19 year olds could be due to minimum wage effects. The male minimum wage was extended to females in 1974. Under this explanation, it would be expected that there would be a reasonably sharp jump in the gender pay gap between youth and older workers, as one moves from a wage-setting regime where minimum rates of pay are more prevalent to a situation where wages are more likely to be above the minimum. An alternative explanation, that draws on a more gradual widening of the female wage disadvantage with age, is that the measure of labour market experience included in the conventional education and experience earnings equation becomes increasingly error prone among older workers.

A second pattern evident in the studies is that the gender wage gap is larger among the better educated than it is among the less-well educated (OECD 2011). The greater wage disadvantage experienced by tertiary educated females compared to their counterparts without post-secondary qualifications is presumably a reflection of the glass ceiling effect reported by Kee (2006). This may also be linked to institutional factors. The graduate labour market is a relatively high-wage market, with average starting salaries well above the average for non-graduates of a similar age. Preston (2001, pg. 199) argues that “Females benefit from institutional regulation (e.g. minimum wage laws) when it comes to wage determination”. It would therefore be expected that as institutional regulation would have little impact on the graduate labour market the graduate gender wage gap could be significant.

From this perspective, a study of gender wage discrimination in the graduate labour market has much appeal. It will permit assessment of the relative strengths of the countervailing ‘young age’ and ‘high level of education’ influences on the gender wage gap. This is one aim of the current chapter. Moreover, the analyses will be undertaken using perspectives from the overeducation/required education/undereducation literature. This seems particularly apt, given the changes in the higher education participation rates of males and females in recent decades. Up to the early 1970s, the participation rate of males at most levels of education exceeded that of females (Le and Miller 2002). Since then, however, the relative standing has been reversed. For example, The Australian (2011d; 2011e) reports that over the 2000 to 2009 decade, the higher education attainment rate was 39 percent for females, and only 26 percent for males. This greater representation of females among graduates raises the question of whether it is reflected in females being more likely to be overeducated. In other words, given that females are more likely to engage in higher education, it might be that larger proportions of them are in jobs which are not suited to their level of educational attainment. Related to this, it is of interest to see how individuals fare in the graduate labour market if they are not matched properly to their jobs, whether any penalty to such education-occupation mismatch differs for males and females, and whether the overeducation phenomenon contributes to the gender pay gap in the graduate labour market. These seemingly important issues are addressed below.

The rest of this chapter is organised in the following manner. Section 2 reviews the literature on overeducation, with an emphasis on studies in this literature that examine gender differences. The gender differences in educational mismatch are discussed in the context of the ‘job search’ hypothesis (Frank 1978). These are followed by a discussion on the methodology and measurement issues of the Blinder-Oaxaca decomposition methodology. Section 3 presents the methodology to be used in the statistical analyses for this chapter. Section 4 presents and discusses the results of the estimations. Finally, a conclusion is offered in section 5.

5.2 Literature Review

5.2.1 Over-, Required and Under-Education (ORU)

There is a well-developed literature on the incidence and earnings effects of Over-, Required, and Under-education (ORU). This literature has its origins in Freeman (1976), though the empirical framework that is now commonly used is due to Duncan and Hoffman (1981). The key concept considered is that while most individuals will be ‘matched’ to their jobs on the basis of their education, some will not be. Individuals with education in excess of that required by the job are considered ‘overeducated’. Conversely, individuals who have less education than that required for the job are taken to be ‘undereducated’. The labour market outcomes of matched and mismatched individuals could differ.

Various conceptual frameworks and measurement issues in this literature are discussed in Hartog (2000) and Leuven and Oosterbeek (2011). A discussion of the empirical frameworks which have been used by studies examining ORU can be found in McGuinness (2006). Each of these studies offers a summary of the empirical findings in the overseas literature, while a survey of the Australian literature is presented in Miller (2007). A number of findings have emerged from the empirical studies. While some of these findings have been covered in the literature reviews in earlier chapters, they are briefly described here. The first finding relates to the definition of educational mismatch.[37] A number of studies have shown that whereas the estimated wage effects are robust regardless of the approach adopted, the measured incidence of overeducation depends on the definition of mismatch employed (Hartog 2000). The objective approaches, which will be used in the analysis below, are explained in more detail in section 3.

[37] See Chapter 2.

The second finding relates to the incidence of educational mismatch in the labour market. Hartog's (2000) review found that, on average, a substantial 40 percent of workers are not correctly matched to their jobs.[38] Third, while the earnings returns to being overeducated are positive, they are less than the earnings returns on required education. Returns to surplus years of education typically range from one-half to two-thirds of the returns to years of required education. Fourth, workers who are undereducated earn more than their peers with the same level of education but who are working in a correctly matched (and hence lower level) job. This might be attributed to the presence of unobservable factors, such as innate ability or the propensity to work hard, such that these undereducated individuals are able to enter jobs which they would otherwise be unqualified for. Fifth, it has been reported that there are differences between males and females in both the incidence of education-occupation mismatch, and the wage effects of such mismatch.

5.2.2 The Job Search Hypothesis

Studies of gender differences in the incidence and effects on wages of education-occupation mismatch have been guided by several theoretical arguments. One of these is the job search hypothesis. This proposes that females are secondary income earners in the household (Frank 1978) and so are more constrained in their job search. This more limited job search is expected to result in females being more likely to be mismatched, and also to incur a larger wage penalty than males from being overeducated. Buchel and Battu (2003) report results that are consistent with this description of the labour market, in that married women were found to be more likely to be overeducated, relative to men or unmarried women. This was particularly so in small, localised labour markets.

However, most studies reject the job search hypothesis. Vahey (2000), for example, restricted his sample to unmarried females (who are unlikely to be a secondary income earner) who were based in the metropolitan area, and compared the ORU earnings effects in this sample to those for the female sample without these restrictions. Vahey (2000) found that most of his ORU dichotomous variables were

[38] Recall that the analysis in Chapter 3 revealed a much higher rate of education-occupation mismatch, at around 61 percent.

statistically insignificant, and the two that were significantly different from zero exhibited impacts which were not reconcilable with the job search theory. Similarly, McGoldrick and Robst (1996) also find no indication that overeducated females are penalised more than males due to geographical constraints in their job search.

A second theoretical perspective is offered by Robst (2007), based on consideration of both the supply- and demand-side factors that could lead to educational mismatch. Supply-side factors include career-oriented ones, such as accepting a promotion, or amenity- and constraint-related reasons, such as accepting a job nearer to home. The demand-side factors typically refer to the inability to find a job that matches the qualification possessed. Robst (2007) found that males were more likely to be overeducated due to career-related reasons, while females were more likely to be mismatched due to family-related reasons, although he acknowledges the possibility of reporting bias due to social norms.

5.2.3 ORU Differences by Gender in the Graduate Labour Market

A number of studies have examined gender differences in educational mismatch in the graduate labour market. There is disagreement in the research findings of these studies, and even within particular studies. Thus, Kler (2005) examined the Australian graduate labour market. He reported that, using the realised matches approach, 38 percent of female graduates were overeducated, compared with 46 percent of male graduates. When the job analysis approach was used, however, there was no gender difference in the incidence of overeducation.[39] McGuinness and Bennett (2007) studied graduate overeducation in Northern Ireland and found that females were more likely to be overeducated than men in their first job, although the gap was narrowed six years later.

Battu, Belfield and Sloane (2000) used three different measures of overeducation in their study of the UK graduate labour market. The two subjective measures used revealed that males were more likely to be overeducated, while the realised matches approach yielded the opposite finding. The absence of a clear pattern regarding the

[39] A comparison of these results for graduates with findings from studies of all workers suggests these are outcomes specific to particular groups. Thus, another Australian study by Voon and Miller (2005), which covered all workers, reported that the incidence of mismatch was 29.5 percent for males and 32.1 percent for females.

relative importance of overeducation for males and females seems to reflect both the measurement issue noted earlier, and differences across the labour markets of the various countries.

The penalties to overeducation among graduates have also been found to differ by gender. Again there is considerable irregularity in the research findings across studies. McGuinness and Bennett (2007), for example, reported OLS estimated coefficients of -11.3 and -22.8 percent for overeducated males and females, respectively. This pattern is also evident in the study by Battu, Belfield and Sloane (2000), though the difference by gender works in the opposite direction in an earlier study by Dolton and Vignoles (2000). Kler's (2005) study of the Australian graduate labour market reported greater returns to surplus education for females compared to males. These studies do not focus on the gender pay gap, or on the contribution that ORU status can make to this in the graduate labour market. These issues are addressed below.

5.2.4 The Blinder-Oaxaca Decomposition

The decomposition method used in the examination of earnings differentials between sub-groups of the population was developed in Blinder (1973) and Oaxaca (1973). It has come to be known as the Blinder-Oaxaca decomposition. In its most widely used form, the decomposition involves the estimation of a standard Mincerian earnings equation separately for the sub-groups of interest. This equation can be expressed as:

(5-1) $logw_i^j = \alpha_0^j + \alpha_1^j X_i^j + \epsilon_i^j$, $i = 1,\ldots,n$; $j = m$ for male and f for female

where $logw_i$ denotes the earnings of individual i, expressed in logarithmic format, and X_i denotes the vector of characteristics hypothesised to impact on earnings. The superscript j identifies the membership of individual i in the male or female groups. The decomposition can thus be written as:

(5-2) $\overline{logw}^m - \overline{logw}^f = \hat{\alpha}_1^m(\bar{X}^m - \bar{X}^f) + \left(\hat{\alpha}_1^m - \hat{\alpha}_1^f\right)\bar{X}^f + (\hat{\alpha}_0^m - \hat{\alpha}_0^f)$

The use of the estimated coefficients, as well as the mean values of variables for both groups, thus allows for a decomposition of the difference between the mean wages of the sub-groups into two portions. The first term on the right hand side of equation (5-2) attributes earnings differences to differences in endowments or characteristics, and is considered the ‘explained’ portion of the earnings gap. In this version of the decomposition the differences in endowments are evaluated using the male coefficients. This implies that the male wage structure is the wage structure that would prevail in the absence of discrimination, that is, it is the non-discriminatory norm. The second term on the right hand side of equation (5-2) attributes earnings differences to differences in coefficients, or returns to human capital characteristics. This portion thus implies unequal treatment of productivity characteristics in the labour market. The coefficient effects, together with the difference between the two constant terms in the estimation as expressed by the third term, form the unexplained portion of the earnings differential. These effects are generally attributed to discrimination in the labour market.

There are also alternative decomposition methods which involve a three-fold decomposition of the earnings difference (see, for example, Jones and Kelley 1984 for a discussion). These decomposition methods involve the addition of an interaction term which captures the joint effect of differences in endowments and coefficients. The interpretation of this interaction term differs, depending on the view of the labour market adopted. The different treatments of this interaction term are described in more detail in the following section. The two-fold decomposition appears to be preferred by researchers in the economics discipline, while the three-fold decomposition seems to be preferred by researchers in the sociology discipline.

5.2.5 Measurement Issues with the Blinder-Oaxaca Decomposition

There are two main measurement issues that have been raised in the decomposition literature. The first issue lies in the choice of the non-discriminatory earnings structure. That is, the results of the decomposition of equation (5-2) above would be dependent on whether the male or female wage structure is used as the non-discriminatory wage structure. This issue has been raised by a number of researchers, including Jones and Kelley (1984), Cotton (1988), Neumark (1988) and Oaxaca and

Ransom (1994). The available research demonstrates that the results of wage decompositions are sensitive to the choice of the non-discriminatory benchmark. In Ferber and Green (1982), for instance, adopting the female wage structure as the non-discriminatory norm yields an estimate of two percent of the earnings differential as the discriminatory component. When the male wage structure was adopted, however, discrimination accounted for 70 percent of the wage differential.

From a theoretical perspective, the choice of the non-discriminatory benchmark depends on the wage structure that is thought to prevail in the absence of discrimination. Where rates of pay in the post-discrimination era are likely to be determined by the wages of the higher earning group, then these should be used to evaluate the endowment effect in the decomposition.[40] In contrast, where rates of pay in the post-discrimination era are likely to be determined by the wages of the lower earning group, then it is the lower earning group's pay that should be used to evaluate the endowment effect in the decomposition.[41] The use of the alternative pay structures in the decomposition also provides a basis for reconciling the two-way and three-way decompositions. Hence, as Jones and Kelley (1984) show, the use of the pay structure of the higher earning group as the non-discriminatory norm in the two-way model is equivalent to adding the interaction term for the three-way model to the endowment component. Similarly, the use of the pay structure for the low earning group in the simple decomposition is equivalent to adding the interaction term for the three-way model to the discrimination component.

The idea that the post-discrimination wage structure would be given by one of the two prevailing wage structures has been argued to be inconsistent with the notion of market determined pay structures. The pay structure that emerges in the post-discrimination era would presumably be somewhere in between the original two sets of pay. Neumark (1988), for example, assumes that both nepotism and discrimination

[40] A typical approach in the literature uses both the male and female wage structures as the non-discriminatory wage structure in alternative decompositions, and the average results from the analyses are reported.

[41] Jones and Kelley (1984) distinguish these decompositions by addressing how one would remove the endowment effect: by reducing any greater endowment of the higher earning group (removing a privilege under their privilege model) or by enhancing any inferior set of endowments of the lower earning group (removing a deficit under their deprivation model). Economists generally view the endowments of the two groups as equalising over the longer term in response to the removal of any differences in pay (see Cotton 1988).

occur at the same time, and the choice of the non-discriminatory structure should consider both scenarios in tandem. He thus suggests the use of a pooled wage structure as the non-discriminatory wage structure, where, in this instance, the pooled wage regression does not include a gender intercept shift. Cotton (1988) proposed the use of a weighted average of the two original wage structures with the weights being given by the employment shares of the groups being examined. The methodology in the Neumark-Cotton approach thus allows for the identification of the portions in the earnings differential that are attributable to nepotism and discrimination.

In a further refinement of this approach, Fortin (2008) shows that the coefficients in the pooled regression could overstate the effects of variables which vary markedly across both groups.[42] To overcome this, Fortin (2008) suggests the inclusion of a gender intercept shift in the pooled wage regression (see Fortin 2008, pg. 898).[43] Fortin's (2008) method allows for the attribution of the gender wage gap to nepotism and discrimination, and is similar to Neumark (1988) and Cotton (1988) in that sense. The Fortin (2008) method appears to represent the preferred approach in the recent literature. An attractive feature of Fortin's (2008) approach is that it is fully compatible with the classic pooled regression approach which includes a dummy variable for the disadvantaged group. That is, the estimated 'discriminatory' portion of the earnings gap from Fortin's (2008) decomposition is equal to the estimated coefficient on the disadvantaged group in a pooled linear regression. Fortin's (2008) examples show that Neumark's (1988) method yields extreme results, and, empirically, her 'regression-compatible' decomposition gives results more similar to Cotton's (1988) approach.

Another issue that has been raised with the decomposition literature lies with the use of dummy variables in the estimating model. It should be noted at this point that this issue relates only to the results of the individual components of the decomposition, and the aggregate result of the decomposition remains the same.[44] The main issue

[42] Fortin (2008) referred to the estimated effects for unionisation and schooling in Neumark (1988), which were larger for the pooled sample compared to the corresponding estimates for the male and female samples.
[43] Alternatively, Fortin (2008) suggests weighting the male and female dummy variables by their percentage in the sample to overcome this issue.
[44] That is, the overall wage gap components remain the same, and only the amounts attributed to the specific coefficient effect vary due to this measurement issue.

that has been addressed is that the results of the decomposition are sensitive to the choice of the base or reference category where dummy variables are entered in the estimating equation (Jones 1983).[45] As Jones and Kelley (1984) note, the choice of the omitted or benchmark category is often arbitrary, as all available options are usually equally logical. They illustrate this using data on earnings and schooling for males and females in Australia. Specifically, they distinguished five categories of schooling levels, and then omitted the highest or lowest level of schooling in alternative estimations of the gender wage gap. The estimates and conclusions differed markedly, depending on the choice of the benchmark scenario. In particular, the estimated results where university education was the omitted category indicated that females have favourable coefficients effects compared to men. This finding was reversed when primary school education was used as the benchmark in their analysis. Jones and Kelley (1984) argue that the differences are substantial, and that these differences point to vastly different conclusions and therefore remedial policy.

Oaxaca and Ransom (1999) illustrate the same point in their empirical example looking at the gender wage gap of college professors. The partial contribution of degree type to discrimination was -19.3 log points, and the contribution of constant term differences was 21.9 log points, when 'No Advanced Degree' was used as the omitted case. Corresponding figures for the alternative specification using 'PhD' as the omitted case were -1.1 log points and 3.7 log points. While the overall impact was unchanged at 2.6 log points, the magnitude and importance of the role degree type plays in contributing or alleviating discrimination were vastly different.

[45] Further, Jones and Kelley (1984) show that the same general issue arises in the case of continuous variables, where the relative size of the components of discrimination in the decomposed wage gap depends on the locations of the zero points of the independent variables in the model. The issue here is that the choice of some, if not most or all, of the zero points of the explanatory variables used in the estimating model is arbitrary. This, in turn, causes the results of the decomposition to be arbitrary and be influenced by the choice of the zero points rather than actual discrimination. Jones and Kelley (1984) illustrated their point using Australian data on income, gender and schooling. They showed that substantial differences emerge in the portion of the income gap attributable to differences in the intercept terms and the estimated coefficients for males and females, when human capital endowments were specified as either years of schooling or age left school. In estimates of the model employing the latter 'age left school' specification, they found that the amount of the income gap attributable to the intercept terms dropped by 40 percent whereas the corresponding amount of the income gap attributable to the coefficients effect is 50 percent higher. This issue remains unresolved and generally serves as a reminder to exercise caution in making comparisons across studies.

More recent studies have proposed solutions to overcome the identification problems stated above. Yun (2005), for instance, suggests an 'averaging approach'. This approach uses the average of the estimated characteristics and coefficients effects obtained using all the various possible reference groups for a particular categorical variable. Further, Yun (2005) illustrated how her approach can be implemented without the need for multiple estimation runs, through a normalisation of the regression equation.[46]

5.3 Methodology

5.3.1 Measurement of Education Mismatch

In the present chapter, two different approaches are used to define educational mismatch. First, the job analysis approach, which was used in the preceding chapter 4, will be used. As mentioned above, this approach uses required levels of education as defined in a job dictionary, specifically, the Australian Standard Classification of Occupations.

In an alternative analysis, information from the 2006 Australian Census of Population and Housing will be used to determine the required levels of education separately for males and females. Specifically, this realised matches, or statistical, approach determines the modal levels of education for the various occupations, separately for males and females. Individuals with education levels above the modal levels are deemed to be overeducated. The reverse holds for the undereducated. The required levels of education defined here are more detailed than that from the ASCO, and consist of the following categories: i) year 10; ii) year 12; iii) certificate; iv) diploma, and; v) bachelor's pass degree. Thus, a total of 40 ORU categories can be constructed in this part of the analysis (that is, eight actual levels times five required levels). While the number of correctly matched and undereducated categories here remains the same as under the ASCO-based approach, the increased number of 36 overeducated categories permits a more detailed look at the earnings effects of being overeducated by larger extents. Further comments on this approach, and its benefits, are offered in a subsequent section.

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[46] Other approaches have been proposed by Gardeazabal and Ugigdos (2004) and Neilson (2000). However, Yun (2005) notes that identical results are produced by all three approaches and the choice of approach adopted should thus be dictated by efficacy or ease.

5.3.2 Estimation Models

The ORU model of earnings can be expressed in the following form:

(5-3) $logw_i = \beta_1 Z_i + \beta_2 D_i^o + \beta_3 D_i^r + \beta_4 D_i^u + \epsilon_i$

where *w* represents the hourly wage for individual i, used in the analysis in natural logarithmic format, Z represents a vector of characteristics correlated with earnings, and D^o, D^u and D^r are vectors of dummy variables indicating if the i^{th} individual is overeducated (D^o), undereducated (D^u), or correctly matched to his or her occupation of employment in terms of education (D^r), as identified in the preceding sub-section. The variables included in Z indicate the graduates' gender, English speaking background, residency status, mode of enrolment, further study status, university group, broad field of study, self-employment status, contract length, industry of employment, sector of employment, year of graduation and labour market experience. Two proxies for experience are used, namely, the age of the graduate and the years of tenure, with both proxies entered into the estimating equation in quadratic form.

In order to obtain a greater understanding of the ORU earnings effects, and their impacts on gender wage differences, a wage decomposition method, as outlined in Blinder (1973) and Oaxaca (1973), is used. A general overview of the Blinder-Oaxaca decomposition methodology, and measurement issues, had been discussed in the literature review section of this chapter, and the wage decomposition equation that will be used in this part of the analysis was presented as equation (5-2). To accommodate the fact that a number of alternative non-discriminatory wage structures can be used in this computation, the decomposition here is based on the average of those which use, respectively, the male ($\hat{\beta}_m$) and female ($\hat{\beta}_f$) wage structures in this regard.[47] The analysis will also incorporate Yun's (2005) 'averaging approach' to overcome the measurement issues raised earlier, and draw comparisons between the results of the conventional decomposition method and those from Yun's (2005) approach.

[47] See footnote 40.

5.4 Results

5.4.1 Results from the ORU Model of Earnings

The results from the estimation of the ORU model of earnings determination are presented in Table 5.1. Table 5.1 presents the results for the full sample in panel (i), for comparison purposes. Estimates for the separate samples of males and females are presented in panels (ii) and (iii), respectively.

As the pooled sample results have been discussed in the preceding chapter, attention is drawn to just the estimated coefficient on gender. The estimated gender wage gap is five percent, and this is much smaller than that traditionally found in the literature, of up to 15 percent (see Borland 1999). As discussed in the introduction, the graduate labour market will be affected by a ‘young age’ effect that will decrease the female wage disadvantage, and a ‘high level of education’ effect that will increase the female wage disadvantage. The modest five percent wage effect in the pooled sample analysis suggests that the former of these is the more important influence. This is explored in a subsequent section.

Further, note that earlier the discussion of results in chapter 4 drew attention to two striking features of the estimated earnings effects associated with overeducation. First, graduate earnings are more closely related to the nature of the job than to the qualification possessed. For example, graduates who work in a certificate level job earn less than the reference group, regardless of the educational level attained. Second, earnings premiums that tend to increase with the level of qualification are observed for graduates in bachelor’s pass degree level jobs. In other words, despite the close linkage of earnings to jobs, there remains a payoff to the acquisition of a higher level of qualification. An exception in this regard is associate degree graduates. These patterns are also observed for the estimations obtained for the separate samples of males and females.

Table 5.1: OLS Estimates of the ORU Model of Earnings

Variable	Full (i)	Males (ii)	Females (iii)
Constant	2.305***	2.233***	2.274***
	(175.708)	(95.120)	(151.039)
Female	-0.048***	(a)	(a)
	(29.159)		
Age#	0.035***	0.038***	0.034***
	(45.334)	(26.984)	(38.731)
Age squared/1000	-0.397***	-0.400***	-0.404***
	(36.847)	(20.527)	(32.903)
NESB#	-0.039***	-0.044***	-0.036***
	(17.352)	(13.066)	(11.803)
Non-Australian#	-0.202***	-0.187***	-0.216***
	(33.694)	(22.988)	(24.338)
Tenure	0.015***	0.016***	0.014***
	(30.517)	(20.954)	(22.485)
Tenure squared/1000	-0.404***	-0.471***	-0.376***
	(17.551)	(13.555)	(12.443)
Double degree#	0.008***	-0.001	0.014***
	(3.016)	(0.218)	(3.939)
Part-time study#	0.086***	0.094***	0.081***
	(43.574)	(30.379)	(31.497)
Further Study#	0.007***	0.012***	0.004
	(3.330)	(3.603)	(1.430)
Go8	0.026***	0.030***	0.024***
	(13.210)	(9.994)	(9.378)
ATN	0.031***	0.028***	0.034***
	(13.777)	(7.856)	(11.696)
IRU#	0.004*	-0.007*	0.011***
	(1.952)	(1.911)	(4.016)
Natural and Physical Sciences#	-0.076***	-0.084***	-0.065***
	(20.422)	(15.260)	(12.916)
Information Technology#	-0.031***	-0.041***	-0.007
	(7.643)	(8.234)	(0.935)
Engineering#	-0.008**	-0.011**	0.012
	(2.006)	(2.456)	(1.413)
Architecture	-0.098***	-0.097***	-0.092***
	(17.467)	(13.191)	(10.684)
Agriculture and Environment#	-0.138***	-0.163***	-0.109***
	(27.394)	(22.880)	(15.294)
Nursing#	-0.113***	-0.152***	-0.098***
	(28.156)	(15.102)	(21.165)
Medicine#	-0.028***	-0.041***	-0.019***
	(8.149)	(6.753)	(4.510)
Education#	-0.062***	-0.075***	-0.052***
	(16.597)	(11.803)	(11.240)
Society and Culture#	-0.058***	-0.065***	-0.048***
	(21.762)	(14.904)	(14.257)
Creative Arts and Others#	-0.117***	-0.134***	-0.102***
	(28.527)	(18.337)	(20.204)
Self-employed	0.015***	0.007	0.017**
	(2.679)	(0.873)	(2.043)
Private sector#	-0.054***	-0.058***	-0.052***
	(25.817)	(15.709)	(20.118)
Short-term employment	-0.095***	-0.099***	-0.093***
	(49.105)	(29.550)	(39.125)

Table 5.1: OLS Estimates of the ORU Model of Earnings (cont.)

Variable	Full (i)	Males (ii)	Females (iii)
oru_dip_cert	-0.216***	-0.186***	-0.234***
	(10.674)	(6.022)	(8.785)
oru_dip_dip	-0.018	-0.018	-0.020
	(1.561)	(1.158)	(1.177)
oru_dip_bach	0.031**	0.019	0.036**
	(2.564)	(1.033)	(2.343)
oru_ascdeg_cert#	-0.185***	-0.147***	-0.220***
	(9.440)	(5.557)	(7.704)
oru_ascdeg_dip	-0.068***	-0.072***	-0.066***
	(6.195)	(4.961)	(3.804)
oru_ascdeg_bach	-0.019	-0.016	-0.035
	(1.155)	(0.688)	(1.471)
oru_bach_cert	-0.156***	-0.160***	-0.150***
	(55.637)	(35.295)	(42.038)
oru_bach_dip	-0.092***	-0.088***	-0.093***
	(27.292)	(17.170)	(20.650)
oru_hons_cert	-0.101***	-0.096***	-0.103***
	(14.606)	(9.065)	(11.428)
oru_hons_dip#	-0.037***	-0.012	-0.053***
	(4.350)	(0.971)	(4.721)
oru_hons_bach	0.027***	0.030***	0.029***
	(7.719)	(6.037)	(5.719)
oru_gcert_cert	-0.082***	-0.072***	-0.094***
	(7.423)	(4.913)	(5.994)
oru_gcert_dip	0.015	0.009	0.012
	(1.563)	(0.674)	(0.807)
oru_gcert_bach#	0.118***	0.100***	0.127***
	(32.361)	(16.294)	(28.118)
oru_gdip_cert	-0.117***	-0.130***	-0.110***
	(12.961)	(9.141)	(9.513)
oru_gdip_dip	-0.008	-0.009	-0.015
	(0.901)	(0.672)	(1.281)
oru_gdip_bach	0.089***	0.093***	0.085***
	(31.084)	(18.749)	(24.412)
oru_mast_cert#	-0.122***	-0.143***	-0.109***
	(14.613)	(12.174)	(9.097)
oru_mast_dip#	0.066***	0.074***	0.041***
	(8.391)	(7.129)	(3.518)
oru_mast_bach	0.183***	0.186***	0.174***
	(63.714)	(41.567)	(45.974)
oru_phd_cert#	0.076***	0.010	0.121***
	(3.249)	(0.289)	(3.803)
oru_phd_dip	0.084***	0.078***	0.089***
	(4.066)	(2.698)	(2.995)
oru_phd_bach	0.199***	0.192***	0.197***
	(39.303)	(26.622)	(27.509)
Industry	Included	Included	Included
Year of Graduation	Included	Included	Included
Observations	569,325	221,746	347,579
Adjusted R^2	0.188	0.218	0.164
F-statistic	1720.73	804.87	928.1

Notes: Absolute values of heteroscedasticity consistent 't'-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively. (a) indicates that the variable was not entered into the estimating equation. # indicates statistical difference for males and females.

The adjusted R-squared values for the male and female analyses are 0.218 and 0.164, respectively. The ORU model of earnings, therefore, can be said to have relatively higher power in explaining the earnings of male graduates. This could be due to two reasons. First, the estimated coefficients for the industry of employment variables indicate that employment in certain industries, such as education and mining, have estimated impacts of greater magnitude for males compared to females. Other industry variables, such as for higher education, construction and engineering, have statistical significance for males, but not for females. Second, due to data unavailability the model does not control for marital status or the number of children the graduates have. These characteristics, arguably, would impact on women more, as the household burden generally falls on women more than men.

An F-test was conducted to see if there were gender differences in the estimated coefficients. This yielded an F-statistic of 21.254, indicating that some or all of the estimated coefficients for males and females differ. A comparison of the coefficients of specific variables for males and females revealed a number where there are statistically significant differences. These are denoted by the $^{\#}$ beside the variable names in the table. For instance, male Information Technology graduates earn 4.1 percent less than male Management and Commerce graduates (the benchmark group in the estimating equation), while the corresponding coefficient for females is insignificant. Male Agriculture and Environment graduates earn 16.3 percent less than the benchmark group, while female graduates in this category are slightly better off, with a smaller earnings disadvantage of 10.9 percent. Similarly, female Nursing graduates earn 9.8 percent less than the reference category while their male counterparts earn 15.2 percent less. These differences are reasonably minor, and affect relatively few in the sample, and so the discussion will focus on the gender differences in the ORU earnings effects.

5.4.2 Gender Differences in the ORU Earnings Impacts

There are a number of differences between males and females with respect to the estimated coefficients on the ORU variables. All of these differences relate to differences in the size of the point estimates, with the sign of the estimated impacts on earnings being consistent for both sexes. The ‘t’-tests of differences between males and females on the specific ORU coefficients indicated that only six of the estimated ORU coefficients differed statistically by gender, namely: i) associate degree graduates working in certificate level jobs; ii) bachelor’s honours degree graduates working in diploma level jobs; iii) graduate certificate graduates working in bachelor’s pass level jobs; iv) masters degree graduates working in certificate level jobs; v) masters degree graduates working in diploma level jobs, and; vi) doctoral graduates working in certificate level jobs. Two general points can be made regarding these six differences. First, the ORU categories involved are heavily concentrated in the diploma and certificate level jobs and, hence, ORU differences by gender can be said to be more likely found for those in lower-level jobs. Second, for these six categories, females were worse off than males in only three categories.

The most substantial penalty to being overeducated is for the associate degree graduates who are working in certificate level jobs (*oru_ascdeg_cert*): Whereas male associate degree graduates in certificate level jobs earn 14.7 percent less than the benchmark group their female counterparts earn 22 percent less than the reference category.

Male graduates with a bachelor’s honours degree working in diploma level jobs have earnings that do not differ statistically from the benchmark group of correctly matched bachelor’s pass degree graduates. Female graduates with the same educational attainment and working in jobs that require a diploma, however, earn 5.3 percent less than the female benchmark category. In the category of graduates with graduate certificates working in bachelor’s pass level jobs, females marginally outperform their male counterparts in earnings. Female graduates in this category earn 12.7 percent more than the reference group, while male graduates here earn ten percent more.

Masters degree graduates working in diploma level jobs (*oru_mast_dip*) have positive returns to their higher qualifications. However, males in this category have an earnings return of 7.4 percent whereas females have a more modest return, of 4.1 percent. Masters graduates working in certificate level jobs (*oru_mast_cert*) fare much worse than this, with males having earnings 14.3 percent less than the benchmark group, and females 11 percent less than the benchmark group.

A considerable gender difference in the magnitude of the ORU earnings impacts is observed for doctoral graduates in certificate level jobs - the most overeducated category. For male graduates, the impact of being overeducated in this instance is statistically insignificant compared to the benchmark group of male bachelor's pass graduates working in matched jobs. Female graduates in this situation, however, get an earnings premium compared to the benchmark group of 12.1 percent for their surplus human capital. Note, however, that female PhD graduates employed in certificate level jobs have earnings around eight percentage points lower than female PhD graduates employed in jobs requiring a bachelor's pass degree.

Of the six estimated coefficients with statistically significant differences between males and females, three (*oru_gcert_bach*, *oru_mast_cert* and *oru_phd_cert*) indicated that females were better off compared to males in terms of the earnings effects associated with overeducation, which is contrary to the predictions of the job search hypothesis outlined above. Clearly, the above comparison of gender differences in the ORU earnings effects gives little support to this interpretation of the labour market. This, however, could be a reflection of the dominance of workers from metropolitan areas in the present analysis, who are not as geographically constrained in their job search.[48]

5.4.3 The Role of Occupation of Employment

There is a high degree of occupational segregation in Australia. While previous studies have shown that this is not detrimental to women's relative rate of pay (see Jones 1983), the linkages with the ORU effects have not been explored. Equation (5-3) was therefore re-estimated for the male and female samples with added controls for occupation. While the education-occupation match variables are created using data on the occupation of employment, fully 103 occupations were used to compile the reference levels of education, and dummy variables for the occupation of employment can also be included in the model provided this is done at a higher level of aggregation. Hence, only 11 dummies for occupational groups were entered into

[48] The data set contains information on the residential and employment postcodes of the graduates. However, these were not entered into the estimating equation, as there were missing values for a substantial number of the respondents.

the estimating equation: within each of these 11 occupational groups there is variation in the ORU variables.

The results of these analyses of the ORU earnings effects are presented in Table 5.2. Panels (i) and (iii) in Table 5.2 replicate the results contained in Table 5.1, for ease of comparison with the estimates with occupational controls, set out in panels (ii) and (iv). One striking feature from Table 5.2 is the direction of impact in the ORU earnings effects as a result of adding controls for occupation. For males, the negative earnings effects associated with the ORU variables are reduced once occupations are taken account of. For example, male graduates with a masters degree who work in certificate level jobs have their earnings disadvantage reduced, albeit modestly, from 14.3 percent, to 11.4 percent. On the contrary, females have their earnings disadvantage exacerbated once occupation is controlled for. This increase in earnings disadvantage can be rather substantial, as in the case of female graduates with graduate diplomas working in certificate level jobs. These female graduate diploma holders originally have an earnings penalty of 11 percent, and this earnings penalty increases by seven percentage points, to 18 percent, once occupation is controlled for. Females, therefore, seemingly enter occupations which are especially detrimental to earnings, and which do not utilise their surplus human capital well.

Table 5.2: Selected Results of the ORU Model of Earnings

Variables	Males (i)	Males (ii)	Females (iii)	Females (iv)
oru_dip_cert#	-0.186***	-0.165***	-0.234***	-0.292***
	(6.022)	(4.455)	(8.785)	(6.914)
oru_dip_dip	-0.018	-0.018	-0.020	-0.077**
	(1.158)	(0.608)	(1.177)	(2.054)
oru_dip_bach	0.019	0.013	0.036**	0.036**
	(1.033)	(0.693)	(2.343)	(2.322)
oru_ascdeg_cert#	-0.147***	-0.125***	-0.220***	-0.300***
	(5.557)	(3.667)	(7.704)	(6.899)
oru_ascdeg_dip	-0.072***	-0.082***	-0.066***	-0.123***
	(4.961)	(3.087)	(3.804)	(3.272)
oru_ascdeg_bach	-0.016	-0.033	-0.035	-0.034
	(0.688)	(1.391)	(1.471)	(1.473)
oru_bach_cert#	-0.160***	-0.138***	-0.150***	-0.217***
	(35.295)	(5.936)	(42.038)	(6.427)
oru_bach_dip	-0.088***	-0.094***	-0.093***	-0.153***
	(17.170)	(4.151)	(20.650)	(4.557)
oru_hons_cert#	-0.096***	-0.089***	-0.103***	-0.177***
	(9.065)	(3.536)	(11.428)	(5.122)
oru_hons_dip#	-0.012	-0.024	-0.053***	-0.116***
	(0.971)	(0.956)	(4.721)	(3.284)
oru_hons_bach	0.030***	0.033***	0.029***	0.033***
	(6.037)	(6.667)	(5.719)	(6.483)
oru_gcert_cert#	-0.072***	-0.061**	-0.094***	-0.173***
	(4.913)	(2.274)	(5.994)	(4.690)
oru_gcert_dip	0.009	0.018	0.012	-0.035
	(0.674)	(0.724)	(0.807)	(0.960)
oru_gcert_bach#	0.100***	0.086***	0.127***	0.125***
	(16.294)	(14.029)	(28.118)	(27.827)
oru_gdip_cert	-0.130***	-0.108***	-0.110***	-0.180***
	(9.141)	(4.051)	(9.513)	(5.106)
oru_gdip_dip	-0.009	-0.004	-0.015	-0.068*
	(0.672)	(0.161)	(1.281)	(1.926)
oru_gdip_bach	0.093***	0.090***	0.085***	0.087***
	(18.749)	(18.393)	(24.412)	(25.173)
oru_mast_cert	-0.143***	-0.114***	-0.109***	-0.177***
	(12.174)	(4.415)	(9.097)	(5.009)
oru_mast_dip#	0.074***	0.076***	0.041***	-0.011
	(7.129)	(3.148)	(3.518)	(0.310)
oru_mast_bach	0.186***	0.173***	0.174***	0.169***
	(41.567)	(38.805)	(45.974)	(45.174)
oru_phd_cert	0.010	0.009	0.121***	0.023
	(0.289)	(0.218)	(3.803)	(0.489)
oru_phd_dip	0.078***	0.074*	0.089***	0.033
	(2.698)	(1.878)	(2.995)	(0.745)
oru_phd_bach	0.192***	0.203***	0.197***	0.202***
	(26.622)	(27.505)	(27.509)	(27.643)
Industry	Included	Included	Included	Included
Year of Graduation	Included	Included	Included	Included
Occupation	Not included	Included	Not included	Included
Observations	221,746	221,746	347,579	347,579
Adjusted R^2	0.218	0.225	0.164	0.167
F-statistic	804.87	753.07	928.1	847.42

Notes: Absolute values of heteroscedasticity consistent ‘t’-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively. # indicates significance for the t-test of difference for the earnings models presented in panels (ii) and (iv).

The difference between males and females in the direction of change in the ORU earnings coefficients when broad occupational controls are added may be linked to gender differences in job mobility. Specifically, once the broad occupational groups are controlled for, the estimated ORU earnings impacts reflect the obtaining of the qualification, as well as the movement within the broad occupational category to where the worker is overeducated, correctly matched, or undereducated, as the case may be. Thus, the negative (positive) shifts in ORU earnings impacts for females (males) suggest the following. Females, upon obtaining their higher qualification, canvass a considerable amount of occupational mobility to minimise the effects of overeducation. This explains why females seem to have more negative overeducation earnings effects once occupational group is controlled for, and there is effectively a constraint placed on this mobility (to within the broad occupational group). Males, however, appear to be initially more constrained in moving within the broad occupational category. It could be that males move across broad occupational groups to appropriate low-paid entry level jobs, and the inclusion of the occupation dummies controls for the low pay in these jobs, and hence is associated with a lowering of the penalties associated with overeducation.

Once again, 't'-tests of differences on the basis of gender were conducted on the estimated coefficients associated with the ORU and occupations variables. There are statistically significant gender differences for eight ORU categories and two occupational categories.[49] For the ORU categories, these are indicated by # beside the name of the variables in Table 5.2. Adding occupational controls thus reveals a marginally higher extent of gender differences in the ORU earnings effects. This, once again, indicates that the applicability of the job search hypothesis to the Australian graduate labour market is likely to be limited. In all, there are only seven estimated coefficients out of the 23 ORU dummy variables which exhibit the effects predicted by the job search theory, although this is more than the three ORU dummy variables which concur with job search theory predictions in the prior analysis without occupational controls. As mentioned above, adding occupational controls results in more favourable shifts in earnings effects for females compared to males,

[49] The two occupational estimated coefficients that are statistically different by gender are those for health, and education professionals. While male health and education professionals earn seven and five percent more, respectively, than the benchmark category of intermediate clerical, sales and service workers, female graduates in the same jobs earn four and five percent less.

suggesting that females are more mobile across occupations. This would also run contrary to the predictions of the job search theory, or alternatively, assist in the explanation of why the job search theory does not apply in the Australian graduate labour market. Even if females (who are hypothesised to be the secondary income earners in their households) are more geographically constrained in their job search, the fact that they are more mobile across jobs could offset the negative earnings effects of having to ‘make do’ with jobs in the immediate vicinity.

5.4.4 ORU Analyses Using Gender-Specific Required Levels of Education

Thus far, the ORU variables have been constructed using the same reference levels of education for males and females. In this section the analyses are undertaken using gender-specific reference levels of education for each occupation. The greater variation across the ORU categories under this approach provides a better basis for using a Blinder-Oaxaca decomposition in the study of the gender earnings gap.

The conventional job classification approach, such as in ASCO, holds that the same educational standard applies for all workers in an occupation. Empirically, however, it often appears that standards differ between males and females. In the ‘reverse regression’ literature, for example, when schooling levels are regressed on income, a typical finding is that to receive similar pay females generally require higher amounts of education (see Goldberger 1984; Kapsalis 1982). Kamalich and Polachek (1982), for example, find that females have around 1.2 years more of schooling, compared to males with similar earnings.

To address this issue, the modal qualification for each gender was obtained for each occupation using data from the 2006 Australian Census. There are 17 occupations, out of the total of 103 listed in the data, in which the modal levels of education differed by gender. Among these 17 occupations, in only 3 instances was the modal level of education higher for males than for females. However, despite the generally higher modal levels of education for females, their incidence of educational match remained unchanged from the corresponding figure found earlier in Chapter 3, at 38 percent. Males, however, are less ‘matched’ to their occupations, with a 30 percent incidence of educational match, four percentage points less than in the preceding section. This difference between males and females is likely to be a consequence of occupational segregation by gender and the lower reference levels of education in the analysis of male graduates.

The results of the estimation of the earnings equation using the gender-specific modal levels of education are presented in Table 5.3. In this set of analyses the ORU variables have names beginning with *cen*. As with the ORU variables in the preceding sections, the *cen* variable names have the attained qualification in the middle portion (*cert* to *phd*), and the modal levels of education at the end portion (*y10* to *bach*).

The adjusted R-squared for the analysis of the full sample is 0.186, which is very similar to the earlier analysis reported in Table 5.1. The adjusted R-squared values for the male and female estimations in panels (ii) and (iii) are 0.215 and 0.162, respectively. Thus, there is no advantage, and perhaps even a slight disadvantage, from using the additional detail available in these alternative measures of required education. At face value, this suggests that the labour market is not overly discerning in this regard. However, the results of the 't'-tests of differences in the estimated earnings coefficients by gender revealed a much larger number of statistically significant earnings effects differences in the Table 5.3 analyses, as compared to those in Table 5.1. These are again denoted by the $^{\#}$ beside the variables' names. Out of the 87 variables in the model, estimated coefficients for 41 of them, or almost half, were found to differ statistically by gender. A review of the estimated coefficients in panels (ii) and (iii) reveals that the magnitudes of earnings effects are generally larger for males, and in some cases are statistically significant for males but not for females. This is similar to the pattern evident in Table 5.1. Looking at fields of study, for example, it is observed that the estimates for the Information Technology and Engineering graduates are statistically significant at the one percent level for males, but are insignificant for females. Moreover, the estimates on Agriculture and Environment, Nursing, and Creative Arts and Others are larger (in absolute terms) for males.

Table 5.3: OLS Estimates of the ORU Model, Gender-specific Required Education

Variable	Full (i)	Male (ii)	Female (iii)
Constant	2.228***	2.120***	2.199***
	(171.798)	(91.246)	(148.410)
Female	-0.049***	(a)	(a)
	(29.650)		
Age#	0.041***	0.044***	0.040***
	(53.392)	(32.029)	(45.767)
Age squared/1000	-0.455***	-0.466***	-0.461***
	(42.603)	(24.032)	(37.899)
Tenure#	0.019***	0.019***	0.017***
	(39.528)	(25.898)	(28.936)
Tenure squared/1000#	-0.538***	-0.609***	-0.502***
	(23.251)	(17.259)	(16.594)
NESB#	-0.044***	-0.050***	-0.040***
	(19.578)	(14.648)	(13.149)
Non-Australian	-0.214***	-0.213***	-0.227***
	(35.822)	(26.568)	(25.612)
Further study#	0.006***	0.010***	0.003
	(2.832)	(3.034)	(0.895)
Go8#	0.021***	0.030***	0.021***
	(11.219)	(9.954)	(8.350)
ATN	0.030***	0.032***	0.033***
	(13.278)	(9.041)	(11.519)
IRU#	-0.000	-0.011***	0.008***
	(0.148)	(2.943)	(2.754)
Natural and Physical Sciences	-0.090***	-0.085***	-0.082***
	(24.251)	(15.413)	(16.351)
Information Technology#	-0.033***	-0.032***	-0.012
	(8.136)	(6.436)	(1.585)
Engineering	-0.021***	-0.013***	0.002
	(5.394)	(2.670)	(0.223)
Architecture	-0.116***	-0.095***	-0.110***
	(20.724)	(12.870)	(12.745)
Agriculture and Environment#	-0.137***	-0.158***	-0.113***
	(27.158)	(22.057)	(15.675)
Nursing#	-0.124***	-0.155***	-0.113***
	(30.761)	(15.201)	(24.178)
Medicine	-0.038***	-0.042***	-0.032***
	(11.018)	(6.886)	(7.479)
Education#	-0.070***	-0.076***	-0.060***
	(18.962)	(11.950)	(13.056)
Society and Culture#	-0.060***	-0.064***	-0.049***
	(22.313)	(14.735)	(14.487)
Creative Arts and Others#	-0.126***	-0.137***	-0.109***
	(30.672)	(18.820)	(21.485)
Self-employed	0.019***	0.014*	0.018**
	(3.285)	(1.720)	(2.215)
Private sector	-0.054***	-0.056***	-0.050***
	(25.374)	(15.084)	(19.336)
Short-term employment#	-0.101***	-0.110***	-0.098***
	(52.295)	(32.906)	(41.398)
cen_dip_y10#	-0.374***	-0.228***	-0.523***
	(6.841)	(3.438)	(3.761)
cen_dip_y12	-0.148***	-0.122**	-0.172***
	(7.326)	(2.453)	(7.221)
cen_dip_cert#	-0.016	0.013	-0.109***
	(1.394)	(0.993)	(3.334)

Table 5.3: OLS Estimates of the ORU Model, Gender-specific Required Education (cont.)

cen_dip_dip[#]	-0.055	-0.350***	0.102***
	(1.255)	(3.237)	(7.991)
cen_dip_bach	0.039***	0.021	0.040***
	(3.230)	(0.932)	(2.613)
cen_ascdeg_y10	-0.312***	-0.275***	-0.232**
	(5.548)	(3.523)	(2.276)
cen_ascdeg_y12[#]	-0.178***	-0.063*	-0.197***
	(7.608)	(1.953)	(6.408)
cen_ascdeg_cert[#]	-0.035***	-0.018	-0.165***
	(3.014)	(1.514)	(3.989)
cen_ascdeg_dip	-0.258***	-0.549	0.016
	(2.979)	(1.169)	(1.358)
cen_ascdeg_bach	-0.008	-0.029	-0.018
	(0.578)	(0.900)	(0.821)
cen_bach_y10	-0.292***	-0.263***	-0.285***
	(30.049)	(22.118)	(14.824)
cen_bach_y12[#]	-0.132***	-0.102***	-0.141***
	(48.965)	(21.102)	(39.460)
cen_bach_cert[#]	-0.109***	-0.040***	-0.085***
	(22.742)	(9.197)	(17.352)
cen_bach_dip[#]	-0.028***	-0.207***	0.018
	(3.453)	(10.521)	(1.393)
cen_hons_y10[#]	-0.284***	-0.217***	-0.379***
	(8.568)	(5.463)	(5.795)
cen_hons_y12[#]	-0.081***	-0.054***	-0.098***
	(12.468)	(5.139)	(11.080)
cen_hons_cert[#]	-0.061***	-0.016	-0.046***
	(4.753)	(1.485)	(3.729)
cen_hons_dip[#]	-0.026	-0.011	0.117**
	(1.020)	(0.246)	(2.416)
cen_hons_bach	0.022***	0.028***	0.023***
	(6.419)	(5.564)	(4.605)
cen_gcert_y10	-0.228***	-0.224***	-0.212*
	(4.958)	(4.480)	(1.919)
cen_gcert_y12[#]	-0.017*	0.019	-0.055***
	(1.866)	(1.387)	(3.837)
cen_gcert_cert[#]	-0.000	0.131***	0.031*
	(0.001)	(16.014)	(1.820)
cen_gcert_dip[#]	0.040	-0.218***	0.066
	(1.441)	(3.240)	(0.907)
cen_gcert_bach[#]	0.145***	0.115***	0.155***
	(40.735)	(15.438)	(34.943)
cen_gdip_y10	-0.318***	-0.362***	-0.264***
	(8.523)	(7.801)	(3.780)
cen_gdip_y12[#]	-0.064***	-0.046***	-0.086***
	(8.260)	(3.327)	(7.733)
cen_gdip_cert[#]	-0.018	0.148***	-0.013
	(1.255)	(16.097)	(1.003)
cen_gdip_dip[#]	0.001	-0.108***	0.118***
	(0.038)	(3.539)	(4.831)
cen_gdip_bach[#]	0.103***	0.082***	0.099***
	(36.836)	(15.462)	(29.132)
cen_mast_y10	-0.351***	-0.354***	-0.317***
	(11.979)	(10.111)	(6.113)
cen_mast_y12[#]	-0.048***	-0.010	-0.082***
	(6.525)	(0.867)	(6.963)

Table 5.3: OLS Estimates of the ORU Model, Gender-specific Required Education (cont.)

cen_mast_cert#	0.055***	0.238***	0.065***
	(4.732)	(38.381)	(5.670)
cen_mast_dip#	0.088***	-0.140***	0.060*
	(4.820)	(3.711)	(1.955)
cen_mast_bach#	0.201***	0.163***	0.191***
	(71.672)	(32.360)	(51.265)
cen_phd_y10	-0.256*	-0.283***	-0.370
	(1.823)	(2.956)	(0.933)
cen_phd_y12	0.107***	0.077**	0.132***
	(6.304)	(2.365)	(5.198)
cen_phd_cert#	0.096**	0.228***	0.145***
	(2.430)	(13.918)	(6.343)
cen_phd_dip	0.188***	-0.020	0.534
	(4.476)	(0.169)	(1.066)
cen_phd_bach#	0.192***	0.172***	0.190***
	(38.078)	(22.609)	(26.514)
Observations	569,325	221,746	347,579
Adjusted R^2	0.186	0.215	0.162

Notes: Absolute values of heteroscedasticity consistent ‘t’-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively. # indicates significance for the t-test of difference. (a) indicates that the variable was not entered in the estimating equation.

The analyses disaggregated by gender, and using gender-specific modal levels of qualifications, are associated with greater variability in the ORU earnings impacts between males and females. Thus, using the ‘t’-tests of difference, 26 of the 39 ORU variables here differ statistically between males and females. This is a larger proportion than that found for the earlier analyses which did not use gender-specific required levels of education, and this is presumably linked to the greater detail used in the construction of the ORU variables in lower-skilled jobs. Second, the magnitude of the earnings differences by gender are substantially larger, compared to those found in the earlier section. For example, males with a diploma, employed in a job with a modal educational level of a Year 10 qualification, earned a substantial 23 percent less than the benchmark group of their male counterparts with a bachelor’s pass degree working in a job where the modal qualification is a bachelor’s pass degree.[50] In comparison, females are much worse off if they are in the same situation, with the earnings effect being negative 52 percent. Earnings effects differences between males and females exceeding ten percentage points are evident in 18 categories, though these are reasonably evenly divided between cases where males are at an earnings advantage and cases where females are at an earnings advantage.

[50] This ORU category consists of farm mangers, and production or transport labourers.

Further, of the 39 ORU earnings coefficients in this section, only 17 exhibited gender differences in earning impacts that are consistent with the job search hypothesis. While this is a larger proportion compared to that found in the previous section (3 out of 23), it still accounts for less than half of the estimated earnings coefficients. Generally, it can be said that the job search hypothesis does not appear to be validated by the findings here for the Australian graduate labour market.

5.4.5 Blinder-Oaxaca Decomposition

As noted in relation to equation (5-2), a Blinder-Oaxaca decomposition can be used to provide a better understanding of the reasons why females have a lower mean rate of pay than males. The results of this decomposition, which uses the average of the female and male wage structures as the non-discriminatory norm, are presented in Table 5.4. In the current data there is a raw gender wage differential of 9.6 percentage points in favour of males. Of this 9.6 percentage points, the Blinder-Oaxaca decomposition revealed that 4.4 percentage points were attributable to the difference in the endowments of the male and female graduates. The remaining 5.1 percentage points, or slightly over half of the wage difference, can be attributed to the difference in coefficients.[51, 52] The ORU variables accounted for a combined, and very small, 0.3 percentage points of the 'endowment' effect.[53] The majority (32 out of 39) of the estimated endowment effects for the ORU variables were, however, statistically significant at the ten percent level or higher.

The negligible combined endowment effect for the ORU variables may seem inconsistent with the findings reported earlier, of males being less likely to be 'matched' to their occupation (30 percent incidence of education-occupation match compared with 38 percent for females) and of there being substantial variation in wages across the ORU categories entered into the estimating equation. An

[51] This 'coefficient' effect is also known as the 'unexplained' wage differential, or discrimination, in the gender wage gap literature.

[52] A two-fold decomposition is performed here, for simplicity in the discussion of results, as well as compatibility with most studies in the economics literature. Performing a three-fold decomposition reveals that the 'third' interaction component is small, at 2.5 percentage points. The endowment and coefficient effects were 3.2 and 3.9 percentage points, respectively.

[53] For the unexplained 'coefficient' component, ORU effects account for a modest 1.5 percentage points, out of the 5.2 percentage points.

examination of the individual endowment effects for the 39 ORU variables shows that these effects are very minute, with the largest estimate being only 0.7 percentage points, for the category of graduates with a masters degree working in certificate level jobs.[54] Moreover, 21 of the ORU estimated coefficients, or around one-half of the ORU variables, were of negative sign, while the remaining 18 were of positive sign. A negative sign means that the removal of that component would lead to a wider gender wage gap, whereas a positive sign indicates that removal of that component would lessen the gender wage gap, ceteris paribus. Thus, these effects cancel out, with the net result being that the ORU endowment effects do not favour either gender. This finding provides a basis for further evaluation of the job search hypothesis. Specifically, as there does not appear to be a clear wage advantage (detriment) caused by the ORU endowments for males (females), the job search hypothesis is not validated, at least for the Australian graduate labour market. It would be of interest, however, to know if these findings hold after the measurement issues that were highlighted in the literature review section are accounted for. These issues are addressed in the following section.

Table 5.4: Estimates from the Blinder-Oaxaca Decomposition

Predicted Male Wage	3.0658***	
	(0.0013)	
Predicted Female Wage	2.9701***	
	(0.0010)	
Raw Wage Gap	0.0957***	
	(0.0017)	
Explained		0.0443***
		(0.0012)
Unexplained		0.0514***
		(0.0018)
Constant		-0.0788***
		(0.0221)
Observations	569,325	

Note: Standard errors are presented in parentheses. ***, ** and * denote significance at the one, five and ten percent levels, respectively.

5.4.6 The Blinder-Oaxaca Decomposition and the 'Averaging Approach'

As an extension to the Blinder-Oaxaca decomposition analysis from the preceding section, and bearing in mind the measurement issues raised in the literature review section earlier, equation (5-2) is re-estimated utilising the 'averaging approach' suggested by Yun (2005). Selected results from this decomposition are presented in

[54] The individual endowment effects are not reported here, but are available on request.

Table 5.5. Panels (i) and (ii) presents the results from the previous decomposition discussed in the preceding section, while panels (iii) and (iv) present the results which have incorporated Yun's (2005) 'averaging approach'. Note that as the results of the overall decomposition do not change, they will not be presented here. Instead, the focus will be on the ORU effects and the change in the constant terms. The first key observation that can be made is that the value of the intercept term is markedly different. The estimate for the intercept term in the previous decomposition was around 7.9 percent, while the corresponding estimate for the current decomposition with deviation contrast coding is 13 percent. This suggests that group membership per se is more important in contributing to the gender wage gap than that indicated from the previous decomposition, where the constant term referred to the outcomes for a single reference group, namely, the bachelor's degree graduates working in jobs that require the level of qualification that they possess.

Looking at the estimated coefficient effects associated with the ORU variables, however, indicates very modest changes. 31 out of the 40 ORU variables have coefficient effects in the decomposition that are statistically significant at the ten percent or higher levels, similar to the 32 out of 39 significant ORU coefficient effects reported under the 'single benchmark' approach from the previous section. The sign on the estimated coefficient effects largely remains unchanged – the only exception is for graduates with an honours degree working in certificate level jobs. The endowment effect for these graduates changed from being of a negative sign, to being positive. The absolute value of the endowment effect, however, remains small, at 0.2 percent.

Further, an examination of the endowment effects in the decomposition for the different levels of required education reveals four general (though not universal) patterns. First, there are few significant gender endowment effects in jobs that require a diploma, and the gender endowment effects in jobs that require a bachelor's degree are mixed. As these are job requirements that are closest to the qualifications of the graduate population, this empirical result indicates that similar sorting outcomes for male and female university graduates occur for such jobs.

Table 5.5: Selected Results from the Blinder-Oaxaca Decomposition and Deviation Contrast Coding

	Single Benchmark		Deviation Contrast Coding	
Variable	Explained	Unexplained	Explained	Unexplained
	(i)	(ii)	(iii)	(iv)
cen_bach_bach			-0.0042***	0.0098**
			(0.0005)	(0.0045)
cen_dip_y10	-0.0001***	0.0001***	-0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_dip_y12	0.0001***	0.0001	0.0000***	0.0001*
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
cen_dip_cert	-0.0002**	0.0003***	0.0000	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
cen_dip_dip	0.0001**	-0.0002***	0.0000	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_dip_bach	0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
cen_ascdeg_y10	-0.0001***	-0.0000	-0.0000**	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_ascdeg_y12	0.0001***	0.0001**	0.0000**	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_ascdeg_cert	-0.0005***	0.0005***	-0.0002*	0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
cen_ascdeg_dip	0.0003***	-0.0003***	0.0002***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
cen_ascdeg_bach	-0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
cen_bach_y10	-0.0040***	0.0003	-0.0032***	0.0006**
	(0.0001)	(0.0002)	(0.0002)	(0.0003)
cen_bach_y12	0.0084***	0.0049***	0.0044***	0.0086***
	(0.0002)	(0.0008)	(0.0005)	(0.0017)
cen_bach_cert	-0.0040***	0.0038***	-0.0003	0.0062***
	(0.0002)	(0.0005)	(0.0004)	(0.0012)
cen_bach_dip	-0.0006***	-0.0013***	-0.0002***	-0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
cen_hons_y10	-0.0003***	0.0002***	-0.0003***	0.0002***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
cen_hons_y12	0.0005***	0.0006***	0.0001*	0.0009***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
cen_hons_cert	-0.0002***	0.0003*	0.0002**	0.0005***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
cen_hons_dip	0.0000	-0.0001	0.0001**	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_hons_bach	0.0002***	0.0003	0.0008***	0.0016**
	(0.0000)	(0.0004)	(0.0001)	(0.0007)
cen_gcert_y10	-0.0001***	-0.0000	-0.0001***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_gcert_y12	-0.0000	0.0005***	0.0000*	0.0006***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
cen_gcert_cert	0.0014***	0.0013***	0.0023***	0.0016***
	(0.0001)	(0.0002)	(0.0002)	(0.0003)
cen_gcert_dip	-0.0000*	-0.0001***	-0.0000	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_gcert_bach	-0.0027***	-0.0015***	-0.0039***	-0.0004
	(0.0001)	(0.0003)	(0.0002)	(0.0006)
cen_gdip_y10	-0.0003***	-0.0001*	-0.0002***	-0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_gdip_y12	0.0002***	0.0004**	0.0000	0.0006***
	(0.0000)	(0.0002)	(0.0000)	(0.0002)

Table 5.5: Selected Results from the Blinder-Oaxaca Decomposition and Deviation Contrast Coding (cont.)

Variable	Explained (i)	Unexplained (ii)	Explained (iii)	Unexplained (iv)
cen_gdip_cert	0.0009***	0.0021***	0.0016***	0.0025***
	(0.0001)	(0.0002)	(0.0001)	(0.0003)
cen_gdip_dip	0.0000	-0.0001***	0.0000*	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_gdip_bach	-0.0030***	-0.0012**	-0.0049***	0.0008
	(0.0001)	(0.0005)	(0.0003)	(0.0010)
cen_mast_y10	-0.0012***	-0.0001	-0.0010***	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
cen_mast_y12	-0.0002***	0.0012***	0.0000	0.0017***
	(0.0000)	(0.0002)	(0.0000)	(0.0003)
cen_mast_cert	0.0079***	0.0061***	0.0109***	0.0071***
	(0.0003)	(0.0004)	(0.0004)	(0.0006)
cen_mast_dip	-0.0000	-0.0002***	0.0000	-0.0002***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
cen_mast_bach	-0.0017***	-0.0027***	-0.0022***	0.0000
	(0.0001)	(0.0006)	(0.0002)	(0.0013)
cen_phd_y10	-0.0000**	0.0000	-0.0000**	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_phd_y12	0.0000**	-0.0001	0.0000**	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_phd_cert	0.0008***	0.0002**	0.0010***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
cen_phd_dip	0.0000	-0.0000	0.0000*	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
cen_phd_bach	0.0013***	-0.0004*	0.0017***	0.0002
	(0.0001)	(0.0003)	(0.0001)	(0.0004)
Total	0.0030	0.0149	0.0067	0.0328
Constant	-0.0788***		-0.1296***	
	(0.0221)		(0.0249)	
Observations	569,325		569,325	

Notes: Standard errors are presented in parentheses. *, ** and *** denote significance at the ten, five and one percent levels, respectively. Panels (iii) and (iv) present results of the two-fold decomposition with deviation contrast coding.

Second, jobs that require certificate level qualifications have endowment effects that favour more highly qualified males. That is, fewer more highly qualified males than females work in these jobs that attract a wage penalty. When this result is combined with the first feature mentioned above, the implication is that male and female graduates are differentially sorted into jobs that require lower-level qualifications.

Third, jobs that require Year 12 education typically have endowment effects that favour males. As graduates in these jobs are overeducated, and their overeducation status is associated with lower wages, this endowment effect in favour of males must arise because females are more likely than males to be in these intermediate level jobs.

Fourth, jobs that require Year 10 education typically have endowment effects that favour females. Applying the reasoning advanced above, this suggests that males are more likely than females to be in these low-skilled jobs.

In the case of the coefficients effect, there are three findings of note. First, the coefficient effects for jobs that require either a diploma or bachelor's pass degree tend to be associated with a negative effect. In other words, this component of the wage decomposition acts to lessen the male wage advantage that would otherwise occur.

Second, the coefficient effects for jobs that require either a certificate or Year 12 schooling tend to be positive. In other words, the overeducation wage effects associated with university graduates working in these jobs tend to favour males, and lead to a widening of their wage advantage.

Third, the low-skilled jobs requiring only Year 10 are typically associated with similar wage effects for males and females, so that the coefficient effects in the wage decomposition for these jobs are usually not statistically significant. Thus, the decomposition indicates that while the overall wage effects are slight, there are interesting patterns in the data that suggest that there are systematic factors impacting the wage determination process when it is examined from the ORU perspective.

A comparison of the overall contribution of ORU earnings effects to the gender wage gap reveals changes of a moderate scale. Recall from the previous section that ORU earnings effects accounted for a total 0.3 percentage point impact on the endowment effect. Further, the unexplained portion of the gender wage gap, or the coefficient effect, attributed to ORU effects was 1.5 percentage points. Under the 'averaging approach', these values are 0.7 and 3.3 percentage points, respectively. The endowment and coefficient effects of the gender wage gap attributable to ORU can thus be said to have doubled. In the case of the endowment effects, ORU earnings effects can be said to play a minor role - they still account for only 17 percent of the overall endowment effect for the model. The coefficient effect of the gender wage gap attributable to ORU, however, is substantial. ORU earnings effects account for roughly two-thirds of the (modest) estimated coefficient effect of five percentage points. Nevertheless, the finding from the previous section, that the ‘job-search’ hypothesis is not validated in the Australian graduate labour market, is reinforced by the decomposition utilising Yun’s (2005) ‘averaging’ approach, given the small endowment effects associated with ORU.

5.4.7 The Gender Wage Gap and Age

The Blinder-Oaxaca decomposition indicated a standardised gender wage gap of 5.2 percentage points. This gender wage gap is of similar size to that estimated by the female dummy variable in the ORU models of earnings in the preceding sections. Further, recall that in an earlier section it was noted that the relatively small gender wage gap observed in the present study might be due to the focus on labour market entrants. Thus, the pooled regression will be used in a more detailed examination of the gender wage gap effect by age. Two approaches are considered in this examination. First, the sample was disaggregated by age groups, and equation (5-3) was estimated separately for each age group. [55] The results indicated that for graduates aged 35 years and below, the gender wage gap was around 4.5 percent. Thereafter, the gender wage gap widened considerably. Females aged 36 to 40 years earned six percent less. Those aged 46 to 50 years experienced earnings eight percent lower than their male counterparts. Female workers aged more than 56 years old earned 13 percent less. These estimates were all significant at the one percent level. As age increases, both males and females enter higher-wage positions, but the female wage disadvantage widens. This provides some support for the ‘glass ceiling’ found in other studies.

Second, equation (5-3) was estimated on the full sample, with an interaction term between gender and age (*genage* = *female*age*). The inclusion of this term in the model yielded an estimate of -0.013 for *female*, and an estimate of -0.004 on *genage*, both significant at the one percent level. These estimates can be interpreted as follows. The gender wage gap is three percent when evaluated at 25 years of age. For graduates aged 40 years old, the gender wage gap is much wider, at nine percent. This increase in the gender wage gap follows through for increasing years of age, and the gap is a substantial 19 percent for graduates at the (retirement) age of 65 years.

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[55] The results for the full model on these analyses by age groups, and the subsequent pooled regression are not presented in this study, but are available on request.

These findings lend support to the thesis that the relatively small gender wage effect among younger workers, and the larger gender wage effect among older workers, is due to the measure of work experience. Mincer and Polachek (1974) for the US, and Rummery (1992) for Australia, show that changing from a measure of potential work experience to a measure of actual work experience can reduce the standardised wage gap by 40 to 70 percent.[56] The competing hypothesis, that the small gender wage gap for young graduates is due mainly to minimum wage effects, does not seem credible when the gradual changes in the gender wage gap with age are considered.

5.5 Conclusion

This chapter has examined gender differences and educational mismatch in the Australian graduate labour market, using various analyses and perspectives. A number of conclusions can be drawn from this analysis. First, the gender wage gap for the higher educated labour market entrants is smaller than that reported in other Australian studies. Analyses of the change in this with age suggest that it is most likely linked to the measure of work experience included in the estimating equation.

Second, the most substantial penalties to being overeducated are found at the lowest job levels. Most ORU earnings effects do not differ statistically between males and females. Greater earnings penalties and gender differences are found when gender-specific and more detailed required levels of education are used from the Census data than when the gender-neutral ASCO-based standards are employed. Nevertheless, the absence of evidence in either set of analyses that females incur greater earnings penalties than males from their overeducated status suggests that females' overeducation does not arise due to their more limited job search.

A third finding reinforces that of the second point. Adding broad controls for occupation to the model impacts negatively (positively) on the ORU earnings effects for female (male) graduates. This indicates that females are more mobile across

[56] In Rummery (1992) the measure of actual experience was constructed as the number of years worked full time plus a third of the years worked part time. All data were collected retrospectively.

occupations compared to males. Again, this does not support the theorised outcomes under the job search hypothesis.

Fourth, the Blinder-Oaxaca decomposition revealed that ORU effects accounted for only a negligible portion of the gender wage gap. However, the decomposition revealed interesting trends regarding sorting outcomes and ORU earnings effects for males and females. With regard to jobs that require lower education levels, males were more likely than females to be sorted into jobs requiring Year 10 schooling or certificates. At the same time, the coefficient effects in the decomposition indicated that the estimated ORU effects for higher-level jobs that require a diploma or bachelor’s degree tend to narrow the gender wage gap. In contrast, the estimated ORU effects for jobs that require a certificate or Year 12 tend to widen the gender wage gap.

In summary, there is a gender wage gap in the Australian graduate labour market, though this gap is smaller than that found for the aggregate-level Australian labour market. These findings thus favour education as a tool of eliminating discrimination in the labour market. As females are less overeducated than males, despite the larger representation of the former in higher education, there should not be concern that expanding higher education will disadvantage females. This prognosis is reinforced by the finding that the majority of the estimated ORU penalties do not differ statistically between males and females, and the finding that different levels of overeducation of males and females make a minute contribution to the ‘endowment effect’ in the gender pay gap decomposition. At the same time, however, a word of caution is needed. The gender wage gap is larger for graduates in the older age groups and who are in more advanced stages of their career. This ‘glass ceiling’ effect appears substantial. However, whether it is a pure ‘glass ceiling’ effect, or simply a statistical artefact attributable to the use of a poor measure of work experience in the earnings equation, is a moot point. The collection of detailed work histories will be needed if the understanding of this labour market outcome is a priority.

CHAPTER 6

ORU Earnings Impacts: How do They Change with Increases in Tenure?

6.1 Introduction

This chapter examines the change in ORU impacts as work tenure increases. In particular, the sample is disaggregated into four groups based on the graduates' tenure. The first three groups are those with tenure of zero, one year and two years, respectively. The fourth group are those with tenure of three years and above. Each of these groups has a large number of observations, with the sample sizes ranging from 57,580 (for those with tenure = 2) to 209,593 (for those with tenure = 0).

It should be borne in mind that the data here consist of fresh graduates. Hence, those with and without tenure in their jobs can be thought of as the following. There are three categories of graduates. First, there are the graduates who did not work while studying, and commenced their current job following their graduation. Second, the group with zero tenure will also include the graduates who had been working while studying, and, upon graduation, moved to another position or job, and who have thus reported no tenure. The third and last group comprises those with positive tenure in their jobs who commenced working before or while studying for their higher qualifications.

There is, however, one caveat relating to this classification of graduates by tenure. The question relating to tenure in the survey asks about the tenure that graduates have "in this job". This question is rather subjective in the sense that whether it relates to 'job tenure' or firm tenure' is open to interpretation. That is, graduates who were working in a job, and got moved into another job after graduation could answer the question in one of two ways. They could have reported tenure of zero, reflecting their 'new' job or role, or reported a positive amount of tenure, reflecting their experience in the firm.[57]

[57] Consider, for example, a graduate who had been working for two years as an accounting clerk in a firm, and who was moved to the role of an accountant after graduation. This graduate could report tenure of zero to reflect the new job scope, or a tenure of two years.

It is anticipated, however, that the mix of graduates in the zero tenure group is unlikely to pose large problems with regards to the comparison of earnings against graduates with positive tenure. This is due to three reasons. First, graduates with a history of employment who have found a new job, and hence are now in the zero tenure group, are expected to account for only a relatively small proportion of those in this tenure group.

Second, the impact of firm-specific experience gained in the lower-level job on earnings in the current, higher-level position, is expected to be small, especially as the job level and extent of education-occupation mismatch is held constant. Third, where some of these graduates have obtained their current position due to a job search external to their previous firm, their prior general labour market experience will be partially captured in the age and age squared variables. With regards to the comparison on the incidence of overeducation, the same reasons apply, albeit to a lesser extent for the latter reason.

This aspect of the dataset affects the issues that can be addressed with it. The conventional approach is typified by the study by de Oliveira *et al.* (2000), who examined the effects of overeducation on earnings as tenure or firm-specific experience is accumulated after graduation. However, in the present study the research question that needs to be posed is, 'Are there differences in the ORU effects for graduates who have accumulated job tenure while studying and graduates who did not work while studying?'. With regards to the former group of graduates who have some tenure in their jobs, whether the ORU effects differ by the length of job tenure they have is also of interest, and will also be examined in this section. To provide a framework for interpreting the changes in the ORU effects with tenure from this perspective, a review of the applicable labour market theories and their respective predictions of the ORU earnings effects is in order. There are five of these theories: i) the searching and matching model; ii) human capital theory; iii) the technological change hypothesis; iv) assignment theory, and; v) the screening hypothesis. For two of these, namely, technological change and screening, there are predictions for the tenure effects in the current study that differ from those in analyses of datasets with a more conventional tenure variable.

The remainder of this chapter is organised in the following manner. Section 2 presents a review of the five labour market theories and the *a priori* expectations of the change in ORU impacts with increasing tenure under each of the theoretical frameworks. Section 3 describes the methodology used, while section 4 presents the results of the analysis.[58] Section 5 concludes.

6.2 Labour Market Frameworks

6.2.1 Searching and Matching Model

Hartog (2000) gives an explanation of the incidence of ORU as tenure increases under the job searching and matching theory. This theory states that individuals move across jobs when they are able to secure one which has a higher job level, and thus their current job is the job with the highest job level available at present.[59] Under this scenario, job tenure cannot be said to have clear correlations with job levels, as there are opposing forces at work. That is, a worker who is currently in a job with a particularly high level would be likely to remain in this job for a lengthy period of time, since the likelihood of getting a job with a higher level is lower. At the same time, a worker who has just received a particularly high level job offer, and therefore switched jobs, would have a very low level of job tenure, due to the job switch. It is thus unclear if job levels (and hence, educational (mis)match) would increase or decrease with rises in job tenure.[60] This sorting process over time appears to preclude making predictions on changes in the incidence and earnings effects of ORU with tenure, either in conventional datasets or in the current dataset.

6.2.2 Human Capital Theory

Under the human capital theory interpretation, workers may choose to invest in more (formal) education in order to compensate for other human capital deficiencies, such

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[58] This chapter includes an examination and discussion of the differences in the incidence of ORU as tenure progresses. While these seem more suited to have been included as part of Chapter 3, it has been left to this stage as the tenure variable in the data is unique and requires some understanding before the results can be interpreted in the correct context.

[59] Hartog (2000) argues that job mobility is likely to be upward, where the move is done voluntarily. This view is in line with studies such as Sicherman (1990).

[60] This statement addresses the overeducated. For the undereducated, increases in job levels would increase the extent of undereducation. Thus, increases in job tenure have ambiguous effects for the overeducated, and would increase the extent of educational mismatch for the undereducated. However, given the dominance of the overeducated in the present study, this statement is a fair one to make.

as the lack of experience, or ability (see, for example, Sicherman 1991 and Alba-Ramirez 1993). In other words, educational qualifications are used as substitutes for other forms of human capital, such that workers in the same job, who have differing levels of educational qualifications, could have similar levels of human capital.

An alternative, and complementary, explanation of the same situation would be that overeducated workers choose jobs with lower educational requirements to obtain the requisite experience in order to bolster their chances of getting a more correctly matched job (de Oliveira *et al.* 2000), and/or to acquire skills which would be useful in their subsequent career or occupation (Sicherman 1990). These views were found to be valid by Sicherman (1990), whose study found that overeducated workers tend to have less experience or training. Further, overeducated workers were found to have higher rates of firm and occupational mobility, *ceteris paribus*. Conversely, undereducated workers had much higher amounts of on-the-job training, and also had more experience. Overeducation would be a transitory situation under this interpretation, as workers would transition to jobs commensurate with their qualifications in the future, as they accumulate experience or other human capital over time. Undereducation, however, would be a long lasting situation, as workers who are compensating for their lack of formal qualifications with other forms of human capital would continue to be undereducated, unless they obtain higher qualifications.

These interpretations of human capital theory have two different implications for the incidence of ORU with increasing tenure. If the individuals were overeducated as a result of formal qualifications being obtained as a substitute to other human capital deficiencies, the incidence of overeducation will not change with increases in tenure. However, where overeducated individuals had entered their jobs for the purpose of accumulating job experience in order to prime themselves for a better job subsequently, the incidence of overeducation should change with increases in job tenure, as positive job tenure indicates an unsuccessful job search. At the same time, individuals who succeed in getting a better matched job subsequently as a result of accumulating job experience in their previously overeducated jobs will report zero tenure. Thus, where the job search interpretation under human capital theory is applicable, the incidence of overeducation is expected to fall over time as some graduates succeed in getting a higher level job.

Human capital theory also offers predictions on the change in ORU earnings effects as tenure is accumulated. Under the interpretation of human capital substitution, the wages of the overeducated are expected to increase as job skills are accumulated. However, where the overeducated have made a deliberate choice to be overeducated in their jobs in order to gain experience while searching for a job elsewhere, it would be expected that the accumulation of job tenure will not have any impact on wages.

These predictions remain unchanged with the current dataset. As with the conventional view on the accumulation of job skills, graduates with tenure in the current dataset, who have primarily seen time with the firm as an opportunity for job training, would also be expected to experience positive impacts on wages due to the larger amount of job experience that they have. However, where the graduates have mostly engaged in job search while with the firm, there is expected to be less or little job training, and thus tenure would have little or no impact on wages. Thus, the predictions on the wages of the overeducated are the same, irrespective of the difference in the current dataset compared to those in conventional studies, under the human capital theory interpretation of the labour market.

6.2.3 Technological Change Hypothesis

de Oliveira *et al.* (2000) argued that technological change might also be an explanation for ORU in the labour market. They argued that advancements in technology could lead to jobs requiring higher levels of skills than those obtained by the currently employed workers. As the upgrading of skills takes time and incurs costs, this causes a mismatch, and the currently employed workers are considered undereducated. However, hiring standards by the employers might be raised, and, therefore, new job entrants with higher educational qualifications relative to their older counterparts in the same job would be considered or perceived as overeducated. Under this scenario, undereducated workers would have less long-term value to the firm, and as such the firm will not invest in their training. Their relative wage should therefore decline with job tenure, and thus will be reflected in an increasing wage penalty associated with undereducation.

Overeducated workers are more valued by their employers due to the more 'appropriate' level of education they have, and hence are expected to be favoured in on-the-job investment decisions. Accordingly, their earnings should increase with job tenure, which would be associated with a reduction in any initial wage penalty associated with their overeducated status. This view is shared by Kler (2005), who finds a large incidence of overeducation in the Australian graduate labour market, but also reports that young male graduates experience no wage penalty associated with overeducation.[61] Kler (2005) suggests that the finding of younger male graduates having no wage penalties for being overeducated could be attributed to "fast paced technological change that has significantly altered occupational requirements" (Kler 2005, pg. 67).

With the current dataset, however, any of the on-the-job investments into the overeducated graduates with positive job tenure considered under the technological change hypothesis would not have (yet) occurred, as the higher qualifications are recently obtained, and there is thus no basis for any change in wage expectations for the overeducated with job tenure. Specifically, the incidence and wage effects across tenure groups are expected to be the same. There is one caveat, however, relating to the above prediction. Overeducated graduates may have been identified as part of the firm's future prior to obtaining their most recent higher qualification, and thus may already have had on-the-job training invested into them in tandem with their own educational investment. If this scenario holds true, the overeducated graduates with tenure would be expected to earn more.

Technological change theory also predicts a stable incidence of overeducation across tenure groups. As overeducation is a symptom of job classifications changing slower compared to the rising technological requirements in the labour market, or that the higher skill levels required are more applicable to labour market entrants, there is no

[61] The findings for female graduates were mixed. Overeducated female graduates experienced minor wage penalties if they were in full-time work. Female graduates working part-time had a relatively higher wage penalty associated with being overeducated when the realised matches method was used, but not for the objective method.

expectation that the incidence of overeducation will vary across tenure groups. This is particularly valid for the current study due to the larger number of labour market entrants in the sample and the use of the 'job analysis' method in defining overeducation. The incidence of undereducation is expected to stay the same as tenure increases, although the extent of undereducation increases, as the increase in technological requirements, and hence higher qualifications, serves to amplify the education-job gap for the undereducated.

6.2.4 Assignment Theory

McGuinness (2006) has referred to assignment theory as the middle ground between the 'extreme' theories of human capital theory and the job competition (searching and matching) model. Specifically, human capital theory hypothesises that earnings are dependent on the characteristics of the individual (education and experience, for instance) while the job competition model treats earnings as being primarily dependent on the characteristics of the job. In the assignment theory framework, heterogeneous workers are assigned to different jobs, on the basis of their individual characteristics, such as educational qualifications, and the characteristics of the job, such as the required level of education. One distinguishing feature of this labour market model is that the level of earnings, as McGuinness (2006) puts it, "is the equilibrium outcome to the solution of the assignment problem", and "plays an allocative role in the economy rather than simply being rewards for the possession of particular characteristics". Under this interpretation of the labour market, an individual can be assigned to a job if the individual's characteristics match, or exceed the job requirements. In this context, it would be expected that overeducation occurs when: i) there is a larger supply of highly skilled labour; ii) there is a smaller demand for highly skilled labour; or, iii) a combination of the two factors aforementioned. Thus, in a competitive job market, individuals will engage in further education in order to be matched with a better job. Since the graduates with positive tenure have already entered their current jobs before they obtained their current qualification, it can be assumed that the current qualification is obtained for the purpose of being matched to a higher level job. Thus, the ORU earnings effects are expected to be similar, regardless of the length of job tenure. As the incidence of overeducation under assignment theory is dependent on the prevailing labour market conditions at the time of job entry, comment on the expected changes in overeducation as tenure increases is also precluded under this labour market theory.

6.2.5 Screening Hypothesis

The screening model (Arrow 1973) contends that the purpose of education is to serve as a filter, or as its name implies, a screen by employers to sort individuals by ability, in the absence of more knowledge about their true capabilities. Thus, all things constant, a higher qualification could be taken as a 'signal' of higher ability. Further, to the extent that higher qualifications are unreliable indicators of the average true productivity or ability, lower wages will be offered to the graduates on job entry (Aigner and Cain 1977). It would thus be expected that where a worker gained entry to a job on the basis of qualifications, the employer would, over time, gain additional knowledge about the ability of the worker, and wages would increase once the new information regarding the worker's true ability is obtained.

However, recall that one distinct feature of the current dataset is that graduates who have been promoted within the firm, or who have switched jobs after attaining their recent higher qualification, are likely to be categorised as part of the zero tenure group. Thus, graduates who have tenure and are mismatched in their current jobs are either 'stuck' in this state of education-job mismatch, or are experiencing the effects of a slow-adjusting labour market since they are not being channelled into jobs more appropriate for their educational levels. In the case of the former, it is likely that these 'stuck' graduates have been identified through the screening process to be of lesser ability.

For the conventional measurement of tenure effects (such as those in de Oliveira *et al.* 2000), two sources of noisy information pertaining to the graduates exist. For a graduate with zero job tenure, the noisy information relates to: i) the innate abilities or unobserved characteristics of the individuals; and ii) the quality of the degree and thus its match with the requirements of the firm. For a worker with positive tenure, and especially those in the higher tenure categories in the current study, the latter, but not the former, factor will operate. Hence, comparisons of graduates with zero tenure against those with positive tenure should reveal the relative importance of innate abilities or unobserved characteristics in the noise. In studies utilising conventional datasets, both sources of noise will diminish with increases in tenure. Under the current analysis, however, changes in wages are expected only where the uncertainty regarding the graduates' innate abilities is relatively important.

The change in the incidence of overeducation for the various tenure groups in the current dataset under the screening hypothesis is less clear. As aforementioned, employees will be screened twice, once upon job entry, and once again over the course of their job tenure. Graduates with zero tenure will thus have been subject to the first screening, but not, in the majority of cases, for the second (on-going) screening process. Graduates with tenure would have been screened over the course of their tenure as well, and those who remain overeducated despite a higher qualification are presumably those who have had their shortcomings revealed over the course of their tenure. Under this scenario, the incidence of overeducation would be expected to rise if relatively large numbers of graduates are less able, and are not suitable to be placed in a higher level job, even with the added qualification.

The review of labour market theories, as well as their predictions on the ORU earnings effects and incidence across tenure groups, has been covered in this section. Overviews of the predicted effects of ORU as tenure increases will be covered in the next two sections, which examine changes in the incidence and earnings effects of ORU across tenure groups, respectively.

6.3 Methodology

The estimation model used in the analysis of graduate earnings for this chapter is based on the ORU model of graduate earnings. This model is similar to the one used in the preceding chapters and can be expressed as:

(6-1) $logw_i = \beta_1 Z_i + \beta_2 D_i^o + \beta_3 D_i^r + \beta_4 D_i^u + \epsilon_i$

where *w* represents the hourly wage, used in the analysis in natural logarithmic format and Z represents a vector of characteristics correlated with earnings. D^o, D^u and D^r are vectors of dummy variables indicating if the individual is overeducated

(D^o), undereducated (D^u), or correctly matched to his or her occupation of employment in terms of education (D^r), as identified in the preceding chapters. The variables included in Z indicate the graduates' gender, English speaking background, residency status, mode of enrolment, further study status, university group, broad field of study, self-employment status, length of employment, industry of employment, sector of employment, year of graduation and labour market experience. Note here that while the preceding chapters used quadratic specifications of age and tenure as proxies for experience, only the quadratic form of age is entered into the estimating equation here, for obvious reasons.

6.4 Results

6.4.1 Incidence of ORU across Tenure Groups

As mentioned above, the theories of searching and matching, and assignment do not make any predictions on the change in the incidence of ORU as tenure increases. There are, however, different predictions under human capital theory, technological change theory, and the screening hypothesis. In summary, the theories of human capital and technological change predict a similar incidence of overeducation across tenure groups, while the screening hypothesis predicts a rising trend.

The incidence of overeducation for the various tenure groups is presented in Figure 6.1. In addition, the data contain information about whether the graduate is actively seeking another job, and the sample is subdivided on this basis.[62] Specifically, those looking for work could be viewed as being dissatisfied with aspects of their current job, including mismatch status, and so would be expected to be associated with a higher incidence of overeducation.[63]

[62] Specifically, those employed can be divided into four subcategories: i) Employed full-time and looking for another job, ii) Employed full-time and not looking for another job, iii) Employed part-time and looking for a full-time job, and iv) Employed part-time and not looking for another full-time job.

[63] Again, the incidence of undereducation is less than one percent for each tenure group and sub-category. Therefore, these data are not presented, and the sum of the overeducated and correctly matched approximates 100 percent.

Figure 6.1: Incidence of Overeducation, by Tenure Groups and Job Search

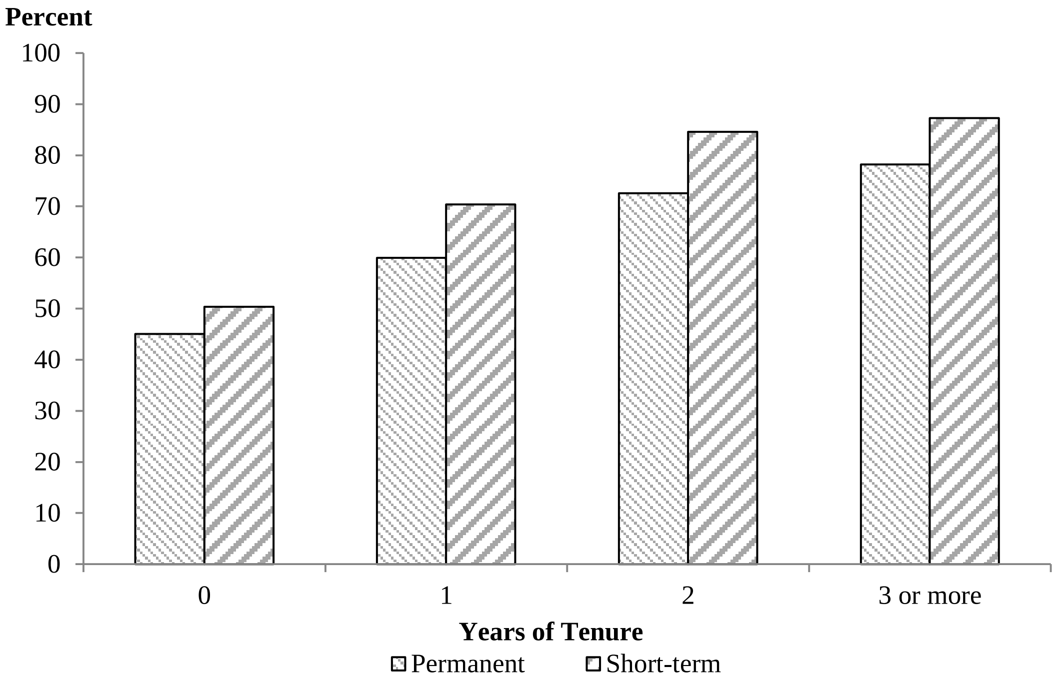
There are a couple of striking features about Figure 6.1. First, looking at the first column for each tenure group, the incidence of overeducation for the full sample increases as job tenure is accumulated. As the GDS survey was administered four months following the completion of graduates' respective qualifications, the fact that a large and increasing incidence of overeducation is observed across these tenure groups indicates that the labour market is rather sluggish in adjusting and repositioning these graduates into more suitable jobs or occupations. At the same time, this increase in overeducation with increasing tenure rules out the theory of technological change, and the 'human capital substitution' interpretation of human capital theory. The screening hypothesis seems to be the most valid among these labour market theories, and the increasing incidence indicates that there is a relatively large number of the 'less able' among the more intensely screened graduates with greater tenure, perhaps due to the rapid higher education expansion observed in recent years. This symptom of increasing overeducation is unlikely to abate, as the Australian federal government has 'uncapped' the number of publicly funded undergraduate student places from 2012 onwards. The Group of Eight universities has also expressed concerns over the loss of quality in student intakes, and also outcomes due to the inability of the higher education sector to absorb the large increases in numbers (The Australian 2010c).

Second, while the increasing trend of overeducation with tenure is evident for all sub-categories, the incidences of overeducation across the tenure groups are dramatically lower for those not seeking to change jobs, compared to those who have indicated that they intend to look for another full-time job, or change from part-time to full-time jobs. Thus, overeducation could be said to have some impact on job dissatisfaction.

The data were also disaggregated on the basis of the length of employment, that is, whether the graduates were employed on a permanent or short-term basis. Comparison of the differences in overeducation status between these two groups will reveal further information on the applicability of human capital theory to the contemporary graduate labour market. Under human capital theory, it is hypothesised that some workers are deliberately overeducated in their current jobs in order to gain experience, which will prepare them for a better job subsequently. Thus, it is predicted that overeducation will be more prevalent among individuals who are employed on a short-term basis.

The incidences of overeducation based on employment length are presented in Figure 6.2. The information presented in Figure 6.2 indicates that a larger proportion of the overeducated can be found in the group employed on contracts which were less than a year in length, as opposed to those employed on a longer-term basis. This finding applies across all tenure groups.

Figure 6.2: Incidence of Overeducation, by Tenure Groups and Employment Length



The analysis of the incidence of overeducation by tenure groups indicates that overeducation is prevalent even for those with higher amounts of job experience. However, this is unsurprising, as this job experience has been accumulated prior to the obtaining of the most recent higher qualification. It was observed that the incidence of overeducation increases with tenure, even for those who do not intend to switch jobs, although a larger proportion of the increase in the overeducated lies among those who have expressed a desire to change jobs in the future. Following the analysis of the incidence of overeducation across tenure groups, an analysis of the differences in ORU earnings effects across tenure groups, as well as how those earnings effects relate to the predictions of the labour market theories discussed above, will be conducted. This is covered in the following section.

6.4.2 Overview of the Discussion on Labour Market Theories

The discussion of the various labour market theories in an earlier section has led to predictions on how the ORU earnings effects are expected to differ across tenure groups. For clarity, these expectations are set out in Table 6.1. The predicted ORU earnings effects under the conventional approaches taken by existing studies, for the same labour market theories discussed above, are presented in panel (iii) of Table

6.1, while the corresponding predictions that take into account the unique feature of the current dataset are presented in panel (iv). In summary, the searching and matching theory does not offer an explanation on the variation of the ORU earnings effects across tenure groups. The two theories of technological change and assignment generally predict no change in the ORU earnings effects across tenure groups, although the former does allow for small increases in earnings if firms are forward looking in making their human capital investments in employees. Human capital theory and the screening hypothesis support the notion of similar earnings effects across all tenure groups, although the wage penalty associated with being overeducated may also be expected to decline under human capital theory. The following section presents the empirical analyses disaggregated by tenure groups.

Table 6.1: Summary of Expected ORU Earnings Effects

Labour Market Theory (i)	Mismatch Type (ii)	Conventional (iii)	Current Dataset (iv)
Searching and Matching	Overeducated	No prediction on earnings	No prediction on earnings
	Undereducated	No prediction on earnings	No prediction on earnings
Human Capital Theory	Overeducated	Wage penalty declines with tenure, or stays the same	Wage penalty declines with tenure, or stays the same
	Undereducated	Wage penalty declines with tenure, or stays the same	Wage penalty declines with tenure, or stays the same
Technological Change	Overeducated	Wage penalty declines with tenure	No impact on earnings as tenure increases, or slight increases
	Undereducated	Wage penalty declines with tenure	No impact on earnings as tenure increases
Assignment	Overeducated	ORU incidence and earnings depend on relative amounts of labour demand and supply - no prediction	ORU incidence and earnings depend on relative amounts of labour demand and supply - no prediction
	Undereducated	ORU incidence and earnings depend on relative amounts of labour demand and supply - no prediction	ORU incidence and earnings depend on relative amounts of labour demand and supply - no prediction
Screening	Overeducated	Wages increase with tenure	Wages are similar across tenure groups, unless information on individual ability is relatively important
	Undereducated	Wages increase with tenure	Wages are similar across tenure groups, unless information on individual ability is relatively important

6.4.3 Analyses on the Earnings Effects, by Tenure Groups

The results of the estimations for the various tenure groups are presented in Table 6.2. The coefficient of variation for the dependent variable for each of the tenure groups was also calculated. The values of the coefficient, starting from the group with no tenure to the group with the most tenure, were 0.189, 0.214, 0.230 and 0.201, respectively. These values are indicative of a widening earnings distribution as tenure increases. Further, it is interesting to note that the adjusted R-squared for the four tenure groups increases from 0.107 in panel (i) to 0.226 in panel (iv). This indicates that the explanatory power of the model increases the longer the graduates have been in their current job. The larger R-squared values for graduates with more job experience could be interpreted as the graduate labour market being much more rigid at entry, with the attributes of each graduate, including the characteristics of their schooling, being rewarded or penalised only after some time spent in the labour force. Once again, the 't'-statistics indicate that most of the estimated coefficients are statistically significant at the one percent level.

The F-statistics and partial R-squared values were calculated for the sets of variables entered in the regressions, for the different tenure groups.[64] These are presented in Table 6.3. Reading the partial R-squared values across the rows allows for the observation of how the explanatory power of these sets of variables change across the tenure groups.

[64] The dependent variable entered in the regressions for these calculations is the real wage.

Table 6.2: OLS Estimates of the ORU Model of Earnings, by Tenure Groups

Variables	Tenure=0 (i)	Tenure=1 (ii)	Tenure=2 (iii)	Tenure>3 (iv)
Constant	2.475***	2.189***	2.070***	2.243***
	(128.839)	(85.899)	(49.596)	(73.351)
Female	-0.026***	-0.047***	-0.070***	-0.068***
	(10.192)	(14.340)	(12.086)	(21.571)
Age	0.022***	0.041***	0.051***	0.045***
	(18.638)	(26.936)	(22.037)	(27.853)
Age squared/1000	-0.340***	-0.651***	-0.754***	-0.627***
	(14.596)	(21.168)	(18.207)	(23.520)
NESB	-0.014***	-0.053***	-0.068***	-0.040***
	(3.894)	(12.059)	(9.133)	(8.943)
Non-Australian	-0.132***	-0.209***	-0.265***	-0.212***
	(13.821)	(20.696)	(15.366)	(13.243)
Double degree	0.020***	0.007	-0.002	-0.014
	(5.888)	(1.159)	(0.134)	(1.606)
Part-time study	0.093***	0.084***	0.064***	0.073***
	(24.915)	(23.637)	(10.486)	(18.542)
Further study	-0.008**	0.002	0.016**	0.021***
	(1.993)	(0.518)	(2.537)	(5.601)
Go8	0.015***	0.026***	0.044***	0.040***
	(5.068)	(6.800)	(6.470)	(10.380)
ATN	0.033***	0.030***	0.051***	0.024***
	(8.991)	(6.525)	(6.674)	(5.777)
IRU	0.002	0.010**	0.018**	0.001
	(0.732)	(2.149)	(2.189)	(0.283)
Natural and Physical Science	-0.091***	-0.067***	-0.073***	-0.056***
	(13.900)	(9.883)	(6.055)	(7.725)
Information Technology	-0.025***	-0.020***	-0.029**	-0.029***
	(3.587)	(2.711)	(2.138)	(4.103)
Engineering	0.024***	-0.011	-0.026**	-0.008
	(3.652)	(1.477)	(1.976)	(1.097)
Architecture	-0.099***	-0.112***	-0.094***	-0.070***
	(9.506)	(10.691)	(6.312)	(6.735)
Agriculture and Environment	-0.113***	-0.138***	-0.120***	-0.164***
	(12.833)	(14.785)	(7.664)	(17.009)
Nursing	-0.115***	-0.115***	-0.104***	-0.099***
	(16.994)	(12.868)	(7.055)	(13.678)
Medicine	-0.016***	-0.050***	-0.040***	-0.018***
	(2.645)	(7.397)	(3.066)	(2.794)
Education	-0.047***	-0.060***	-0.083***	-0.075***
	(6.923)	(7.431)	(6.383)	(12.714)
Society and Culture	-0.049***	-0.060***	-0.053***	-0.060***
	(10.337)	(11.726)	(6.366)	(12.888)
Creative Arts and Others	-0.110***	-0.110***	-0.116***	-0.114***
	(16.050)	(14.254)	(8.964)	(13.976)
Self-employed	0.027**	0.033***	-0.019	-0.011
	(2.373)	(2.870)	(1.022)	(1.234)
Private Sector	-0.035***	-0.061***	-0.066***	-0.057***
	(10.965)	(13.313)	(8.116)	(14.151)
Short-term employment	-0.075***	-0.104***	-0.131***	-0.115***
	(28.213)	(28.220)	(18.128)	(22.008)

Table 6.2: OLS Estimates of the ORU Model of Earnings, by Tenure Groups (cont.)

Variables	Tenure = 0 (i)	Tenure = 1 (ii)	Tenure = 2 (iii)	Tenure > 3 (iv)
oru_dip_cert	-0.266***	-0.226***	-0.260***	-0.171***
	(6.451)	(5.784)	(3.128)	(7.078)
oru_dip_dip	-0.053	-0.051	-0.054	-0.026**
	(1.264)	(1.323)	(1.527)	(2.098)
oru_dip_bach	0.047**	0.063**	0.075**	-0.018
	(2.241)	(2.338)	(2.199)	(0.918)
oru_ascdeg_cert	-0.297***	-0.151***	-0.166**	-0.191***
	(3.321)	(3.427)	(2.447)	(10.755)
oru_ascdeg_dip	-0.059	-0.042	-0.095***	-0.085***
	(0.763)	(1.091)	(5.057)	(6.316)
oru_ascdeg_bach	0.035	-0.008	-0.074	-0.044**
	(0.760)	(0.320)	(1.049)	(1.976)
oru_bach_cert	-0.150***	-0.131***	-0.145***	-0.172***
	(32.176)	(25.848)	(14.902)	(28.294)
oru_bach_dip	-0.075***	-0.070***	-0.112***	-0.104***
	(13.725)	(11.102)	(9.059)	(15.334)
oru_hons_cert	-0.090***	-0.082***	-0.089***	-0.129***
	(8.946)	(5.578)	(4.171)	(8.931)
oru_hons_dip	-0.022*	-0.021	-0.068*	-0.059***
	(1.793)	(1.420)	(1.870)	(2.861)
oru_hons_bach	0.024***	0.045***	0.059***	0.051***
	(5.102)	(6.620)	(4.104)	(3.968)
oru_gcert_cert	-0.073**	-0.084***	-0.102***	-0.097***
	(2.308)	(3.737)	(3.234)	(6.325)
oru_gcert_dip	0.052	0.017	-0.048	0.000
	(1.585)	(0.639)	(1.179)	(0.034)
oru_gcert_bach	0.149***	0.150***	0.104***	0.095***
	(13.192)	(17.131)	(9.845)	(18.137)
oru_gdip_cert	-0.153***	-0.104***	-0.086***	-0.118***
	(6.811)	(5.643)	(3.876)	(8.927)
oru_gdip_dip	-0.002	0.004	-0.034	-0.021*
	(0.103)	(0.207)	(1.065)	(1.825)
oru_gdip_bach	0.050***	0.104***	0.101***	0.096***
	(11.013)	(15.984)	(10.508)	(18.600)
oru_mast_cert	-0.090***	-0.102***	-0.146***	-0.123***
	(5.398)	(7.264)	(6.885)	(7.316)
oru_mast_dip	0.106***	0.045***	0.053***	0.057***
	(6.647)	(2.737)	(2.585)	(4.735)
oru_mast_bach	0.185***	0.206***	0.181***	0.162***
	(29.219)	(35.504)	(19.786)	(35.404)
oru_phd_cert	0.127***	0.105***	-0.072	0.021
	(3.365)	(3.114)	(0.838)	(0.417)
oru_phd_dip	0.091**	0.091***	0.002	0.092**
	(2.455)	(2.986)	(0.034)	(2.099)
oru_phd_bach	0.251***	0.203***	0.153***	0.180***
	(19.995)	(23.759)	(10.343)	(20.066)
Observations	209,593	148,449	57,580	153,703
Adjusted R-squared	0.106	0.171	0.205	0.225
F-Statistic	355.34	421.23	209.63	562.77

Notes: Absolute values of heteroscedasticity consistent ‘t’-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively.

Table 6.3: F-Statistics and Partial R-Squared Values for Variable Sets, by Tenure Groups

Set of Variables	Tenure = 0		Tenure = 1		Tenure = 2		Tenure > 3	
	F-Stat.	Partial R^2	F-Stat.	Partial R^2	F-Stat.	Partial R^2	F-Stat.	Partial R^2
Personal Characteristics	247.61	0.007	591.10	0.024	286.23	0.032	631.00	0.024
Study Characteristics	94.68	0.004	77.10	0.004	22.31	0.003	61.03	0.003
Industry of Employment	114.71	0.010	126.10	0.013	43.83	0.011	115.22	0.013
Broad Field of Study	104.55	0.005	55.08	0.004	17.41	0.003	66.48	0.004
Year of Graduation	41.57	0.002	29.34	0.002	8.00	0.001	42.21	0.002
ORU	128.64	0.017	138.29	0.023	51.20	0.021	180.24	0.025

Note: P-values were highly significant for all sets of variables, across all tenure groups

The partial R-squared values in Table 6.3 indicate three findings of interest. First, the sets of variables for study characteristics, broad field of study and year of graduation only played minor roles in determining graduate earnings. Second, the ORU earnings effects were substantial explanatory factors of graduate earnings, and in most cases were the second most important contributor (after personal characteristics), for all the different tenure groups. Third, personal characteristics, the variable set with the highest partial R-squared, was a substantial contributor to the explanation of graduate earnings for graduates with one year or more of tenure, but accounted for only 0.7 percent of the variation in earnings for those without any tenure. Again, this suggests that the graduate labour market is rigid at entry, and any premium or penalty associated with personal attributes surfaces only after some time in the labour market. The relative importance of employment related characteristics, such as the ORU and industry effects, over broad field of study and other schooling characteristics, also suggests that it is what one does in the labour market, and not what one studied (or how, or even where, one studied) that determines earnings.

Moving on to a discussion of the estimated coefficients in Table 6.2, it is apparent that a few empirical observations can be drawn. The estimated coefficient for gender in panel (i) indicates that female job entrants earn 2.6 percent less than their male counterparts. As mentioned above in the discussion for the full sample, it seems that there is a minimal amount of gender discrimination in the graduate labour market. However, going across panel (ii) to panel (iv) of Table 6.2 clearly demonstrates that females incur a greater wage penalty the longer they remain in their jobs. One year of tenure increases the wage disadvantage to almost five percent, while having tenure of two years increases the wage disadvantage yet further to seven percent. For tenure of three years and above, the wage disadvantage remains at around seven percent, suggesting that the gender discrimination levels off as tenure increases above three years.[65] This is consistent with the evidence presented in Borland (1999), who reported a standardised hourly wage gap across the entire workforce of around ten percent, a figure comparable with the estimates for the higher tenure groups in the present study.

To explore this further, the sample with three years or more of tenure was further disaggregated, and equation (6-1) was estimated for graduates with increasing years of tenure.[66] These analyses revealed that as the years of tenure increased, female graduates experienced an increasing earnings disadvantage. For example, as mentioned above, female graduates earned seven percent less than their male counterparts at two years of tenure. A similar wage gap was observed for female graduates up to six years of tenure, but the wage gap increased slightly to eight percent for the female graduates with eight years of tenure, and to ten percent for those with ten years of tenure in the firm. Thereafter, there is a decline in the extent of this earnings disadvantage, as the estimates for graduates with 11 or more years of tenure indicate that females earn 6.5 percent less than males. This latter group accounted for only four percent of the sample.

As the higher tenure groups are also higher wage groups, these estimates reveal that a 'glass ceiling' exists, even in the higher education labour market, and females experience greater earnings penalties the longer they have been in a specific job. The empirical finding here is also consistent with the analysis of the partial R-squared values earlier, where personal characteristics were found not to contribute much in explaining variations in graduate earnings for graduates starting in new jobs, but had relatively higher explanatory power for those with one year or more of job tenure.

[65] This is supported by earlier findings in Chapter 5. The earlier analysis of the gender wage gap for workers from various age groups indicated that the gender wage gap was wider among older workers. Specifically, females aged 35 years and below earn 4.5 percent less than their male counterparts, while females aged 56 years and older earn 13 percent less than their male peers.

[66] The specific results of these analyses are not reported here, but are available on request.

The estimated coefficients for the experience proxy, age, indicate that the returns on this human capital measure increase with tenure. However, the estimates of age squared also increase with tenure while remaining negative in sign, indicating that the decline in returns to experience is more intense among the higher tenure groups. For example, when evaluated at twenty five years of age, those with no tenure in their current job can expect returns of less than one percent on their experience. The corresponding estimate for those with two years of tenure is slightly higher, at 1.3 percent. Those with three years or more of tenure in their current job experience returns of 1.4 percent on their labour market experience, similar to those with two years of tenure. These findings are suggestive of complementarity between the forms of human capital captured by the age and tenure variables.

Non-English speaking graduates have a very modest earnings disadvantage, of 1.4 percent, when they are fresh in their jobs with no firm-specific experience. However, this earnings disadvantage increases, by almost 3.5 percentage points, once they reach their first year of tenure in their respective jobs. Those with two years of tenure earn 6.8 percent less than their English speaking counterparts. Seemingly, the disadvantage of language background is very modest at the beginning of graduates' careers in their firms, and increases the longer they stay in their jobs. This is similar to what is observed in the case of gender, and again complements the earlier finding that personal endowments play a stronger role in determining earnings after some time in the labour market.

Graduates without Australian residency status share the same trend in earnings disadvantage, though on a larger scale. Fresh graduates in a new job start off in the labour market with a 13.2 percent earnings disadvantage, which more than doubles to nearly 27 percent when they have been in their job for two years. The estimate for being of non-Australian residency status decreases to 21.2 percent among the highest tenure group distinguished, and this reduced effect may be associated with an adjustment effect that takes place in the longer term. However, with earnings around one-fifth lower than their counterparts with residency status even after three years, the earnings penalties are still substantial.

Graduates from a combined degree program have a very modest earnings premium on entry into their firm, compared to graduates without a double degree. However, this premium is not evident among the higher tenure groups. This implies that the additional human capital gained from a double degree program does not appear to add value to graduate earnings. Birch, Li and Miller (2009) observed the same results in their study, noting that the modest premium does not justify the additional costs involved in procuring the additional knowledge in another discipline. A study of double degree programs by Moulton *et al.* (2011) found that a large number of double degree programs are “essentially two unrelated and poorly integrated courses placed side by side”. In effect, due to the omission of ‘sub-majors’ from double degree programs, graduates from these programs have not learnt essential knowledge which is highly valued by employers. One example of this can be found in double degree programs which include engineering. Moulton *et al.* (2011) found that, in one instance, 16 subjects were dropped from the bachelor’s of engineering and bachelor’s of business dual degree program, including three core subjects. The very modest premium on double degree programs could be simply a reflection of the fact that these programs do not offer ‘double the value’ (The Australian 2011b), and, in many cases, omit key components of a discipline which would have been offered in a single ‘stand alone’ degree.[67]

There are some differences in the estimated coefficients on university groups across the job tenure groups. For the Go8 and ATN graduates, modest premiums of 1.5 and 3.3 percent, respectively, over the earnings of graduates from Other universities, are experienced by workers in a new job. Among those who had been in their job for two years at the time of graduation, slightly lower earnings advantages of 4.4 and 5.1 percent, respectively, were recorded. Go8 graduates with three years of job-specific experience were characterised by the same level of premiums, while their peers from the ATN had a smaller premium of 2.4 percent.[68] This volatility in the earnings

[67] On a separate note, the findings in this study have prompted the Australian Teaching and Learning Council to call for a change in the way these double or combined degree programs are marketed, since they do not offer ‘double’ the degree, nor ‘combine’ degrees in an inter-disciplinary way. However, the findings in the earlier Chapter 3 do indicate that a double degree offers graduates a reasonably higher chance of being correctly matched to their jobs.

[68] The proportion of graduates from the Go8 and Other university groups changed for the sample with two years of tenure. The proportion of Go8 graduates decreased from around 30 percent (tenure = 1) to 27 percent (tenure = 2). More noticeably, the proportion of Other university graduates increased from 38 percent to 42 percent, of the total sample.

effects associated with the institutional groups appears to show that the type of university attended does not have a robust effect on earnings outcomes in the Australian labour market.

6.4.4 ORU Effects on Earnings across Tenure Groups

In this section, the ORU earnings effects for different tenure groups are discussed. Following on from the discussion thus far in the earlier analyses of ORU earnings effects, graduates from each level of educational attainment are discussed in turn. The estimated coefficients on the ORU effects from Table 6.2 are graphed in Figure 6.3 to Figure 6.10.

A few comments at this point will assist in the interpretation of the figures. First, it should be noted that the horizontal axis no longer denotes the education required for each job. Rather, the horizontal axis indicates the particular tenure group. In this way, following the shape of the curves from left to right allows an observation of the general trend in the ORU effects for greater job tenures.

Second, the estimates for each level of education required for a job are graphed as a separate curve. Once again, statistically insignificant estimates are represented by 'grey' markers, as was done for the graphs in Chapter 4. The benchmark group here is, again, the appropriately matched bachelor's pass degree graduates in occupations that require the same qualification, in each particular tenure group.

Third, the ORU earnings effects generally appear to be characterised by a trend of stability across the various tenure groups. Thus, F-tests were conducted on each of the estimated ORU coefficients, for the four estimations by tenure groups, to see if they were statistically the same across the four sets of estimations. The results of these F-tests are listed in Table 6.4. The results of these F-tests indicated that out of the 23 ORU categories, 11 had estimated coefficients that differed across equations, while the remaining 12 had coefficients that were statistically the same for the four tenure groups. These will be discussed in turn, together with the discussion of the ORU earnings effects for each qualification group.

Table 6.4: F-test of Statistical Equality of Coefficients across Tenure Groups

Variable	χ2	Prob > χ2	Variable	χ2	Prob > χ2
Diploma			Grad. certificate		
oru_dip_cert	4.88	0.1809	*oru_gcert_cert*	0.70	0.8743
oru_dip_dip	1.12	0.7714	*oru_gcert_dip*	4.12	0.2493
*oru_dip_bach***	10.10	0.0177	*oru_gcert_bach****	41.11	0.0000
Associate deg.			Grad. Diploma		
oru_ascdeg_cert	2.34	0.5040	*oru_gdip_cert*	4.98	0.1734
oru_ascdeg_dip	1.70	0.6366	*oru_gdip_dip*	1.99	0.5737
oru_ascdeg_bach	3.36	0.3399	*oru_gdip_bach****	70.14	0.0000
Bachelor's pass			Masters		
*oru_bach_cert****	26.91	0.0000	*oru_mast_cert*	5.10	0.1649
*oru_bach_dip****	21.29	0.0001	*oru_mast_dip***	8.83	0.0317
oru_bach_bach	(a)	(a)	*oru_mast_bach****	36.10	0.0000
Bachelor's honours			PhD		
*oru_hons_cert**	6.69	0.0823	*oru_phd_cert**	6.56	0.0873
oru_hons_dip	3.82	0.2812	*oru_phd_dip*	1.53	0.6757
*oru_hons_bach****	12.54	0.0057	*oru_phd_bach****	31.48	0.0000

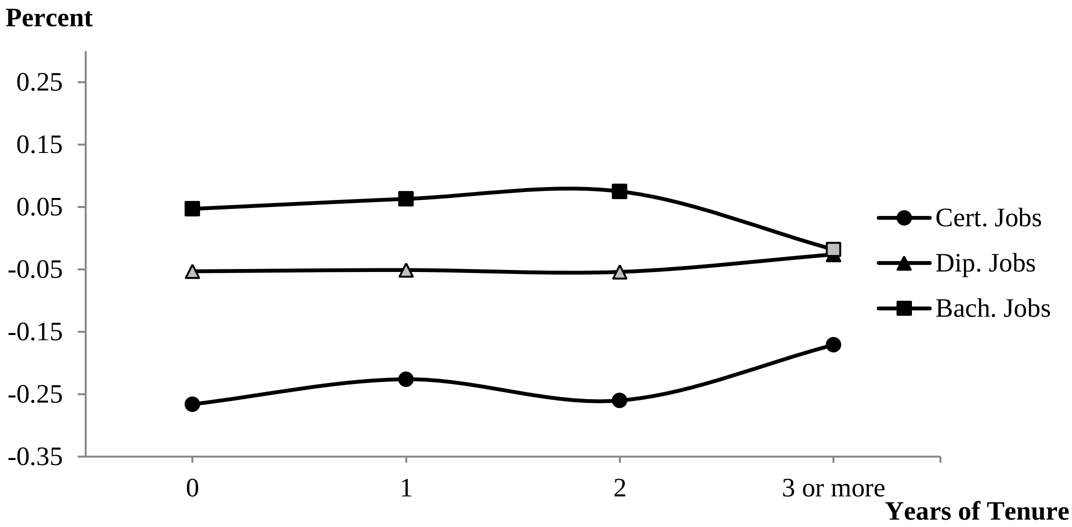
Notes: *, ** and *** denote significance at the ten, five and one percent levels, respectively. (a) indicates non-applicability.

6.4.5 Diploma Graduates

The estimated ORU coefficients for diploma graduates are presented in Figure 6.3. There is the expected hierarchy in the estimated coefficients, in that diploma graduates in jobs which require a bachelor's pass degree earn more than their counterparts in jobs that require a diploma, who, in turn, earn more than those in jobs that require only certificate level qualifications. Recall that the diploma graduates category is one of the smallest educational groups in the sample, and this size factor is accentuated with the disaggregation into four tenure groups. This possibly accounts for the statistical insignificance of a number of the estimated coefficients.

An initial examination of the estimated coefficients for the overeducated graduates at this qualification level, and who work in certificate level jobs, seems to indicate some variability across tenure groups. For diploma graduates who have no job tenure, a substantial earnings disadvantage, of around 27 percent, is experienced relative to the bachelor's pass degree graduates with bachelor's pass degrees. However, among those with three years or more of job tenure, the earnings disadvantage is only 17 percent less than the benchmark group. Thus, while the earnings penalty associated with being overeducated for diploma graduates working in certificate level jobs appears to diminish, as one considers the higher tenure groups, the null hypothesis that the earnings effects are the same cannot be rejected (see Table 6.4). Similarly, the null hypothesis that the earnings effects for diploma graduates working in correctly matched jobs that require a diploma are the same across the four tenure groups cannot be rejected.

Figure 6.3: ORU Earnings Effects by Tenure Groups, Diploma Graduates



In comparison, the undereducated diploma holders working in bachelor's level jobs, and who have no job tenure, earn around five percent more than the appropriately matched reference group of bachelor's pass graduates.[69] This earnings premium was marginally higher, at 7.5 percent, among the group with two years of job tenure. Moreover, the F-test of equality indicates that the estimated coefficients for the undereducated graduates here are statistically different. However, excluding the statistically insignificant and lower estimate for the graduates with three or more years of tenure from the null hypothesis yields an F-test result which indicates that the estimated ORU coefficients for graduates in the first three tenure groups are statistically the same.

Thus, it can be said that the three curves for diploma graduates are indicative of ORU earnings effects which are stable across tenure groups, or in other words, that the earnings effects displayed in Figure 6.3 are basically indistinguishable from straight lines. The equality in the wage effects to being undereducated and overeducated

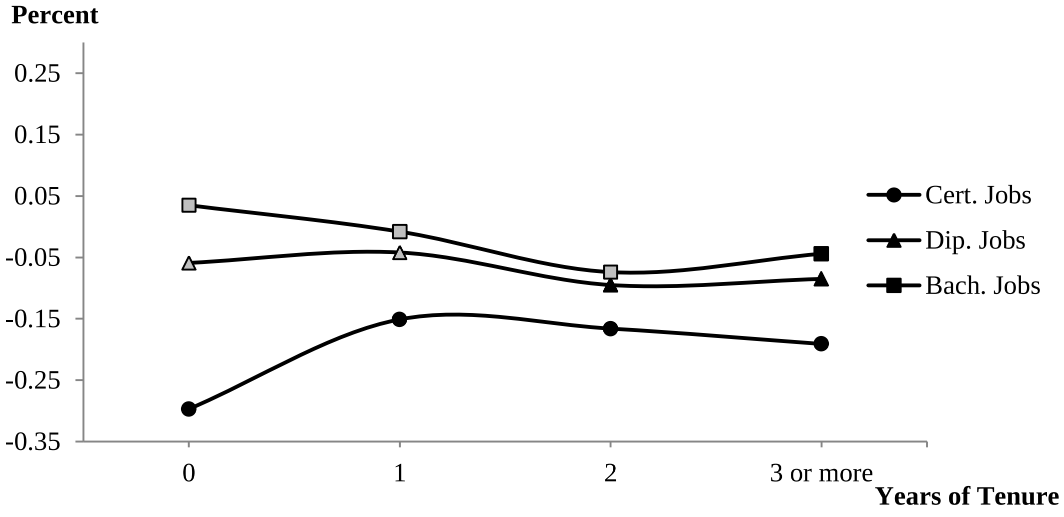
[69] As noted in Chapter 4, the undereducated are likely to possess some favourable but unobserved characteristics that have enabled them to obtain a higher level job. These unobserved favourable would contribute to an earnings advantage as well.

observed for diploma graduates lends credence to the human capital, technological change and screening views, and do not favour any of the above labour market theories in particular.

6.4.6 Associate Degree Graduates

Figure 6.4 charts the estimated ORU coefficients for associate degree graduates. This figure is characterised, again, by the hierarchy in earnings according to the level of qualifications required in the job.

Figure 6.4: ORU Earnings Effects by Tenure Groups, Associate Degree Graduates



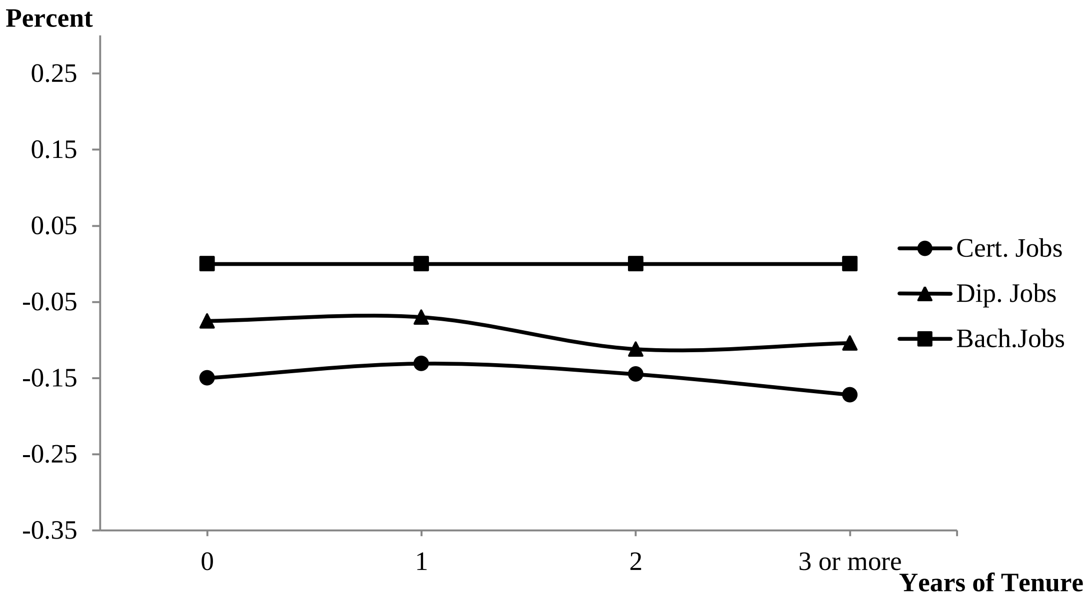
The associate degree graduates are another relatively small group in the sample, being even smaller than the diploma graduates. Again, it is to be noted that a number of the estimated coefficients are statistically insignificant. Moreover, the changes in the estimated coefficients between the different tenure groups are irregular. For instance, the most overeducated group of associate degree graduates working in certificate level jobs, and who have zero tenure, experience earnings substantially lower than the benchmark category, by almost 30 percent. For the group who have one year of tenure in their jobs, however, the earnings disadvantage is halved to around 15 percent.

However, the F-test of the null hypothesis that the relative earnings positions of this group of mismatched associate degree holders is the same across tenure groups fails to reject this null hypothesis. Similarly, the F-tests for the other two job categories indicate that the ORU coefficients are statistically the same, across tenure groups. Thus, for associate degree graduates, the general trend for all three groups appears to be that of stable, and persistent earnings penalties. While the ORU earnings effects are stable across groups, all graduates with this level of educational attainment experience earnings penalties, regardless of whether they are overeducated or undereducated.

6.4.7 Bachelor's Pass Degree Graduates

The estimated coefficients for the overeducated bachelor's pass degree graduates working in certificate and diploma level jobs are presented in Figure 6.5. The bachelor's pass degree graduates working in jobs that require a bachelor's degree are correctly matched to the job requirements, and are the benchmark group in the regression analysis, as indicated by the horizontal line of 0.00. All the other wage effects are interpreted as relative to the earnings position of this benchmark group.

Figure 6.5: ORU Earnings Effects by Tenure Groups, Bachelor's Pass Graduates



Bachelor's pass degree graduates in jobs that require either a diploma or certificate level qualification are overeducated, and the curves for both groups indicate that there are earnings penalties associated with this overeducated status. Bachelor's pass degree graduates working in certificate level jobs earn around 15 percent less than their counterparts working in a job matched to their bachelor's degree, for those with zero tenure, while those in the higher job category requiring a diploma earned 7.5 percent less than the benchmark group. Note that the earnings disadvantage of the overeducated tends to be greater when the higher tenure groups are examined. Moreover, these estimates were found to differ statistically according to the results of the F-tests of equality, which are significant at the one percent level.

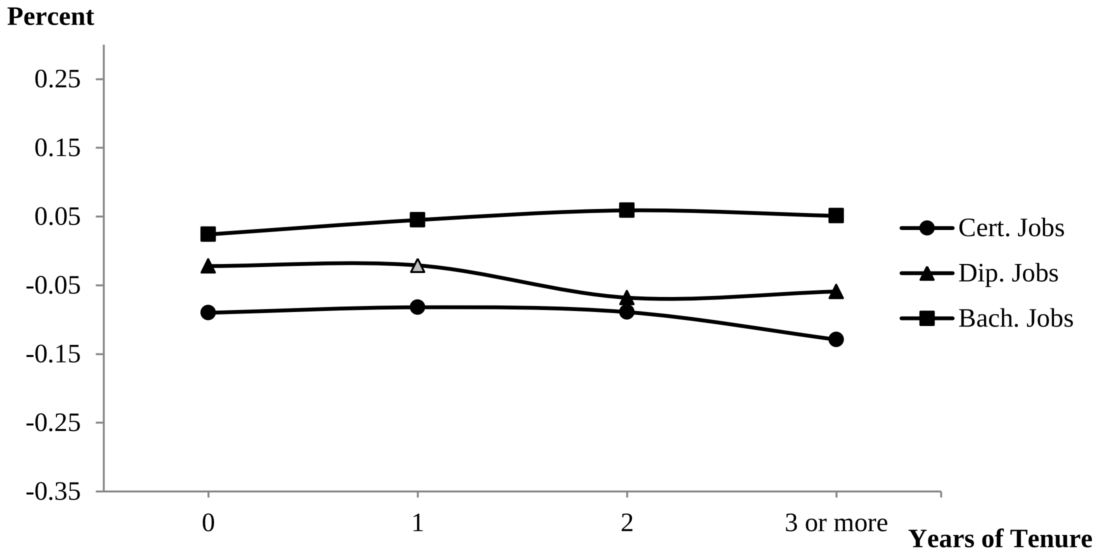
The graduates working in diploma level jobs fare slightly better, earning from seven to 11 percent less than the benchmark group. While the variance in the ORU earnings effects across tenure groups here does not appear to be considerable, the trend appears to be one of increasing wage penalties associated with being overeducated.

This pattern of an increase in the earnings penalties associated with overeducation as higher job tenure groups are examined is different from that for the diploma and associate degree graduates. The relative earnings outcomes of overeducated bachelor's pass degree graduates seem to provide some support for the screening hypothesis. That is, the increase in earnings penalties for the groups with positive tenure suggests that more able workers are being promoted into more correctly matched jobs. In other words, the lower earnings observed for the overeducated groups with higher tenure could be attributed to the lower mean (and unobserved) levels of ability for those who have been screened, or 'filtered'. At the same time, the small dissipation of the uncertainty wage discount (Cain and Aigner 1977) observed for those with positive tenure (and who have not been promoted), indicates that the screening process is not important.

6.4.8 Bachelor's Honours Degree Graduates

The ORU earnings effects for bachelor's honours graduates are shown in Figure 6.6. The observed changes in the estimated ORU coefficients for graduates with a bachelor's honours degree are moderate as higher tenure groups are examined, following on from the pattern in the earlier discussion. The F-tests of equality indicate that the estimated ORU earnings effects are the same across tenure groups, for bachelor's honours degree graduates working in diploma level occupations, but differ statistically for those in the highest and lowest job categories which require a bachelor's pass degree, and a certificate, respectively.

Figure 6.6: ORU Earnings Effects by Tenure Groups, Bachelor's Honours Graduates



The curves for the bachelor's honours degree graduates overeducated in the lower level certificate level jobs indicate that the estimated earnings effects are similar for the graduates with zero, one and two years of tenure. These graduates earn around nine percent less than the benchmark category. However, the honours graduates working in certificate level jobs, and who have three years or more of job tenure, have a modestly higher earnings penalty (by four percentage points), at 13 percent. Further, the exclusion of this last group yields a F-test result which indicates that estimates for the first three tenure groups are statistically similar. Thus, earnings differ only for the graduates with the highest levels of tenure.

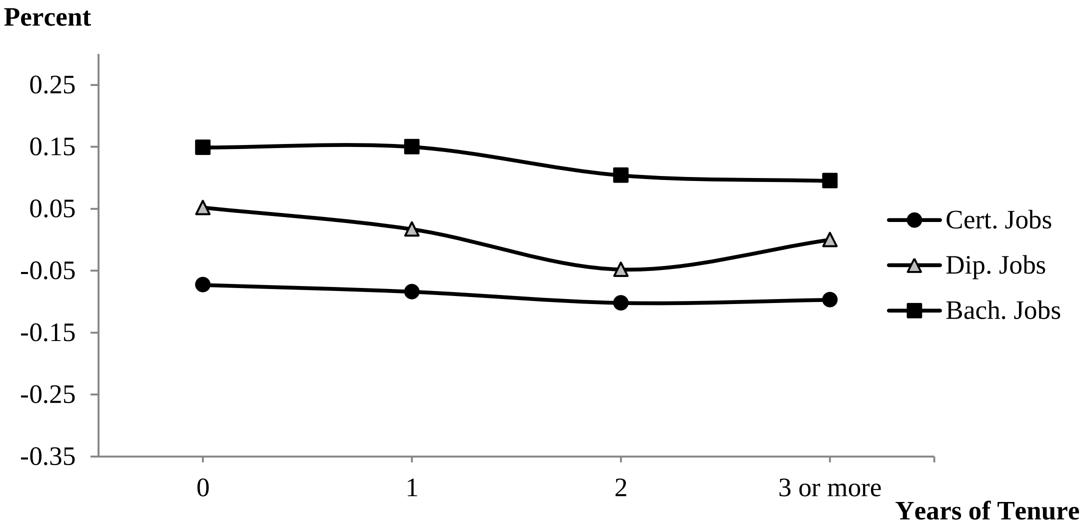
In contrast, an increasing, and statistically different, trend is observed for the graduates in the highest category of bachelor's pass degree jobs. Nevertheless, the variance in the estimated ORU coefficients is very modest. While the earnings advantage experienced by honours graduates in bachelor's pass level jobs who have three years or more of job tenure is double that observed for their counterparts with zero tenure, the difference, of just 2.6 percentage points, is negligible.

The trend for graduates at this level of educational attainment can be interpreted thus. Stable ORU earnings penalties are found for the bachelor's honours graduates at the lower job levels, regardless of the level of tenure. For bachelor's honours graduates in the higher bachelor's pass degree level jobs, a very small earnings premium, of three percentage points, is observed. This is, again, consistent with the interpretation that a screening process which does not result in job mobility is a relatively unimportant function of the labour market.

6.4.9 Graduates with Graduate Certificates

The estimated ORU coefficients for graduates with graduate certificates are presented in Figure 6.7. The estimates for graduate certificate holders working in diploma level jobs were all statistically insignificant, presumably due to their relatively small proportion, of only half a percent of the sample. Their counterparts in certificate and bachelor's pass level jobs were observed to have statistically significant estimates for all tenure groups. The estimated ORU earnings impacts for graduate certificate holders were observed to be small across the tenure groups, in line with the trend found for the other qualification groups thus far. The F-tests indicated that only the estimated coefficients for graduate certificate holders working in bachelor's pass degree level jobs were statistically different, whereas the estimated coefficients for graduate certificate holders in diploma or certificate level jobs were statistically stable across tenure groups.

Figure 6.7: ORU Earnings Effects by Tenure Groups, Graduate Certificate Graduates



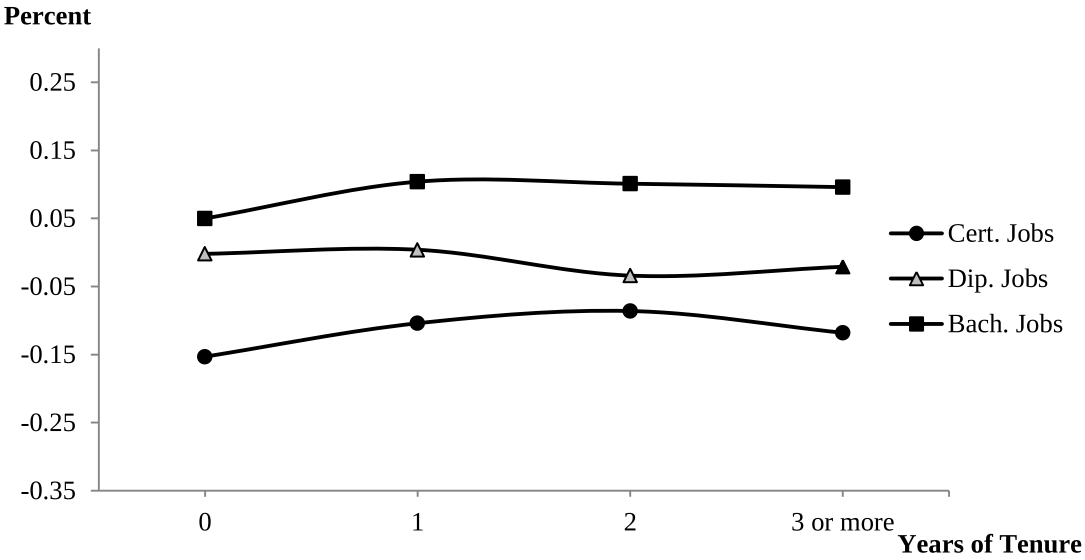
The least overeducated graduate certificate holders in bachelor's pass degree level jobs exhibit a modest decline in the earnings advantage relative to the reference category for the groups with higher amounts of tenure, as those in this job category with three years or more of tenure were observed to have an earnings premium five percentage points lower than those with no tenure.

The findings for graduate certificate holders thus indicate that at the lower job levels, ORU earnings effects are stable, going from those with no tenure to those with the highest levels of tenure. For those working in the highest job categories requiring a bachelor's pass degree, however, a smaller ORU earnings premium, by five percentage points, is observed for the graduates in the higher tenure groups, particularly for those with two years or more of tenure. Separate F-tests of equality confirm this, as the estimates on *oru_gcert_bach* were statistically the same between those with zero and one year of tenure, and for those with two and three or more years of tenure.

6.4.10 Graduates with Graduate Diplomas

The estimated ORU earnings effects for graduates with graduate diplomas are presented in Figure 6.8. The estimated coefficients for graduate diploma holders in diploma level jobs were all statistically insignificant, with the exception of those in the three years or more tenure group, who were observed to have a statistically significant, but very modest earnings penalty of two percent, relative to correctly matched bachelor's pass degree holders. The F-test of equality in Table 6.4 indicates, that the null hypothesis that these earnings effects for graduate diploma holders employed in diploma level jobs are the same across the tenure groups, cannot be rejected. Thus, a pattern appears to be emerging here. Stable ORU earnings effects are typically observed for the lower job categories, across tenure groups, at all levels of higher qualifications discussed thus far. Statistically different estimates across tenure groups are found only at the bachelor's pass degree job level.

Figure 6.8: ORU Earnings Effects by Tenure Groups - Graduate Diploma Graduates

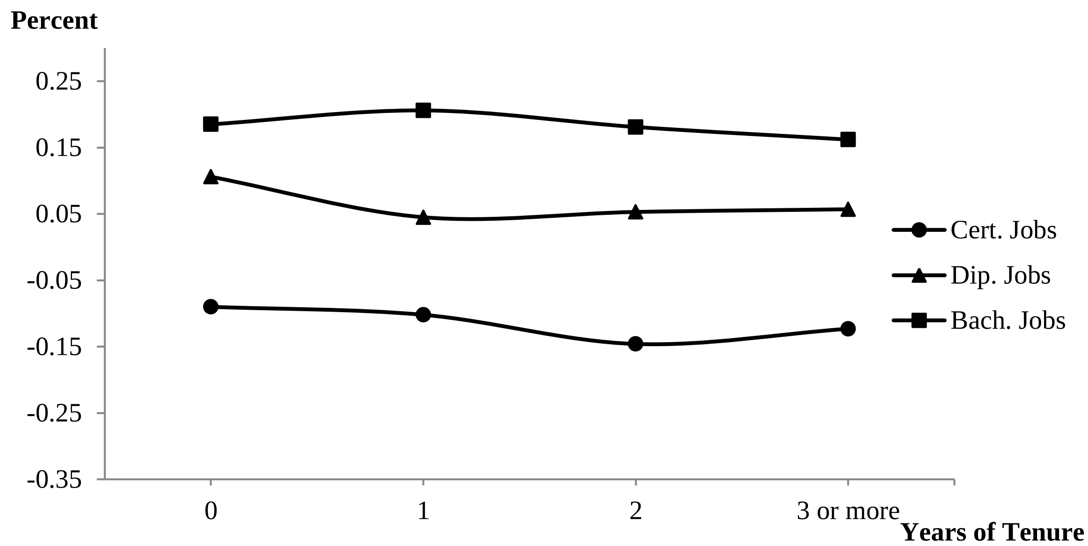


The variation in the earnings effects across tenure groups for graduate diploma holders in the highest job category of bachelor's pass degree level jobs can be described as one of modest increases, as the analysis moves across groups with increasing amounts of tenure. That is, the earnings premium for graduates working in bachelor's pass degree level jobs appears to be larger for those with one year of tenure relative to those with no tenure. However, the earnings effects for the groups with two and three or more years of tenure do not seem to be drastically different, compared to graduates with one year of tenure. Indeed, excluding those without tenure in the F-test of equality yields a result confirming the statistical similarity in estimated ORU earnings effects for the tenure groups with positive tenure. Therefore, for graduate diploma holders working in bachelor's pass degree jobs, the only statistically important change in the estimated ORU earnings impacts occurs between those with zero and one year of tenure. A more detailed discussion of this will be offered in the concluding remarks.

6.4.11 Masters Graduates

Figure 6.9 presents the results of the ORU analysis for masters degree graduates. The ORU earnings effects for masters degree graduates in all three job categories are observed to be fairly stable across the tenure groups. Modest differences between the estimated ORU coefficients are observed between the zero and one year of tenure groups. The F-test estimates in Table 6.4 indicate that the ORU estimated coefficients were statistically different between tenure groups, for masters degree graduates working in diploma or bachelor's pass degree level jobs. The largest observed difference, of a five percentage points higher earnings penalty, occurs for masters degree graduates working in diploma jobs, between the groups with zero and one year of tenure. A separate F-test of equality which excludes the group with zero tenure reveals that the estimates for masters degree graduates working in diploma level jobs who have positive tenure are statistically the same.

Figure 6.9: ORU Earnings Effects by Tenure Groups, Masters Graduates

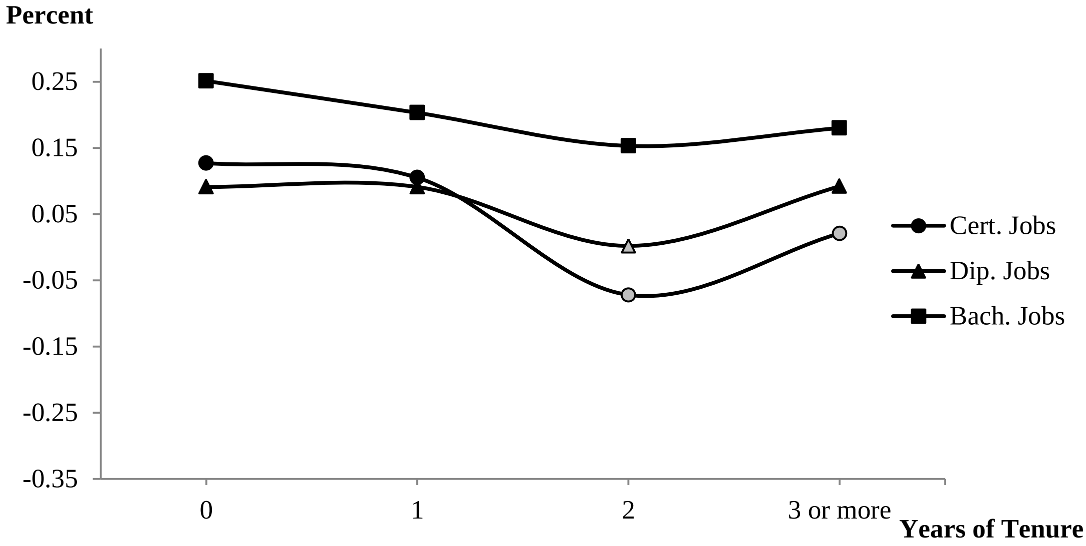


Masters degree graduates working in jobs which require a bachelor's pass degree experience reasonably high earnings premiums, of around 19 percent, relative to that of the benchmark group of appropriately trained bachelor's pass degree graduates, when those with no job tenure are considered. The group with one year of job tenure, however, has a slightly higher earnings premium of around 20.5 percent. A separate F-test which omits the masters degree graduates with one year of tenure indicates that the estimates for the other tenure groups are statistically different, despite their similarity in magnitude. Thus, there exists variability across tenure groups, for masters graduates working in jobs requiring a bachelor's pass degree, although the economic significance of these changes is modest at best, and change is mostly apparent when comparing the groups with zero and one year of tenure.

6.4.12 Doctoral Graduates

The estimated earnings effects for doctoral graduates are presented in Figure 6.10. Note that, as with the diploma and associate degree graduates, the doctoral graduates are a relatively small group, and the smaller numerical representation thus accounts for the statistical insignificance and irregularity for some of the estimates.

Figure 6.10: ORU Earnings Effects by Tenure Groups, Doctoral Graduates



The F-test estimates in Table 6.4 indicate that the ORU estimates for doctoral graduates in certificate and bachelor's pass degree level jobs are statistically different across tenure categories. However, note that the estimates for the graduates with two or three or more years of tenure in the certificate level jobs category are statistically insignificant. When these estimates were excluded in a separate F-test, the estimated ORU coefficients for PhD graduates working in certificate level jobs, and who had zero or one year of tenure, were found to be the same, statistically speaking. The estimated ORU coefficients for PhD graduates working in bachelor's pass degrees level jobs were, however, statistically different across the tenure groups. For the PhD graduates in bachelor's pass degree level jobs, the earnings premium appears to be smaller when graduates with longer amounts of tenure are considered.

6.5 Conclusion

The discussion of results for the analyses disaggregated by tenure groups has revealed some general patterns. Generally speaking, the estimated ORU earnings effects are stable for the graduates working in the lower job categories requiring a diploma or certificate. This is confirmed by the F-test estimates presented in Table 6.4, where the majority of the estimates for graduates in diploma or certificate level jobs were statistically the same across tenure groups. This empirical finding does not favour any labour market theory in particular. However, where the estimates were found to differ statistically across tenure groups, exclusion of the estimated coefficients for those with zero tenure (such as for *oru_mast_dip* and *oru_hons_cert*) changed the result of the earlier F-tests, such that the respective estimates for those with one year to three years or more of tenure were statistically the same. Thus, any change in the ORU earnings effects takes place in the first year of tenure. This would be expected under the predictions of the screening hypothesis.

The ORU earnings effects were found to differ across tenure groups for the graduates working in the highest job level requiring a bachelor's pass degree. Two observations can be made as to the pattern of the ORU earnings effects at this job level. First, the variation in ORU earnings effects across tenure groups is very modest for all the different qualifications considered. Second, a decrease in the earnings premium as the higher tenure groups are examined is generally observed, although there are exceptions, such as the graduate diploma and bachelor's honours degree graduates. At the same time, a decrease in the earnings disadvantage for the undereducated diploma graduates in the higher tenure groups is also observed. These findings concur with the expectations of the screening model, which predicts moderate changes in the ORU earnings effects as tenure increases. The theories of human capital and technological change, which share the prediction on the stability of the ORU earnings effects across tenure groups, but also allow for smaller ORU earnings penalties as tenure is accumulated, do not appear to be validated by the analysis in this section, as smaller ORU earnings penalties were not observed for the vast majority of the graduates. Therefore, the screening hypothesis appears to be the most applicable labour market theory to the Australian graduate labour market.

Another interesting finding relates to the composition of those with zero tenure. As stated in the introduction to this chapter, this tenure group comprises of graduates new to the labour market, as well as relatively experienced workers who have obtained a new job upon obtaining their higher qualifications. The finding that graduates who have tenure experience larger penalties than those with no tenure thus makes sense, when this quirk in the data is taken accounted of, and when the screening hypothesis is considered. The graduates in the zero tenure group who have been directed to a new and presumably higher level job upon completing their qualifications are those who are more able, and have come out well in the screening process. However, this only applies to the higher level bachelor's pass degree jobs. Graduates in the lower level diploma and certificate level jobs have adverse earnings outcomes of the same magnitude, irrespective of tenure.

Further, recall that the earlier analysis on the incidence of overeducation by tenure groups revealed that overeducation is more prevalent among those with greater amounts of tenure. Hence, the overall picture of ORU effects is not a rosy one. The higher incidence of overeducation amongst those with tenure suggests that job experience and a higher formal qualification may not be enough to compensate for other (unobserved) shortcomings of the graduates. This rising incidence of overeducation could be a sign of a very slow-adjusting labour market, which has not directed higher qualified graduates into a more suitable job after four months of completing their higher qualification.[70] However, it is more likely that the overeducated graduates with tenure have had their shortcomings revealed throughout the course of their tenure, and notwithstanding their recent higher qualification, are not given the opportunity to move to a better job. This could explain the higher incidence of overeducation amongst those seeking another job.

[70] An increasing incidence of overeducation as tenure increases is observed when the sample is restricted to just bachelor's pass degree graduates.

CHAPTER 7

The Influences of University Attended and Field of Study on ORU Earnings Impacts

7.1 Introduction

In this chapter, the focus shifts from an examination of ORU earnings impacts by personal attributes, to the study of ORU earnings effects by institutional attributes. In particular, the roles of university quality and field of study are examined.

Overeducation has been empirically shown to be associated with substantial earnings disadvantages, but there does not appear to be any easing in the demand for higher education. As set out in Chapter 1, the global trend appears to be that of increasing participation in higher education. Governmental policies at the federal level, such as the uncapping of Commonwealth supported student places in universities from 2012 onwards, are encouraging the attainment of higher education. Under the 'Education Revolution' of the current Labor government, a target of having 40 percent of Australians aged 25 to 34 years attain a bachelor's degree or above by the year 2025 has been set. Recent estimates by the OECD suggest that Australia is well on track to achieving this target (The Australian 2011a; OECD 2011).

On a separate but related note, Australian universities have attempted to distinguish themselves on the basis of quality in recent times. For example, university websites typically contain references to graduate outcomes, university rankings or accreditations and endorsements. These statements of quality can also be found on the websites of university groups. The website of the prestigious Group of Eight universities, for example, state that they are "consistently the first choice of the majority of highest qualified Australian school leavers" (Group of Eight 2011b). For some universities who have done well in the world universities rankings, announcements on their current ranking feature prominently on their websites. At the same time, it is also on the basis of 'product differentiation' that the Group of Eight universities are making their case for deregulation of student university fees (The Australian 2010a).[71]

[71] At present, university fees in Australia are strictly regulated and apply to all universities.

It is unclear, however, of the role that university quality, whether actual or perceived, plays in the determination and consequences of educational mismatch in the labour market. Accordingly, the in-depth analysis of graduate outcomes, in the Overeducation, Required, and Undereducation (ORU) context, in this study will be beneficial to policy makers of higher education, as well as to individuals in their decision to undertake higher education.

Recall that earlier analyses looking at the incidence of educational mismatch in Chapter 3 found that ATN universities' graduates were the most appropriately matched to their jobs, with about half of ATN graduates being in a job that requires their attained level of qualifications. Conversely, only a third of Go8 graduates are appropriately trained, while IRU and Other university graduates performed marginally better compared to Go8 graduates. When only bachelor's degree graduates are considered, two-thirds of ATN graduates are appropriately trained, while the proportion of appropriately skilled graduates from the other three university groups improved to around 50 percent.

The remainder of this chapter is organised as follows. Section 2 provides a review of studies which examine the relationship between institutional quality and earnings. Section 3 describes the methodology used in the analysis of graduate earnings, while section 4 discusses the results of the statistical analyses. Section 5 concludes.

7.2 Literature Review

A limited number of studies, usually from the US, examine the link between institutional quality or prestige, and graduate earnings. An even smaller number of studies within this literature examine the link between institutional quality and overeducation.

These studies have used a variety of measures as indicators of quality.[72] For instance, Smart (1988) used information on student entry levels, expenditure per student and tuition fees as indicators of institution quality. Belfield and Fielding (2001) used

[72] These measures can be generally categorised into either resource-related measures (student expenditures, for example) or prestige effects (research rankings, for example). McGuinness (2003) theorises that the former impacts on graduate earnings through faster accumulation of human capital while the latter influences earnings though peer effects, or research spillovers.

expenditure per student, while Birch, Li and Miller (2009) based their measure of university quality on another study by Valadkhani and Worthington (2006), who ranked Australian universities based on a number of measures, including student expenditure, research output, number of doctoral student completions, and other research measures. Robst (1995) used average aptitude test scores, expenditure per student, and prestige rankings as indicators of quality.

While it is apparent that a range of quality measures have been used in these studies, they have generally come to the same conclusion. That is, institution quality has positive, but small impacts on graduate earnings. James *et al*. (1989), for instance, estimate that less than two percent of the variance in graduate earnings can be attributed to college quality effects. Similarly, Birch, Li and Miller (2009) found that the earnings of Australian graduates were very similar across institutions. The institution quality premium reported by Smart (1988) was about three percent.

Thus far, only three studies have examined the link between institution quality and its effects on ORU.[73] McGuinness (2003) found that for Northern Ireland graduates, university quality effects varied according to the degree class obtained. Specifically, university quality appeared to play a more important role for graduates with lower degree classes, and enabled these graduates to obtain better jobs and earnings compared to their counterparts with the same degree class from lower ranked institutions. These university quality effects were particularly large for graduates from certain faculties, such as Social Science and Medicine. Nevertheless, these effects could only be established for the graduates' first job after graduation, and no discernible link could be found for graduates two to four years after graduation.

A study of US graduates by Robst (1995) uncovered links between college quality and the onset of overeducation. In particular, the aforementioned three measures of college quality were each separately linked to decreases in overeducation. Where test scores were used as the indicator of college quality, 20 percent of graduates in the top quartile were found to be overeducated, while 44 percent of those in the lowest quartile were overeducated. Similar figures were found when student expenditure

[73] These studies were discussed in the literature review in Chapter 3, but warrant a further mention due to their relevance to the present chapter.

was used as a proxy for quality. When the graduates were sorted by prestige ratings, the quality effect on overeducation was exacerbated, with 52 percent of graduates in the lowest quartile being overeducated, while the corresponding figure for those in the highest quartile was 16 percent. Moreover, Robst (1995) reported that the influences of college quality extended relatively far into the graduates careers, and overeducated graduates from higher quality institutions were much more likely to be correctly matched subsequently. [74] This latter result is thus at odds with McGuinness's (2003) finding that institution quality effects are short-lived. Finally, a study by Berggren (2010) on Swedish university graduates indicated that graduates from more prestigious universities were much more likely to be matched to their occupations in terms of educational levels.

7.3 Methodology

Prior to a discussion of the estimation model used in the analysis of graduate earnings, some points are offered in relation to the way institutions are categorised. Only broad university groupings of the institutions are used in the main set of analyses, as the Code of Practice for the GDS restricts the identification of individual institutions (AVCC-GCCA 2001). Thus, the universities are grouped according to their own groupings of: i) The Group of Eight (Go8); ii) Australian Technology Network (ATN); and, iii) Innovative Research Universities (IRU). The remaining universities which do not belong to any of the three groups above are categorised as 'Other universities'.[75] A listing of the universities and their respective groups can be found in Appendix C.

The Go8 universities are considered the most prestigious and research intensive universities in Australia. In a study comparing Australian universities, the Go8 universities were typically the top-ranked in both expenditure-per-student and research-based measures of university quality (Valadkhani and Worthington 2006). At the same time, the Go8 universities are consistently the highest-ranked institutions in well-known rankings of world universities, such as the Shanghai Jiao Tong rankings and The Times Higher Education World University Rankings (ARWU

[74] The time periods of the data used by Robst (1995) were 1976 and 1985, one decade apart.

[75] In a subsequent section of the present chapter, the analysis will be extended to (unnamed) individual institutions, so as to explore the variability of graduate earnings across institutions at a more detailed level.

2011; THE 2011). The relative quality of the other universities is less clear. While the Go8 maintains their leadership in rankings regardless of the measure of university quality used, the ranking within the ATN and IRU universities varies considerably, depending on the measure.[76] Assessing the quality of other universities outside the Go8 is complicated by the fact that they do not appear in some rankings, or are ranked in a broader manner.[77]

The analysis of ORU earnings impacts will utilise the Vahey (2000) model of ORU earnings effects.[78] This model can be written as:

(7-1) $logw_i = \beta_1 Z_i + \beta_2 D^o{}_i + \beta_3 D^u{}_i + \beta_4 D^r{}_i + \epsilon_i$

where w represents the hourly wage, used in the analysis in natural logarithmic format, Z represents a vector of characteristics correlated with earnings, and D^o, D^u and D^r are dummy variables indicating if the individual is overeducated (D^o), undereducated (D^u) or correctly matched (D^r). The proxies for experience that will be used in the analyses are the age of the graduate and the years of tenure in the present job, with both proxies entered into the estimating equation in quadratic form. Equation (7-1) will be estimated separately for each broad university group.

7.4 Results

The results of the analyses disaggregated by university groups are presented in Table 7.1. Panels (i) to (iv) present the results for Go8, ATN, IRU and Other university graduates, in that order. As with the earlier analyses, most of the estimated coefficients for each university group are statistically significant at the one percent level. The adjusted R-squared values for each of the university groups range from 0.176 to 0.228.

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[76] The methodology used in university ranking differs, and while the Go8 are typically the top ranked universities from Australia, the rankings of other universities are more volatile.

[77] For example, the ARWU ranking lists the top 100 universities, and the remaining institutions are ranked in groups such as 101-150, 151-200, and so on.

[78] The analyses of the present chapter were also undertaken using the Verdugo and Verdugo (1989) model. The benefit to using the Verdugo and Verdugo (1989) approach lies in its relative brevity, although the tradeoff is the loss of some detail from the Vahey (2000) model. Nevertheless, the results are qualitatively similar. This alternative set of results provided the basis for a paper titled "Overeducation in the Australian Graduate Labour Market: The Role of University Attended and Field of Study", presented to the 22nd Australian Labour Market Research Workshop, held at the University of Canberra in February 2012.

Table 7.1: OLS Estimates of the ORU Model, by University Groups

Variable	Go8 (i)	ATN (ii)	IRU (iii)	Other (iv)
Constant	2.208***	2.259***	2.395***	2.375***
	(90.580)	(79.726)	(81.151)	(107.682)
Female	-0.049***	-0.043***	-0.034***	-0.052***
	(17.341)	(10.246)	(7.894)	(19.274)
Age	0.041***	0.038***	0.026***	0.033***
	(28.117)	(22.317)	(15.518)	(25.632)
Age squared/1000	-0.437***	-0.439***	-0.298***	-0.383***
	(22.272)	(18.151)	(12.748)	(21.045)
NESB	-0.052***	-0.017***	-0.027***	-0.054***
	(13.940)	(3.409)	(4.107)	(13.629)
Non-Australian	-0.197***	-0.243***	-0.144***	-0.186***
	(18.991)	(17.840)	(8.232)	(19.043)
Tenure	0.013***	0.016***	0.017***	0.013***
	(12.424)	(14.902)	(13.032)	(19.227)
Tenure squared/1000	-0.369***	-0.519***	-0.525***	-0330***
	(6.995)	(10.599)	(7.272)	(10.551)
Double degree	0.015***	-0.013	0.002	0.020***
	(3.901)	(1.551)	(0.206)	(3.742)
Part-time study	0.087***	0.067***	0.074***	0.098***
	(22.138)	(14.786)	(13.913)	(31.430)
Further study	0.004	0.008	0.015***	0.003
	(0.968)	(1.539)	(2.639)	(0.943)
Natural and Physical Science	-0.085***	-0.039***	-0.055***	-0.086***
	(14.185)	(3.734)	(6.186)	(12.713)
Information Technology	-0.037***	-0.000	-0.029**	-0.043***
	(5.172)	(0.024)	(2.116)	(6.775)
Engineering	-0.021***	0.018**	0.067***	-0.030***
	(3.262)	(2.130)	(5.719)	(4.026)
Architecture	-0.124***	-0.067***	-0.082***	-0.107***
	(13.810)	(7.100)	(2.670)	(8.134)
Agriculture and Environment	-0.174***	-0.147***	-0.066***	-0.124***
	(21.256)	(7.132)	(4.848)	(15.520)
Nursing	-0.140***	-0.099***	-0.068***	-0.119***
	(15.651)	(10.275)	(7.658)	(18.740)
Medicine	-0.035***	-0.030***	0.008	-0.046***
	(5.389)	(3.579)	(1.018)	(7.796)
Education	-0.102***	-0.041***	-0.041***	-0.065***
	(12.797)	(4.557)	(3.978)	(11.984)
Society and Culture	-0.061***	-0.071***	-0.028***	-0.064***
	(12.856)	(10.461)	(4.191)	(14.949)
Creative Arts and Others	-0.112***	-0.124***	-0.083***	-0.131***
	(15.490)	(12.340)	(7.375)	(19.649)
Self-employed	0.043***	0.000	0.045***	-0.003
	(4.148)	(0.007)	(2.595)	(0.371)
Private Sector	-0.043***	-0.065***	-0.056***	-0.054***
	(10.394)	(13.048)	(10.465)	(16.215)
Short-term employment	-0.096***	-0.089***	-0.077***	-0.102***
	(27.863)	(18.505)	(16.619)	(31.872)

Table 7.1: OLS Estimates of the ORU Model, by University Groups (cont.)

Variable	Go8 (i)	ATN (ii)	IRU (iii)	Other (iv)
oru_dip_cert	-0.241***	-0.255***	-0.160**	-0.162***
	(10.041)	(3.017)	(2.063)	(4.451)
oru_dip_dip	-0.053***	-0.145***	-0.077	0.001
	(2.653)	(2.784)	(1.210)	(0.041)
oru_dip_bach	0.016	-0.016	0.151***	0.041**
	(0.858)	(0.459)	(3.143)	(2.201)
oru_ascdeg_cert	-0.218***	-0.297***	-0.232***	-0.159***
	(3.578)	(3.922)	(2.692)	(7.633)
oru_ascdeg_dip	-0.002	-0.120**	-0.103	-0.062***
	(0.046)	(2.019)	(1.207)	(5.417)
oru_ascdeg_bach	0.007	-0.013	-0.077	-0.021
	(0.161)	(0.221)	(0.944)	(1.136)
oru_bach_cert	-0.138***	-0.162***	-0.125***	-0.168***
	(25.391)	(23.101)	(18.318)	(38.449)
oru_bach_dip	-0.096***	-0.096***	-0.070***	-0.090***
	(14.758)	(11.795)	(8.094)	(16.952)
oru_hons_cert	-0.089***	-0.165***	-0.104***	-0.088***
	(8.846)	(5.608)	(6.877)	(6.462)
oru_hons_dip	-0.035***	-0.006	-0.020	-0.043**
	(2.777)	(0.204)	(1.315)	(2.302)
oru_hons_bach	0.035***	-0.009	0.019*	0.052***
	(7.378)	(0.814)	(1.905)	(6.787)
oru_gcert_cert	-0.147***	-0.028	-0.119***	-0.071***
	(5.227)	(1.213)	(3.393)	(4.655)
oru_gcert_dip	-0.001	0.039**	0.048***	0.012
	(0.047)	(1.963)	(2.844)	(0.721)
oru_gcert_bach	0.122***	0.116***	0.137***	0.116***
	(14.816)	(13.352)	(17.244)	(21.087)
oru_gdip_cert	-0.105***	-0.176***	-0.104***	-0.095***
	(5.169)	(7.043)	(5.203)	(7.754)
oru_gdip_dip	-0.060***	-0.030	0.021	0.017
	(2.992)	(1.298)	(0.966)	(1.478)
oru_gdip_bach	0.106***	0.077***	0.098***	0.091***
	(17.845)	(11.183)	(14.877)	(20.231)
oru_mast_cert	-0.147***	-0.134***	-0.156***	-0.100***
	(10.090)	(5.778)	(4.094)	(8.486)
oru_mast_dip	0.037***	0.104***	0.042	0.070***
	(2.663)	(6.406)	(1.384)	(5.803)
oru_mast_bach	0.181***	0.173***	0.208***	0.178***
	(34.957)	(24.324)	(22.900)	(39.540)
oru_phd_cert	0.050	0.128***	0.064	0.064
	(1.543)	(2.580)	(0.831)	(1.305)
oru_phd_dip	0.060*	0.026	0.160***	0.116**
	(1.926)	(0.709)	(6.205)	(1.969)
oru_phd_bach	0.200***	0.161***	0.194***	0.202***
	(27.869)	(9.190)	(13.300)	(20.067)
Industry	Included	Included	Included	Included
Year of Graduation	Included	Included	Included	Included
Observations	159,092	108,387	73,858	227,988
Adjusted R-squared	0.228	0.176	0.192	0.177
F-statistic	619.98	313.84	285.65	694.87

Notes: Absolute values of heteroscedasticity consistent ‘t’-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively.

A number of differences can be observed with regard to the determinants of graduate earnings across the university groups. Panels (i) and (iv), for example, indicate that non-English speaking graduates from Go8 and Other universities earn about five percent less than their English speaking counterparts. Non-English speaking ATN and IRU university graduates, however, have a lower earnings disadvantage, at 1.7 and 2.7 percent, respectively. Across university groups, there is also a ten percentage points difference in the earnings penalty associated with being an Australian non-resident. ATN graduates who are not Australian residents earn 24.3 percent less, compared to their Australian peers. IRU graduates who are non-residents have a lower earnings penalty, of 14.4 percent.

The earnings effects of the fields of study also differ amongst the university groups. For instance, Science graduates from the Go8 earn 8.5 percent less than their peers who studied Management and Commerce, a result similar to that experienced by graduates from Other universities. ATN Science graduates, on the other hand, experience only about half that impact, with an estimated coefficient of -3.9 percent.

Self-employment status also has different impacts on the earnings of graduates from different university groups. The self-employed Go8 and IRU graduates earn about 4.5 percent more than their salaried counterparts, while the estimated coefficients for ATN and Other university graduates are very small, and also statistically insignificant.

Another interesting difference is that Engineering graduates from the Go8 and Other universities have negative earnings impacts, while ATN and IRU Engineering graduates have positive earnings impacts, compared to the reference group of Management and Commerce graduates. Agriculture and Environment graduates in the IRU universities earn about 6.6 percent less than the benchmark group, but fare relatively better than the same type of graduates in the Go8, who experience almost three times the earnings penalty, as they have earnings 17.4 percent lower. The differences in the earnings impacts of the different fields of study across university groups could be a reflection on their comparative advantages in teaching or industry linkages.

7.4.1 Earnings Effects of ORU, by University Group

The earnings effects of the ORU variables are discussed in this section. The ORU model of earnings exhibits interesting variations across the graduates of different university groups. In order to keep the discussion focussed and the findings apparent, the discussion here will once again be conducted in turn by the level of qualifications obtained. Further, the ORU coefficients will be graphed for each level of qualifications attained, with each curve showing the earnings effect for a different university group.

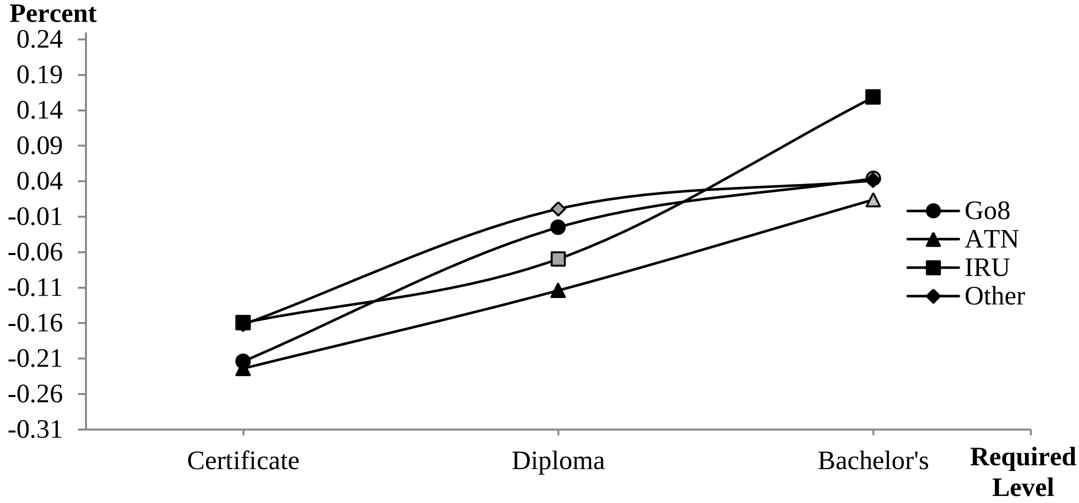
To facilitate the comparisons across university groups, the estimated ORU coefficients from Table 7.1 are adjusted to take into account the 'university group' effects from Table 4.2 earlier. For example, the results from Chapter 4 in the earlier analysis for the full sample indicated that, on average, a Go8 graduate can expect to earn 2.6 percent more than graduates from Other universities. Thus, the ORU estimated coefficients for the Go8 university group will be adjusted upwards by 2.6 percent. The ORU coefficients for graduates of the rest of the university groups are adjusted in the same fashion. In this way, more precise and insightful comments on the different impacts of the ORU variables across university groups can be offered, as the 'university group' effect would have been taken into account.

Estimated coefficients which are statistically insignificant are represented by the grey graphed points, instead of black. The reference categories here are the correctly trained bachelor's pass degree graduates, from each respective university group. Generally speaking, the shape of the curves accord with that reported in the literature, as the results here indicate that earnings penalties increase as the extent of overeducation increases.

7.4.2 Diploma Graduates

The earnings effects for diploma graduates are presented in Figure 7.1. As mentioned above, this category consists of undereducated, overeducated and correctly matched workers. Relative to the benchmark category of the correctly matched bachelor's pass graduates from their respective university groupings, these graduates generally have lower earnings, which is expected, due to the lower educational attainment of this group. A fair amount of variability exists across the university groups at all the job levels.

Figure 7.1: ORU Earnings Effects by University Groups, Diploma Graduates



The undereducated diploma graduates working in jobs that require a bachelor's pass degree tend to earn more than those working in correctly-matched diploma level jobs. However, again there is wide variation in the predicted earnings across the university groups, and two of the earnings effects (for the Go8 and ATN diploma graduates) are statistically insignificant. Other universities graduates, however, earn four percent more. Nevertheless, this earnings premium pales in comparison with that of the IRU graduates here, who earn a substantial 15 percent more than the benchmark group.[79] In summary, the striking feature of Figure 7.1 is the apparent tendency for wages to follow the types of jobs held.

Diploma graduates who are correctly matched in diploma-level jobs earn more than their over-educated counterparts employed in certificate level jobs. In several cases, the earnings effects for this correctly matched category are statistically

[79] As mentioned above, diploma graduates who are undereducated in a bachelor's level job could be earning more due to having a previous higher qualification. Checking the data confirms this, as 40 percent of the IRU graduates working in bachelor's degree jobs have a previous qualification at a bachelor's degree or above, a proportion much higher than the average of 20 percent for all diploma graduates. Excluding these graduates with prior higher degrees, and re-estimating equation (7-1) for all university groups yielded findings similar to what has been reported above. While the estimated coefficient for IRU diploma graduates working in bachelor's pass level jobs decreased to 11.6 percent, it is still high in comparison to the corresponding category in other university groups.

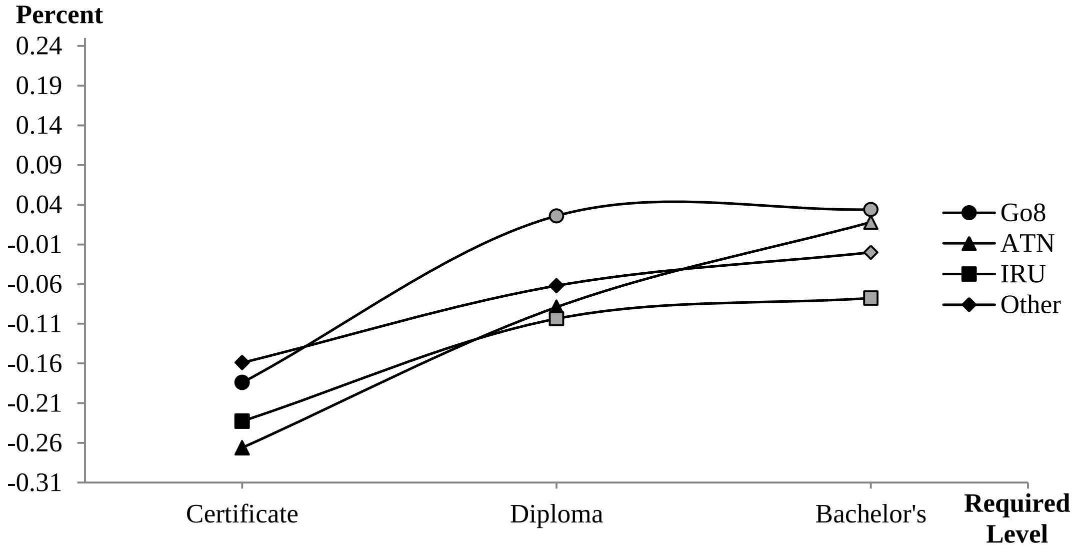
indistinguishable from the earnings of bachelor's pass degree graduates from their university group who are employed in the high earnings jobs that require bachelor's pass degrees. IRU and Other universities graduates are the ones who fall into this category of having earnings that do not differ statistically relative to the omitted category. Go8 and ATN graduates, however, earn 2.7 percent and around 11 percent less, respectively. The spread of the data points in Figure 7.1 indicates that there is a substantial amount of variance in the earnings effects across university groups in this category, with Go8 and ATN graduates being relatively worse off in terms of earnings.

Looking at the overeducated diploma graduates who are in a certificate level job, it is observed that they have quite a poor earnings outcome regardless of the institution attended. Nevertheless, there is also some variation in their earnings prospects across the groups of universities. The overeducated graduates from Go8 and ATN universities have earnings just over 20 percent lower than the adequately trained bachelor's pass graduates from the same university group. The IRU and Other universities graduates in the same category, however, are a little better off, with earnings only about 16 percent less than the reference group. In this regard, the IRU and Other university groups fare better than the other two university groups, even after taking into account the slightly higher earnings experienced by the average graduates from the Go8 and ATN universities.

7.4.3 Associate Degree Graduates

Figure 7.2 presents the estimated ORU coefficients for associate degree graduates. Associate degree graduates who work in certificate and diploma level occupations are considered overeducated, while those in a bachelor's degree level job are undereducated. It can be easily observed from Figure 7.2 that there are substantial differences in the ORU earnings effects for associate degree graduates from different university groups. This is particularly so for the overeducated associate degree graduates working in certificate and diploma level jobs, as their (undereducated) counterparts working in bachelor's pass level jobs have earnings which are statistically indistinguishable from the bachelor's pass degree graduates, correctly matched to a job requiring a bachelor's pass degree.

Figure 7.2: ORU Earnings Effects by University Groups, Associate Degree Graduates



As mentioned above, the estimated coefficients for the undereducated category of those working in bachelor’s pass degree professions are statistically insignificant for all university groups, although the size of the estimated coefficients, and therefore the shape of the curves, accords with expectations. Again, wages tend to follow jobs, and the relationship in this regard is reasonably similar across the four groups of universities considered here.

The middle category of associate degree graduates working in diploma level jobs is also overeducated, though to a lesser extent than those in certificate level jobs. This is reflected in the lesser magnitude of the earnings penalties experienced by those in diploma level work. The graduates from the ATN earn nine percent less, while Other universities graduates experience earnings penalties half of that amount, at roughly six percent. Go8 and IRU graduates have earnings that do not differ statistically from those of the reference category. In this regard, it appears that the overeducated ATN associate degree graduates who work in either certificate or diploma level jobs fare the worst, while graduates from the other three university groups have mixed performances.

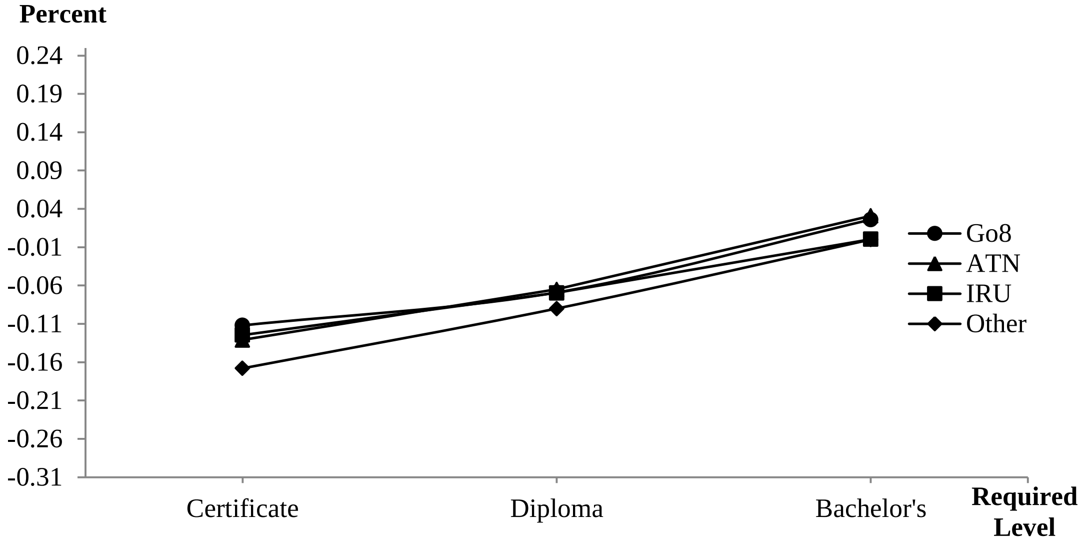
For those overeducated in certificate level jobs, graduates from all four university groups experience lower earnings relative to the benchmark group. These earnings penalties range from 16 percent for graduates from Other universities, to almost 27 percent for ATN graduates. Go8 and IRU graduates fall in the middle here, earning 19 and 23 percent less, respectively.

Thus far, the analyses of the diploma and associate degree graduates have indicated a pattern of earnings reasonably consistent with the ORU literature with regards to the ORU earnings profile. There are, however, a number of statistically insignificant earnings effects and one apparent outlier finding. These could be linked to the size of these qualifications groups, particularly when the sample is disaggregated by university group. Those with diploma or associate degree level qualifications are each less than 0.7 of one percent of the total sample, and represent as little as 0.07 of one percent of the sample within specific types of universities. In comparison, bachelor's pass degree graduates make up 60 percent of the entire sample, and those correctly matched in this category are the largest ORU category, comprising 37 percent of the entire sample. There are relatively fewer graduates with higher qualifications, compared to the number of graduates with bachelor's degrees. However, those with higher degrees are still a sizable group, even for the disaggregated university groups. Masters graduates account for almost 15 percent of the sample, and even the smaller higher degree groups, such as the doctoral graduates, make up for around 2.7 percent of the total sample, and number in excess of 15,000 graduates. The following analyses on these relatively larger groups of graduates arguably provide sounder findings.

7.4.4 Bachelor's Pass Degree Graduates

The estimated ORU coefficients for bachelor's pass degree graduates are presented in Figure 7.3. The plotted points in Figure 6.3 indicate that there is some variation in earnings for the overeducated bachelor's pass degree graduates (working in jobs requiring only a diploma or certificate level qualification) of different university groups, although these variations are narrower than those observed in other degree types.

Figure 7.3: ORU Earnings Effects by University Groups, Bachelor's Pass Graduates



Overeducated graduates from Other universities working in diploma level jobs earn nine percent less than the omitted category, although this is a considerable improvement compared to those in certificate level jobs. For the other graduates in this category, the university grouping does not seem to make much of a difference, as the plotted coefficients are all 'clustered' around the minus seven percent point. Hence, for graduates with bachelor's pass degrees, university groups seem to play very small roles, and there are only minute differences in the ORU effects on earnings. Thus, taking into account the estimated effects on university groups, bachelor's pass graduates are a very homogeneous group in terms of earnings, and have very similar ORU earnings effects. Graduates from the Other universities generally fare the worst, but earn only roughly three percent lower in comparison to graduates from other university groups.

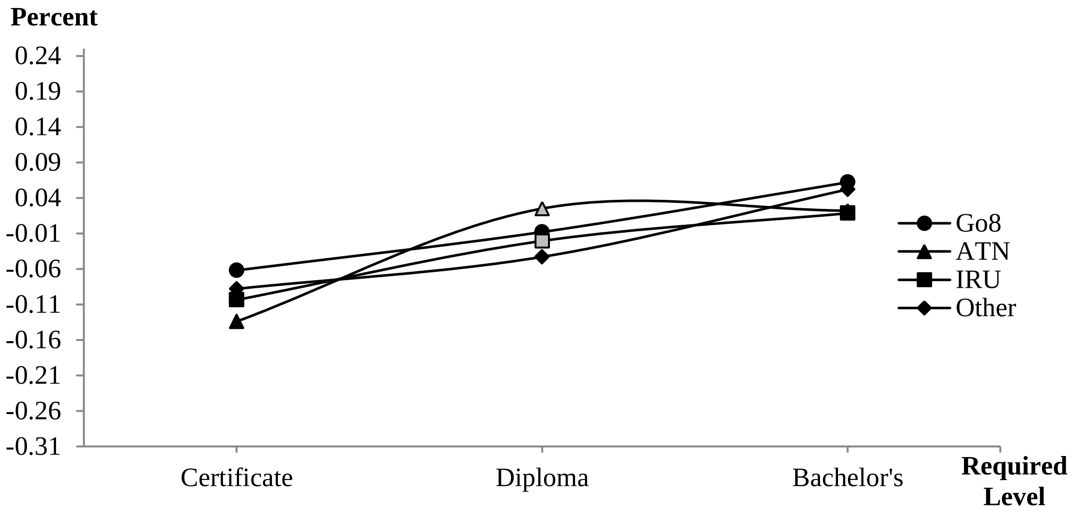
For those overeducated in a certificate level job, Go8 graduates have the least earnings penalties of 11 percent, relative to their well-matched counterparts in a job requiring a bachelor's degree. IRU and ATN graduates are a little worse off, earning about 13 percent less than the benchmark group, while Other universities graduates have earnings around 17 percent lower.

Thus, there are two clear conclusions from the study of the bachelor's pass degree graduates, where there are numerous graduates for each university group in each of the job match/mismatch categories. First, the central message from the aggregate level analyses, that wages tend to follow jobs, carries over to the analyses for each university group. Second, and related to the first finding, no university group is able to offer its graduates protection from the adverse consequences of failing to find a job that matches the graduates' level of qualifications. In other words, the Australian job market is largely blind to institutional quality differences - or these do not exist in terms of differences that can realistically be expected to impact earnings.

7.4.5 Bachelor's Honours Degree Graduates

Figure 7.4 plots the estimated ORU coefficients for graduates with an honours degree. Those with this level of educational attainment are considered overeducated in all three job categories, as are the other graduates in the rest of the discussion. Generally, the signs and magnitudes of the estimated coefficients are similar to those in the bachelor's pass degree category above. Further, the estimated ORU effects for the diploma and bachelor degree job levels do not differ much across university groups.

Figure 7.4: ORU Earnings Effects by University Groups, Bachelor's Honours Graduates



Graduates who work in a bachelor's pass level job have very small positive earnings impacts, of up to five percent. These small positive effects, of two to five percent across university groups, can also be interpreted as estimates of the 'honours' premium. The small premium associated with a bachelor's honours qualification is consistent with that found in earlier studies, such as Chia and Miller (2008), who found no honours premium in the case of graduates from one of the Go8 universities, and Birch, Li and Miller (2009), who found a small premium of five percent for Australian graduates. There is, thus, little observed earnings variation between university groups for this category. As noted above, for bachelor's pass graduates, those who have an undergraduate qualification experience very similar ORU earnings effects, regardless of university group.

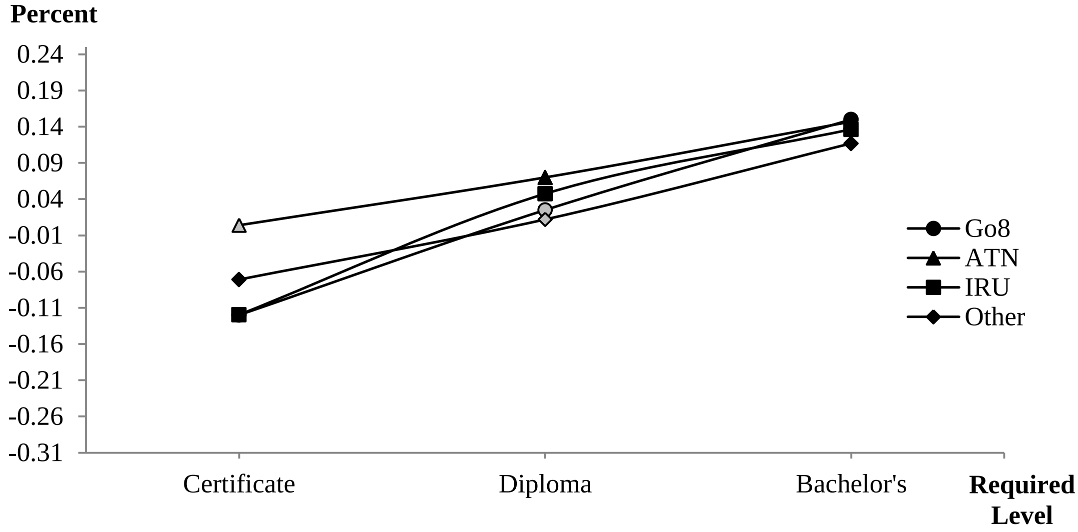
Graduates from all university groups have very small negative earnings impacts for being overeducated in a diploma level job. For graduates from the ATN, the very small negative earnings effect of being overeducated at this level was offset by the positive earnings effect associated with their university group. Graduates from the Go8 and IRU university groups have negligible ORU earnings effects, while graduates from Other universities are the worst off in this category, as they earn around four percent less.

For the overeducated graduates in certificate level jobs, a spread of earnings can be observed. Go8 graduates experience the least detriment associated with their overeducation, as lower earnings of around six percent are estimated for this group. The ATN graduates in this category are much worse off, as they have an earnings penalty of over double this amount, at 13 percent.

7.4.6 Graduates with Graduate Certificates

The estimated ORU coefficients for graduates with graduate certificates are presented in Figure 7.5. Figure 7.5 indicates that the overeducated graduates perform very differently in terms of earnings for jobs which require a certificate level qualification, depending on the university group they come from. These differences become narrower for these graduates overeducated in diploma level jobs, and there are very minor differences across institution types for those who are the least overeducated in jobs requiring a bachelor's degree. These findings seem to indicate that a larger variability in earnings across university groups occurs when jobs that require lower levels of qualifications are considered, or at the highest extent of overeducation.

Figure 7.5: ORU Earnings Effects by University Groups, Graduate Certificate Graduates



There are only minor earnings differences across university groups for the graduates working in bachelor's degree jobs, who all earn roughly 12 to 14 percent more than their peers in the reference group. However, a relatively higher amount of variability in graduate earnings across the university groups can be seen for graduate certificate graduates overeducated in diploma level jobs. Small positive earnings effects of up to seven percent are observed for the overeducated graduate certificate holders from ATN universities, while IRU graduates earn five percent more than the benchmark group. Graduates from the two other university groups, however, have earnings that do not differ significantly from the earnings of the relevant benchmark groups.

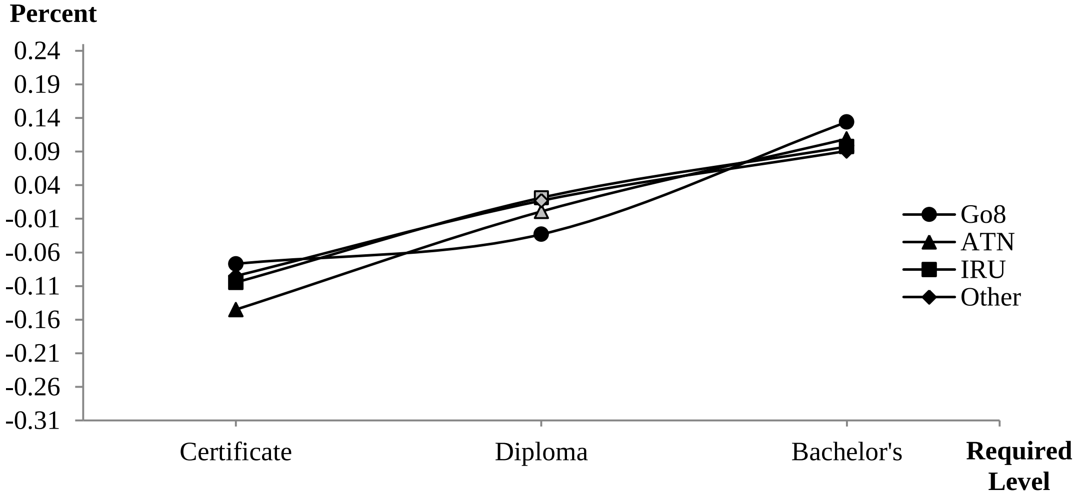
For the graduates who are the most overeducated in certificate level jobs, earnings penalties ranging from seven percent for Other universities graduates, to around 12 percent for Go8 and IRU graduates, are observed. Somewhat surprisingly, the university group that performs the worst in this category is the Go8, while those from Other universities have less than half the earnings penalty. ATN graduates have earnings that do not differ statistically from the benchmark group of adequately trained bachelor's degree students.

Thus, the main message that emerges from the study of the graduate certificate level qualifications is that those employed in the modal job category of bachelor's pass degree earn very much the same regardless of the type of university they attended. Greater differences in earnings arise when the more atypical job types, of diploma and certificate levels, are considered.

7.4.7 Graduates with Graduate Diplomas

The estimated ORU coefficients for graduate diploma holders are plotted in Figure 7.6. The shape of the curves for ATN, IRU and Other universities graduates are consistent with expectations. However, the curve for the Go8 graduates is strikingly different in shape, as it indicates an increasing return to overeducation.

Figure 7.6: ORU Earnings Effects by University Groups, Graduate Diploma Graduates



From Figure 7.6, it can be seen that the shape of the curves for the ATN, IRU and Other universities graduates are very similar, particularly for the latter two groups. Amongst these three universities, ATN graduates appear to fare the worst, as its curve is the lowest on the graph.

The overeducated graduates working in jobs at the bachelor's degree level experience an earnings premium, regardless of the type of institution attended. There is only a small difference, of up to four percent, in the earnings premium across university groups, as the estimated earnings effects range from nine percent, for Other universities graduates, to 13 percent, for Go8 graduates. The ATN and IRU graduates have very similar earnings impacts to those of the graduates from the Other universities. This homogeneity in the earnings effects of overeducation for jobs requiring a bachelor’s pass degree follows on from the discussion of the lower qualifications earlier.

Graduate diploma graduates, who are overeducated in jobs requiring a diploma, mostly have earnings that are not statistically different from those of the bachelor’s pass degree graduates who are correctly matched to jobs that require the same level of education. Graduates from only one university group, the Go8, earn about three percent less than the benchmark group of bachelor’s pass degree holders. In contrast, graduates from the other university groups have earnings that do not differ statistically from the reference category.

For jobs requiring a certificate, the overeducated graduate diploma holders from the ATN have substantially lower earnings compared to the benchmark group of correctly matched bachelor’s pass degree graduates, as they earn 15 percent less. Graduates from the other three university groups also experience earnings penalties compared to the reference group. Specifically, the graduates from the other university groups who are overeducated by the same extent have similar earnings penalties, of roughly eight to ten percent. The ATN graduates, thus, lag behind by up to five percent, even after the ‘ATN premium’ is taken into consideration.

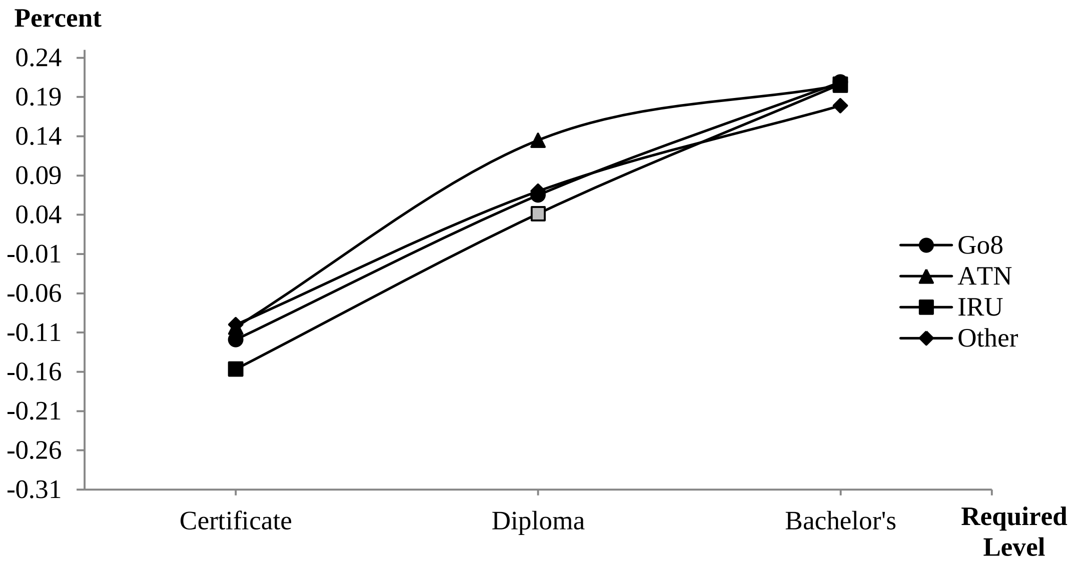
As mentioned above, the curve for Go8 graduates is of a different shape compared to the other three university groups, and also departs from the stylised shape in the empirical literature. This, however, appears to be influenced heavily by the graduates in the diploma level jobs category. The estimated coefficients for Go8 graduates in the other two categories do not vary much from the other university groups. However, for those in diploma level jobs, the size of the estimated coefficient is markedly lower, and is the only statistically significant earnings effect in this job category.

The other feature of Figure 7.6 is the broad similarity of the findings with those in Figure 7.5 for the graduate certificate graduates. That is, there are modest differences across types of universities for the modal job category of bachelor’s pass degree, and greater variation in earnings outcomes when the more atypical jobs, characterised by far greater levels of overeducation, are considered.

7.4.8 Masters Graduates

The curves in Figure 7.7, which plots the estimated ORU coefficients for masters graduates, tell a slightly different story. It seems that, with the exception of the ATN university group, the penalties to being overeducated are linear, and do not exhibit any of the accelerated decline in earnings associated with being more overeducated.

Figure 7.7: ORU Earnings Effects by University Groups, Masters Graduates



All the holders of masters degrees are overeducated, but only those working in jobs requiring either a bachelor's pass degree or a diploma actually earn more than the benchmark group of bachelor's pass degree graduates working in a (correctly matched) job requiring a bachelor's pass degree. Masters graduates who end up in jobs that require only a certificate level qualification fare far worse in terms of earnings than this benchmark group.

The earnings gains to masters graduates in jobs requiring a bachelor's pass degree, compared to bachelor's pass degree graduates, are evident for all the university groups. These premiums are high, and are all roughly around the 21 percent mark, for graduates of three out of the four university groups. Graduates from the Other universities do not do as well, but still earn 18 percent more than the reference group of well-matched bachelor's pass graduates.

The positive earnings effects for overeducated masters graduates who work in diploma level jobs are characterised by a modest amount of variability across university groups. Go8 masters graduates, for instance, earn six percent more than their appropriately matched counterparts with a bachelor’s degree. ATN graduates, however, earn more than twice that, with earnings estimated to be higher by 14 percent. Graduates from the Other university group earn seven percent more than the benchmark group, while IRU graduates have earnings that do not differ statistically from the reference group. In other words, the theme of the analyses for the lower-level qualifications, of there being greater variability in earnings across types of universities the more extensive the level of overeducation, carries over to the masters graduates.

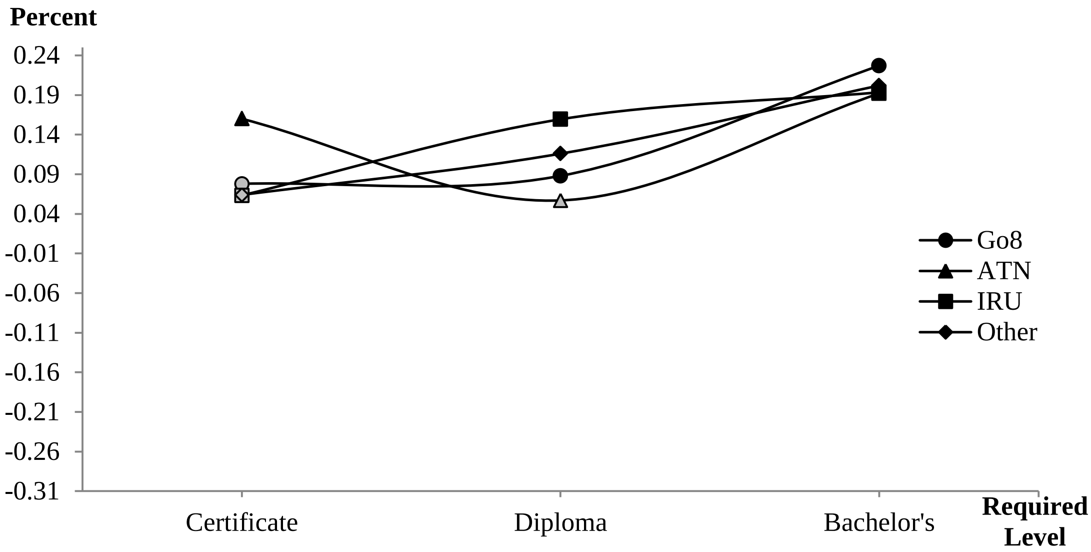
The substantial penalties to being overeducated in a job requiring a certificate for masters graduates arise for each type of university. These earnings penalties differ by university group, however, ranging from around ten percent in the case of ATN and Other universities graduates, to around 16 percent for the IRU graduates. Go8 graduates are in the middle, earning 12 percent less than the base category. Certainly, Other and ATN universities’ masters graduates perform better than their counterparts from the Go8 and the IRU in this category.

7.4.9 Doctoral Graduates

The doctoral graduates have curves which have rather different shapes to the general pattern observed for the other graduates, as illustrated in Figure 7.8. In particular, for the ATN, Go8 and Other universities graduates, the curves are slightly ‘bowed’ at the diploma level job category. This implies that graduates with a PhD fare relatively badly at this level of overeducation. For ATN graduates with a PhD, the curve dips sharply for those in diploma level jobs. However, the estimated earnings coefficient for that category is statistically insignificant.

All doctoral graduates are overeducated. In contrast to the masters level degree graduates, all doctoral graduates earn more than the benchmark group from their university of bachelor’s pass degree graduates working in jobs that require only a bachelor’s degree. The extent of these advantages dissipates, however, the more extensive is the level of overeducation. Moreover, while the earnings effects associated with this modal category of jobs requiring only a bachelor's degree are in a fairly narrow band, those for the jobs requiring lower level qualifications, and particularly those for the diploma level jobs, exhibit greater variability.

Figure 7.8: ORU Earnings Effects by University Groups, Doctoral Graduates



The substantial earnings premium to overeducated doctoral graduates in bachelor's degree level jobs occurs within each group of universities. Graduates from the ATN, IRU and Other university groups have an earnings premium of about 19 percent here, relative to their counterparts who have a bachelor's pass degree and who are in jobs categorised as appropriate for this level of qualification. PhD graduates from the Go8 have marginally higher earnings premiums, and earn 23 percent more.

The doctoral graduates who are employed in diploma level jobs earn less than their counterparts from the same type of university who work in jobs that require a bachelor's pass degree. Moreover, as noted above, a larger amount of variability across the earnings of PhD graduates from different university groups is observed for those in diploma level jobs. Go8 graduates have a modest return to overeducation of nine percent, relative to the benchmark group. Graduates from Other universities experience a premium almost twice that of Go8 graduates, at around 12 percent. IRU graduates have the highest earnings returns, of 16 percent, in this category.

For occupations requiring a certificate, doctoral graduates from the ATN have earnings premiums of 13 percent relative to their appropriately matched peers who have bachelor's pass degrees. Doctoral graduates who work in the same sort of jobs, but are from the other university groups, have earnings that do not differ statistically from their respective undergraduate counterparts.

7.4.10 Summary of Results

The findings from the analysis of ORU earnings effects for the various university groups can thus be summarised as follows. First, the tendency for wages to follow jobs, which was found in Chapter 4, is reinforced by the findings of the analysis in the present chapter. Specifically, graduates with higher qualifications experience earnings premiums compared to their peers with lower qualifications. These earnings premiums, however, decline with overeducation status. Second, a comparison of ORU earnings effects across institution groups indicates that no university group emerges as a dominant leader in terms of graduate earnings, and that there are 'winners' and 'losers' in each qualification category. Further, large disparities in ORU earnings effects occur at the atypical job categories requiring a certificate or diploma. Smaller differences in ORU earnings effects across institution groups are observed for graduates who are in jobs requiring a bachelor's pass degree.

7.5 A Further Analysis of Institutional Earnings Effects

7.5.1 Institutional Earnings Effects at a Detailed Level

This section examines the institutional earnings effects in greater detail, through the use of a more detailed specification of the dummy variables for the universities. Recall, that in Chapter 4, the earnings effects observed for the various university groups were very small. Specifically, graduates from the Go8 and ATN university groups were observed to have earnings advantages of 2.6 and 3.1 percent, respectively, relative to the benchmark group of Other universities. IRU graduates had a positive but negligible earnings premium of 0.4 percent.

These small institutional effects indicate that the labour market treats university graduates homogeneously, and that institutional quality or reputation plays a very minor role in the labour market.[80] A way to explore this issue further would be to disaggregate the university groups and estimate the earnings effects for individual institutions in a pooled regression. This will allow for the separating out of the variability in institutional earnings effects that might be hidden within the current aggregation by university groups.

Thus, equation (7-1) is estimated for the full sample, but with added controls for individual institutions. Note that the data description in Chapter 2 highlighted that one of the rules in the Code of Practice for the GDS dataset prohibits the undermining of the reputation and standing of individual institutions. Thus, to preserve anonymity of the institutions, the institution dummy variables are named in such a way that indicates their identity in a certain university group, but does not specifically identify the institution. For example, Go8 institutions are coded as *go8_1*, *go8_2*, …, g*o8_8* universities.

The results from this analysis are presented in panel (i) of Table 7.2. As the variables of interest here are those for the individual institutions, only those results are presented, although it should be noted that the estimated effects on the other variables were very similar to those presented in Table 4.2 in terms of sign and magnitude. The results in Table 7.2 clearly indicate that there is a large amount of variability in institutional earnings effects, relative to the benchmark case of one of the Other universities (*oth_15*).[81] To illustrate this further, the individual institutional effects are also shown in the form of a scatter plot in Figure 7.9. Further, the institutional effects are grouped vertically based on their university group affiliation. The first ‘line’ of plotted effects are those for the Go8 universities, the second ‘line’ for ATN universities, the third ‘line’ for IRU universities, and the last ‘line’ for Other universities.

Two main points can be made with reference to Figure 7.9. First, as mentioned above, individual universities have markedly different university earnings effects. One of the Other universities fared the worst, with an earnings disadvantage of

[80] An alternative explanation would be that graduates acquire similar amounts of human capital through their degrees. Given the diversity of universities and degree programs, this is unlikely.
[81] The benchmark university for the analysis in this section was chosen at random.

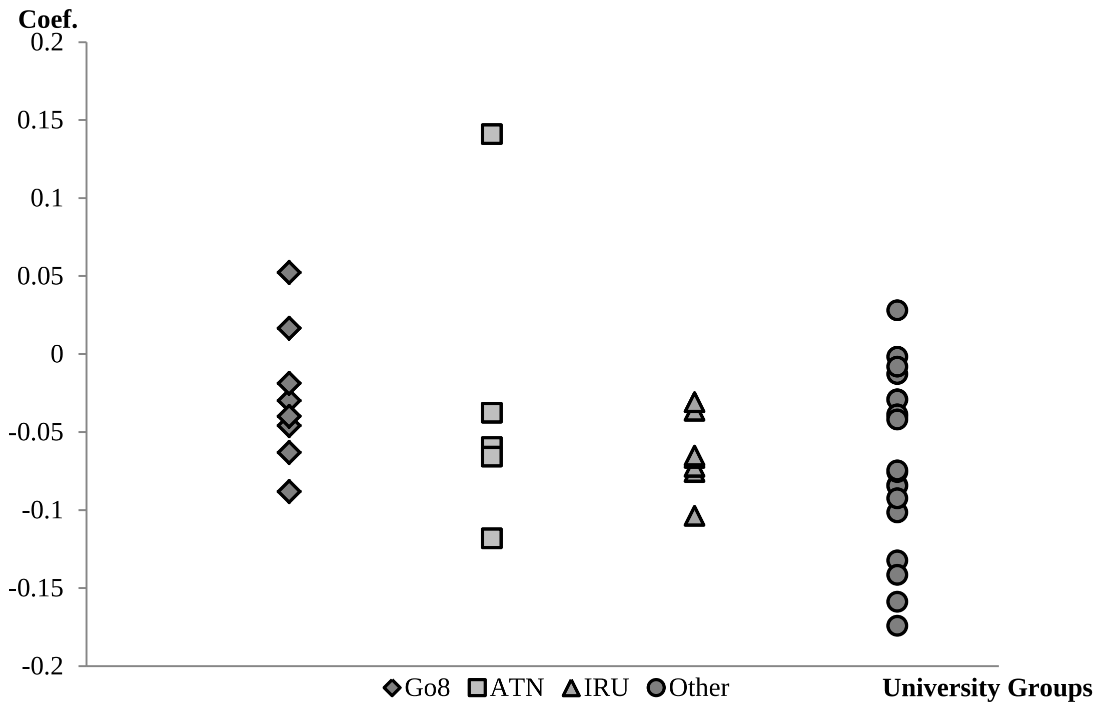
around 18 percent. In contrast, one of the ATN universities had the highest earnings advantage, of nearly 15 percent. There is thus a substantial earnings disparity of nearly 33 percentage points between graduates of these two universities.

Table 7.2: Selected Results from the OLS Estimates of the ORU Model, Detailed Dummy Variables for Institutions

Variable	Full (i)	Bach. (ii)	Variable	Full (i)	Bach. (ii)
go8_1	-0.088***	-0.080***	*oth_1*	-0.002	0.036***
	(10.306)	(6.985)		(0.271)	(4.129)
go8_2	0.017**	0.035***	*oth_2*	-0.084***	-0.080***
	(2.083)	(3.163)		(8.933)	(5.735)
go8_3	-0.030***	-0.024***	*oth_3*	-0.132***	-0.156***
	(4.952)	(2.776)		(11.677)	(8.844)
go8_4	-0.063***	-0.062***	*oth_4*	0.028***	0.096***
	(10.568)	(7.256)		(4.138)	(9.996)
go8_5	0.052***	0.046***	*oth_5*	-0.085***	-0.075***
	(8.189)	(5.112)		(11.465)	(6.236)
go8_6	-0.046***	-0.024***	*oth_6*	-0.076***	-0.065***
	(7.378)	(2.785)		(11.203)	(6.206)
go8_7	-0.019***	0.000	*oth_7*	-0.159***	-0.033
	(2.814)	(0.054)		(4.934)	(0.712)
go8_8	-0.040***	-0.021**	*oth_8*	-0.043***	-0.018
	(5.228)	(2.050)		(4.909)	(1.411)
atn_1	-0.118***	-0.094***	*oth_9*	-0.013	0.012
	(14.431)	(8.192)		(0.941)	(0.591)
atn_2	-0.038***	0.002	*oth_10*	-0.026***	0.002
	(6.349)	(0.176)		(3.836)	(0.184)
atn_3	-0.060***	-0.027***	*oth_11*	-0.029***	-0.057***
	(8.366)	(2.729)		(4.558)	(5.368)
atn_4	0.141***	0.164***	*oth_12*	-0.040***	-0.011
	(19.631)	(15.457)		(5.873)	(1.142)
atn_5	-0.066***	-0.033***	*oth_13*	-0.039***	0.005
	(10.829)	(3.900)		(5.820)	(0.559)
iru_1	-0.076***	-0.049***	*oth_14*	-0.102***	-0.074***
	(11.346)	(4.930)		(11.998)	(6.282)
iru_2	-0.104***	-0.062***	*oth_16*	-0.075***	-0.085***
	(14.841)	(6.153)		(10.834)	(8.566)
iru_3	-0.036***	-0.002	*oth_17*	-0.093***	-0.104***
	(5.989)	(0.281)		(9.349)	(6.203)
iru_4	-0.072***	-0.049***	*oth_18*	-0.042***	-0.045***
	(9.317)	(4.303)		(6.369)	(3.570)
iru_5	-0.067***	-0.037***	*oth_19*	-0.142***	-0.136***
	(8.918)	(3.731)		(9.467)	(6.407)
iru_6	-0.031***	-0.006	*oth_20*	-0.174***	-0.103***
	(4.451)	(0.638)		(7.811)	(3.372)
iru_7	-0.065***	-0.035	Observations	569,325	253,899
	(5.647)	(1.265)	Adjusted R-squared	0.195	0.098

Notes: Absolute values of heteroscedasticity consistent ‘t’-statistics are presented in parentheses. ** and *** indicate significance at the five and one percent levels, respectively. The model included controls for other personal, employment, schooling, and ORU characteristics (see equation (7-1)).

Figure 7.9: Individual Institutional Earnings Effects by University Groups

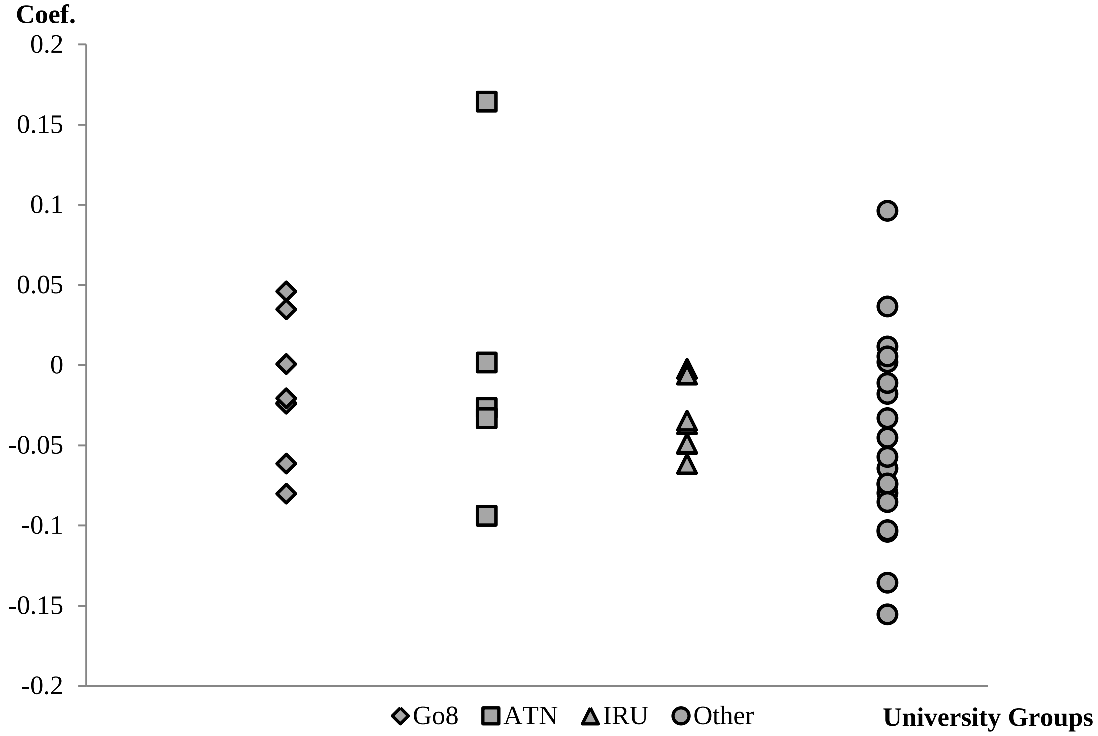


Second, a large amount of variability exists within university groups as well. Going across the plotted coefficients for the various university groups clearly indicates no ‘clustering’ effect. In fact, a large amount of disparity in earnings effects can be observed for the ATN universities, although this university group had the lowest number of institutions in its membership. Admittedly, one of the ATN universities (*atn_4*) is clearly well ahead of the pack compared to its fellow ATN peers, thus accounting for the huge disparity in earnings within the ATN universities. However, the disparity in earnings amongst the other ATN universities is still moderately large, at roughly ten percentage points. The elite Go8 institutions exhibited the same earnings trait, with a disparity of roughly 13 percentage points between the best and worst performing Go8 universities. Two Go8 universities were observed to have positive earnings effects relative to the reference Other university (*oth_15*), while the remaining eight had earnings disadvantages of up to nine percent. The Other university group, which comprises 20 member institutions, have a 20 percentage points gap between its highest and lowest performing universities. It is thus apparent that the earlier estimates on university groups conceal a large amount of variability among individual institutions. On this basis, it can also be said that no individual university group comes across as being superior. That is, there is a reasonable spread of estimated earnings effects within all university groups, and no university groups trend towards higher or lower estimated earnings effects.

Note that the analysis thus far extends to all levels of qualifications. It would, therefore, be interesting to see if the same conclusions can be drawn for only bachelor's degree graduates, and particularly those of limited work experience, so as to capture 'purer' effects of institutional quality. Thus, the model was re-estimated for bachelor's degree graduates no more than 25 years old. These results are presented in panel (ii) of Table 7.2.

The majority of the estimated institutional earnings effects for young bachelor's degree graduates in panel (ii) are very similar to those estimated for the full sample in panel (i). The magnitude and sign of the estimated institutional effects are consistent across the two sets of estimates in most cases, with only one or two percentage points shifts in the estimated earnings impacts. In the case of some institutions, however, there are reasonably large changes in the estimated earnings effects. For instance, graduates from the *oth_4* university were shown in the results of panel (i) of Table 7.2 for all graduates to have an earnings premium of around three percent relative to graduates from the benchmark university of *oth_15*. When only young bachelor's degree graduates are considered, this earnings premium widens to nearly ten percent. Another example would be that of *oth_20* university graduates, who experienced an 17 percent earnings disadvantage relative to the reference group where all qualifications are considered. The corresponding estimate for the restricted sample of bachelor's degree graduates indicates a reduced earnings disadvantage of ten percent. Despite these differences, however, the observations made from studying Figure 7.9 holds. Expressing the estimates from panel (ii) of Table 7.2 in the form of a scatter plot (Figure 7.10) makes this clear, as the overall patterns in Figure 7.10 are very similar to that of Figure 7.9.

Figure 7.10: Individual Institutional Earnings Effects by University Groups (Bachelor's Degree Graduates, Aged 25 Years and Below)



7.5.2 Institutional Earnings Effects - Persistence Across Time

To explore the persistence of these institutional graduate earnings effects across years, equation (7-1) was estimated for the bachelor's degree graduates, separated by year-groups.[82] Specifically, the sample was split into the 1999-2001, 2002-2004, 2005-2007 and 2008-2009 groups. Selected results from these analyses are presented in Table 7.3. Panels (i) to (iv) presents the estimates on the individual institutional earnings effects for the four year-groups, in chronological order.

[82] As the Vahey (2000) model for ORU earnings effects is 'observations-intensive', conducting the analysis for individual years is not feasible, especially as the model is specified for individual institutions.

Table 7.3: Selected Results from the OLS Estimates of the ORU Model, Detailed Dummy Variables for Institutions, by Year-groups

Variables	1999-2001	2002-2004	2005-2007	2008-2009
go8_1	-0.074***	-0.078***	-0.144***	0.038
	(5.870)	(5.078)	(7.065)	(1.350)
go8_2	-0.014	0.009	-0.060***	0.194***
	(0.960)	(0.573)	(2.972)	(7.439)
go8_3	-0.038***	-0.050***	-0.061***	0.078***
	(3.752)	(4.443)	(5.121)	(3.178)
go8_4	-0.079***	-0.081***	-0.111***	0.116***
	(8.935)	(7.429)	(8.330)	(4.833)
go8_5	-0.007	0.007	0.026**	0.181***
	(0.600)	(0.538)	(2.002)	(7.280)
go8_6	-0.057***	-0.072***	-0.075***	0.129***
	(4.498)	(5.924)	(6.207)	(5.600)
go8_7	-0.053***	-0.008	-0.064***	0.121***
	(5.269)	(0.648)	(4.680)	(5.021)
go8_8	-0.088***	-0.063***	-0.093***	0.146***
	(7.787)	(4.574)	(5.260)	(5.496)
atn_1	-0.113***	-0.047***	-0.184***	0.017
	(9.475)	(3.660)	(11.429)	(0.603)
atn_2	-0.089***	-0.055***	-0.042***	0.171***
	(8.695)	(4.725)	(3.659)	(7.552)
atn_3	-0.046***	-0.021*	-0.054***	-0.001
	(4.377)	(1.754)	(4.339)	(0.028)
atn_4	0.004	0.353***	0.046**	0.268***
	(0.373)	(19.126)	(2.364)	(11.440)
atn_5	-0.110***	-0.072***	-0.061***	0.104***
	(13.342)	(6.009)	(5.024)	(4.402)
iru_1	-0.091***	-0.091***	-0.116***	0.103***
	(8.101)	(6.242)	(7.566)	(4.193)
iru_2	-0.082***	-0.041***	-0.170***	0.052**
	(8.336)	(3.373)	(11.960)	(2.032)
iru_3	-0.047***	-0.030***	-0.015	0.033
	(4.904)	(2.655)	(1.250)	(1.270)
iru_4	-0.136***	-0.117***	-0.116***	0.171***
	(9.349)	(6.616)	(7.036)	(6.652)
iru_5	-0.049***	-0.027**	-0.147***	0.075***
	(4.860)	(2.135)	(9.172)	(2.863)
iru_6	-0.091***	-0.047***	-0.071***	0.149***
	(6.504)	(3.586)	(5.422)	(6.247)
iru_7	-0.044***	-0.049**	-0.107***	0.082
	(3.240)	(2.268)	(4.089)	(1.151)
oth_1	-0.039***	0.008	-0.018	0.174***
	(3.572)	(0.656)	(1.399)	(7.362)
oth_2	-0.105***	-0.081***	-0.187***	0.124***
	(7.619)	(3.356)	(8.353)	(3.768)
oth_3	-0.094***	-0.045***	-0.157***	-0.401***
	(7.496)	(2.890)	(7.179)	(6.392)
oth_4	-0.181***	0.000	0.014	0.208***
	(3.150)	(0.004)	(1.220)	(8.869)
oth_5	-0.084***	-0.052***	-0.132***	0.058*
	(7.999)	(3.821)	(8.322)	(1.677)
oth_6	-0.123***	-0.059***	-0.154***	0.150***
	(11.468)	(4.553)	(10.652)	(5.961)
oth_7	-0.113*	0.049	-0.066	-0.090
	(1.865)	(1.020)	(0.964)	(1.034)

Table 7.3: Selected Results from the OLS Estimates of the ORU Model, Detailed Dummy Variables for Institutions, by Year-groups (cont.)

Variables	1999-2001	2002-2004	2005-2007	2008-2009
oth_8	-0.037***	-0.018	-0.075***	0.078**
	(2.809)	(1.306)	(3.856)	(2.007)
oth_9	-0.056	-0.071**	-0.041	0.201***
	(1.631)	(2.254)	(1.281)	(4.759)
oth_10	-0.052***	0.006	-0.051***	0.075***
	(5.328)	(0.501)	(3.224)	(2.952)
oth_11	-0.036***	-0.010	-0.059***	0.034
	(3.566)	(0.887)	(4.555)	(1.278)
oth_12	-0.056***	-0.035***	-0.074***	0.132***
	(5.275)	(2.807)	(4.962)	(4.714)
oth_13	-0.050***	-0.046***	-0.044***	0.130***
	(5.026)	(3.609)	(3.230)	(5.040)
oth_14	-0.073***	-0.071***	-0.139***	0.013
	(6.145)	(5.055)	(7.380)	(0.399)
oth_16	-0.077***	-0.043***	-0.238***	0.071***
	(7.806)	(3.468)	(12.365)	(2.910)
oth_17	-0.063***	-0.068***	-0.171***	-0.008
	(4.475)	(3.814)	(8.021)	(0.219)
oth_18	-0.060***	-0.046***	-0.114***	0.157***
	(4.794)	(3.120)	(7.453)	(5.757)
oth_19	-0.181***	-0.120***	-0.158***	-0.049
	(4.862)	(5.240)	(6.275)	(1.140)
oth_20	-0.072	-0.067*	-0.124***	-0.108*
	(1.283)	(1.728)	(3.686)	(1.759)
Observations	80,597	91,971	105,182	78,937
Adjusted R-squared	0.168	0.157	0.102	0.101

Notes: Absolute values of heteroscedasticity consistent ‘t’-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively.

The results of the year-group analyses reveal a moderate amount of variability in institutional earnings effects in the first three time periods, and varied by a large amount going from the third to fourth time period. This variability in institutional earnings effects can be observed for nearly all institutions. For example, the *go8_4* university’s graduates earned eight percent less than the benchmark *oth_15* university graduates in 1999-2001. This earnings disadvantage widened slightly to around eight percent in 2002-2004, and increased yet again to 11 percent in 2005-2007. However, *go8_4* graduates experienced an earnings advantage of 12 percent relative to *oth_15* graduates in the final time period of 2008-2009. This finding can be generalised to most of the other individual institutions, with few exceptions.

In order to determine whether the estimated institutional earnings effects are statistically persistent over the four time periods, a Spearman test of correlation was conducted for the institutional coefficients sets. The results of this test are presented in Table 7.4.[83] The correlation coefficients in Table 7.4 indicate that statistical associations of a modest scale can be found between institutional earnings effects for the first three time periods, at a magnitude of around 0.5. The institutional earnings effects for the final period are not correlated with those from the first two time periods, but are correlated with those from the third time period. There is, therefore, some observed persistence in the institutional earnings effects across years, although the results from Table 7.4 are indicative of there being an evolving pattern over time.

Table 7.4: Spearman's Correlation Coefficients for the Institutional Earnings Effects Across Time Periods

Time Period	1999-2001	2002-2004	2005-2007	2008-2009
1999-2001	1.0000			
2002-2004	0.5397***	1.0000		
2005-2007	0.5060***	0.5240***	1.0000	
2008-2009	0.1501	0.1397	0.5148***	1.0000

Note: *** denotes significance at the one percent level

7.5.3 ORU Earnings Effects for Individual Institutions

The results from the two preceding sections indicate a fair amount of variability across institutions in terms of earnings effects. Further, the Spearman's correlation coefficients computed for the analyses by year-groups and the institutional earnings effects estimates from Table 7.3 indicate a fair amount of variability across time periods, although it appears that this could reflect the evolving nature of the institutional wage effects. It would therefore be of interest to see if ORU earnings effects differ across individual institutions as well.

Therefore, the ORU model of earnings specified in equation (7-1) was estimated for bachelor's degree graduates from the five ATN institutions, to assess the variability in ORU earnings effects across institutions within this university grouping. The results from these analyses are presented in Table 7.5.

The results in Table 7.5 indicate that ORU earnings effects differ in magnitude across institutions. For instance, bachelor's honours degree graduates from the *atn_3* university, and who are overeducated in a bachelor's pass degree level job, experience an earnings premium of nine percent relative to the correctly matched

[83] A Pearson test of correlation was also conducted, and the correlation coefficients obtained are very similar in terms of magnitude and statistical significance to those from the Spearman test.

bachelor's pass degree graduates from the same university. Honours graduates from the other four ATN institutions, however, have earnings that do not differ statistically from their respective benchmark category of correctly matched bachelor's pass degree graduates. Another example of the institutional differences in ORU earnings effects can be seen from the overeducated honours degree graduates who are working in certificate level jobs. Across the five ATN institutions, the earnings penalty associated with being overeducated for these graduates ranges from ten to 31 percent.

Table 7.5: Selected Results from the ORU Model of Earnings, ATN Institutions

Variables	*atn_1*	*atn _2*	*atn _3*	*atn _4*	*atn _5*
oru_bach_cert	-0.188***	-0.241***	-0.102***	-0.122***	-0.094***
	(7.412)	(22.441)	(6.025)	(6.256)	(8.091)
oru_bach_dip	-0.145***	-0.140***	-0.040**	-0.070***	-0.064***
	(4.462)	(12.010)	(1.974)	(3.419)	(5.297)
oru_hons_cert	-0.102*	-0.150***	-0.181***	-0.306***	-0.109
	(1.917)	(3.165)	(2.609)	(3.664)	(1.148)
oru_hons_dip	-0.049	-0.086*	0.072	0.052	-0.117*
	(0.741)	(1.728)	(1.194)	(0.796)	(1.695)
oru_hons_bach	-0.025	-0.040	0.086***	-0.025	0.040
	(1.400)	(1.592)	(2.610)	(0.710)	(1.224)
Observations	11,176	16,143	10,904	13,333	18,600
Adjusted R-squared	0.113	0.175	0.0924	0.0529	0.119

Notes: Absolute values of heteroscedasticity consistent 't'-statistics are presented in parentheses. *, ** and *** indicate significance at the ten, five and one percent levels, respectively.

To confirm the variability in ORU earnings effects across these institutions, F-tests were conducted for each of the ORU estimates from these analyses. These are presented in Table 7.6.

Table 7.6: F-tests Estimates for ORU Coefficients, ATN Institutions

Variables	$\chi2$	Prob > $\chi2$
*oru_bach_cert****	106.23	0.0000
*oru_bach_dip****	33.22	0.0000
oru_hons_cert	4.65	0.3252
oru_hons_dip	7.39	0.1166
*oru_hons_bach***	13.08	0.0109

Notes: ** and *** denote significance at the five and one percent levels, respectively.

The F-tests estimates in Table 7.6 indicate that three out of the five ORU coefficient sets differed. That is, estimated ORU earnings effects for bachelor's pass degree graduates working in certificate or diploma level jobs, as well as honours degree graduates working in bachelor's pass degree level jobs, differed across the five ATN institutions. Further, Spearman's correlation coefficients were computed for the ORU coefficients for the ATN institutions. These are presented in Table 7.7. The Spearman's correlation coefficients had some values of zero, and in some cases were negative. In most cases, the correlation coefficients were statistically insignificant. This further reflects that ORU earnings effects vary substantially amongst individual institutions, and that institutions do not play a key role in determining earnings outcomes in the labour market.

Table 7.7: Spearman's Correlation Coefficients for the ORU Earnings Effects Across ATN Institutions

Institution	*atn_1*	*atn_2*	*atn_3*	*atn_4*	*atn_5*
atn_1	1.0000				
atn_2	0.8000	1.0000			
atn_3	-0.1000	-0.5000	1.0000		
atn_4	0.0000	0.3000	-0.6000	1.0000	
atn_5	0.8721*	0.8208*	-0.1026	0.3591	1.0000

Note: * denotes significance at the ten percent level

Certainly, the main finding in these sections is that of very small and reasonably variable institutional earnings effects in Australia. At the same time, there appears to be no particular pattern discerned when the various earnings advantages and disadvantages associated with ORU status were linked to institutional prestige. As mentioned earlier in this chapter, the Go8 universities are the highest ranked institutions in Australia, across an array of measures and rankings. However, graduates from these elite universities do not experience a clear advantage in earnings over graduates from other universities (or university groups). Clearly, university prestige is not a main conduit of wage determination in the Australian graduate labour market.

7.6 Conclusion

The analysis of the ORU model of graduates' earnings disaggregated by university groups has revealed a number of findings. Particularly, three main conclusions can be drawn. First, there are generally earnings advantages associated with the acquisition of a higher level qualification, even if it means being classified as overeducated. The ranking by type of university in terms of these earnings advantages varies by qualification, and by the extent of any overeducation with a specific qualification.

Second, within any level of qualification, earnings are lower the greater the extent of any overeducation. These earnings differentials are generally statistically significant. This shows that wages follow jobs and are not exclusively determined by the supply side factors captured by a person's qualifications. Of course, qualifications also matter, as within any type of job, the better qualified earn more. Importantly, this pattern, of earnings being inversely related to the extent of overeducation, holds for each group of universities considered here. In other words, no group of university is able to protect its graduates from the adverse earnings consequences of being overeducated. [84]

Third, there are only relatively minor differences across the groups of universities in the earnings effects in the modal job category that requires a bachelor's pass degree. Greater differences emerge when more atypical jobs characterised by more extensive overeducation are considered, although a number of the earnings effects in these atypical jobs were statistically insignificant. This suggests that the labour market handles 'normal job assignments' routinely (e.g. pays a graduate entry level salary), but a more individualistic approach is applied when dealing with the atypical job assignments, such as the doctoral graduate working in a job that requires only a certificate level qualification. But even with such an individualistic approach in operation, there does not appear to be any advantage to one type of institution over the others. One interpretation of this is that institutional quality is not part of the screening mechanisms that are used in these atypical job assignments.

The estimated ORU impacts on earnings have been shown to differ greatly by the extent of overeducation. One good example would be that of the associate degree graduates, who are penalised by up to 27 percent when they are severely overeducated in a certificate level job, but have earnings that do not differ statistically from the earnings of (correctly matched) workers with bachelor's pass degrees employed in jobs that require a bachelor's pass degree if they are undereducated in a bachelor's level job.

[84] Nevertheless, note that this finding needs to be considered together with the findings in Chapter 3. Graduates from the Go8 and ATN groups were less likely to be overeducated. Thus, institutions do influence overeducation status, but are not able to insulate overeducated graduates from adverse earnings effects.

The estimated ORU impacts differ by university groups as well. For instance, the earnings penalties for diploma holders in a bachelor's degree level job range from four percent for Other universities graduates, to 15 percent for IRU graduates. A number of other trends are observed. With the exception of PhD holders, graduates with other types of degrees all experience earnings penalties if they work in a certificate level job. Hence, for the majority of higher education graduates, it is undesirable to be overeducated to that extent. For graduates working in a diploma level job, having postgraduate or higher qualifications is associated with positive earnings effects. However, in the case of graduate certificate and graduate diploma graduates, these positive earnings effects are rather low, and still reflect the adverse earnings impact of being overeducated.

Securing employment which requires the training of a bachelor's degree is associated with positive earnings impacts. These can go up to a large 21 percent, in the case of masters graduates from the IRU. These findings are largely consistent with the literature on overeducation. Vahey (2000) has a similar spread of the ORU earnings effects, ranging from an earnings disadvantage of 18 percentage points for those who have only some education to an earnings advantage of 15 percentage points for those with a degree. However, given that the present study is focussed on only the higher education labour market, the finding that large penalties and premiums are associated with ORU sends a stark reminder that 'wages follows jobs, and not the individuals'. It is, therefore, not enough to simply obtain higher qualifications, and a graduate must also attempt to ensure that the requirements of the job are matched to the level of qualifications. The finding that the ORU effects differ across university type suggests that the choice of institution plays an important role in determining earnings. However, the results of subsequent analyses reveal a large amount of earnings variability across individual institutions. There is no clear pattern, however, and it is unclear at this stage if it is the institutions who bring their graduates higher wages, or if the type of graduates who typically enrol in those institutions are generally high or low wage earners anyway. The institutional earnings effects were also found to vary across time periods, and estimated ORU effects differ substantially across individual institutions. On the whole, it appears that university groups conceal large amounts of variability in institutional earnings effects, and that institutions do not play a significant role in determining graduate earnings outcomes in the labour market.

Furthermore, the ‘university group’ effects differ for the various levels of qualifications, and no university group comes across as a strong or weak performer on the whole. It might be that each university group has its own comparative advantage, or more plausibly, that the ORU effects differ substantially for each university. In reality, it would be expected that individual institutions have their own strengths and weakness, and the performance of graduates in the labour market would differ across qualifications type and field of study, even within institutions. Thus, for individuals making the decision to engage in higher education, it would be prudent to wisely select a field of study that is in demand (based on the findings of Chapter 3), and then select an institution which has clear advantages in that field of study.

CHAPTER 8

Overeducation in the Australian Graduate Labour Market - What do We Know, and Where do We Go?[85]

8.1 What Do We Know?

The issue of education-job mismatch has attracted considerable attention from academic researchers, policy makers, and individuals alike. Since the beginning of this literature in the 1970s, a number of studies have been devoted to quantifying the extent and impact of educational mismatch in the labour market. In recent years, this issue has become more pertinent due to the expansion of higher education, in Australia and overseas. In Australia, the 'Education Revolution' of the federal Labor Government commenced in 2007, and has been associated with a large expansion in university degree attainment thereon. At the same time, the 'demand driven system' of determining undergraduate places at university commenced in 2012 (Department of Education, Employment and Workplace Relations 2012b). Under this system, undergraduate student places are guaranteed funding. As expected, the number of undergraduate enrolments in Australian universities has increased for the first intake of 2012 (The Sydney Morning Herald 2012).[86] While the longer term impacts of these shifts in education policy remain to be seen, the study of education-job mismatch in the Australian labour market in this thesis will be useful in adding to the debate.

Several issues relating to the central theme of education-job mismatch in the Australian labour market have been explored in this thesis. Chapter 3 examined the incidence and determinants of the education-job mismatch for Australian university graduates, from 1999 to 2009. It has been revealed that there is a high incidence of overeducation, of around 60 percent, in the Australian graduate labour market. Only 39 percent of graduates are correctly matched to their jobs, and less than one percent are undereducated. Further, these figures, obtained using the 'job analysis' approach, are very similar to those obtained using the alternative realised matches approach in Chapter 5. While the incidence of educational mismatch uncovered here is higher

[85] The title of this concluding chapter is adopted, in part, from Hartog's (2000) paper which has been influential in the overeducation literature.

[86] In addition, an article titled 'Unis Lowering the Bar for Top Courses' observed that a number of Australian universities have accepted large proportions of students who do not meet their advertised cut-off university entry scores, into university courses such as law, or biomedicine (The Australian 2012c).

than that found in the overseas literature, it should be borne in mind that the higher incidence is to be expected, due to the focus on the higher educated segment of the labour market. Indeed, another study of the Australian graduate labour market by Kler (2005) reports a similar extent of overeducation.

Furthermore, analysing the incidence of overeducation by year suggests that the high prevalence of overeducated Australian university graduates is not a recent phenomenon. The incidences of overeducation in the Australian graduate labour market are high throughout the period of study, with a slight worsening after the global financial crisis in 2007.

The impacts of educational-job mismatch on graduate earnings have also been assessed. Chapter 4 explored this issue, using the Vahey (2000) model of ORU earnings determination. A number of findings pertaining to the graduate population have been uncovered, using this detailed dummy variable model. First, the undereducated experienced earnings which are statistically insignificant, or mildly positive, relative to the correctly matched bachelor's degree graduates. Second, the overeducated graduates who were employed in lower level certificate or diploma jobs experience substantial earnings penalties. In the case of masters degree graduates who work in certificate level jobs, for example, a substantial earnings penalty of 12 percent was observed. Third, the returns to higher qualifications were positive for those in a bachelor's degree level job, although the marginal returns to the higher qualification decreased rapidly the more extensive the level of overeducation. These findings highlight the tendency for wages to follow jobs, and not qualifications. Higher education policy should thus be more focused on areas of demand or need, rather than a blanket approach to expanding qualification attainment.

The logit models of overeducation have also identified determinants of overeducation in the Australian graduate labour market. The field of study and industry of employment were found to be important in determining overeducation. Graduates from fields of study such as Natural and Physical Science were much more likely to be overeducated compared to Management and Commerce graduates, while graduates in Nursing, or Education, were much more likely to be correctly matched. One issue that arises here relates to the funding structure of university courses in Australia. As mentioned in Chapter 3, there are different ‘bands’ to which courses are allocated, with different levels of subsidies being allocated to each respective band. Courses which fall within the fields of Natural and Physical Science or Agriculture and Environment attract the highest levels of subsidies, but have been revealed to be fields where graduates are most likely to be overeducated (Department of Education, Employment and Workplace Relations 2011a). Certainly, the level of high subsidies in these courses can be argued to have the unwanted effect of encouraging enrolment in courses for which there is insufficient labour market demand.

These have not gone unnoticed in the mainstream media. On the one hand, Australia’s Chief Scientist, Professor Ian Chubb, called for additional government funding to provide scholarships to encourage more studies in science at university (The Australian 2011c). On the other hand, a recent news article in The Australian (2012a) titled “Grads Struggle for Jobs in Science” highlights the bleak employment prospects for science graduates. This article reports that jobs for science graduates are scarce, and that science graduates have difficulty securing employment, even four years after graduation. Another article from The Australian (2012b), titled “Science Boom is a Job Non-Starter”, points to the recent spike in enrolments for undergraduate science courses, by 40 percent between 2008 and 2011. The same article, by Andrew Norton of the Grattan Institute, states that lower proportions of science graduates reported that their degree was required or even important for their jobs, in comparison with health or education graduates. These reports reinforce the findings in this thesis, and emphasise the need to utilise a more targeted approach in linking education policy and labour market demand, or, equivalently, using a more labour market neutral model for funding university places.[87]

A double degree has been found to diminish the chances of being overeducated, probably due to the diversity in career options it offers. Nevertheless, a double degree program has also been found to offer no earnings advantage over single

[87] It is noted that aside from employment outcomes, other indirect (and perhaps, positive) consequences of higher education could arise. This is discussed in a bit more detail in the following section.

degree programs. Thus, prospective students should weigh up these findings against the additional time and monetary investments that are required to complete a double degree. Older graduates, meanwhile, are more likely to be overeducated. However, this is likely to be due to the increased propensity to possess a postgraduate qualification amongst older graduates. When only undergraduates are considered, however, older graduates were found to be less likely to be overeducated. This finding thus favours mature-aged individuals who plan to or are currently undertaking a higher qualification. In other words, mature-aged students are not disadvantaged in the graduate labour market.

Gender, in contrast, did not play a significant role in determining overeducation. While females were more likely to be overeducated than males, the size of the effect was miniscule, at less than one percent. This finding is particularly interesting, as females have a larger representation in the graduate population. Thus, these results suggest that there is no apparent labour market bias against females in the allocation of jobs. Further, the analysis of ORU and the gender wage gap in Chapter 5 indicates that ORU earnings effects do not play a substantial role in explaining the (small) gender wage gap in the graduate labour market. Specifically, the majority of ORU earnings effects do not differ substantially between males and females, and a Blinder-Oaxaca decomposition reveals that ORU earnings effects account for a negligible portion of the gender wage gap. Furthermore, the former finding does not support the job search hypothesis in the Australian graduate labour market, as it runs contrary to the theorised finding of greater ORU penalties being incurred by females under the job search hypothesis.

This finding is reinforced by an alternate set of analyses using the realised matches approach with Census data. The addition of broad occupational controls in the estimating equation reveals greater job mobility across occupations for females compared to males. This, again, invalidates the job search hypothesis for the Australian graduate labour market. As there is greater representation of females in the graduate population, at 60 percent, these estimated ORU earnings effects suggest that the increasing female attainment of university qualifications will not disadvantage females. Nevertheless, analyses by age reveal a larger gender wage gap among older graduates. It is unknown if this can be attributed to a ‘glass ceiling’ effect, or if it is due to the inadequacies of the measure of work experience included in the estimating equation, as highlighted by Rummery (1992). Thus, the collection of detailed work histories will be useful in shedding light on this issue. Nevertheless, the findings of this thesis favour education as a way to close the gender wage gap.

The type of institution attended was found to have modest impacts on the likelihood of overeducation status. The universities were categorised according to their own institutional consortium groupings. Amongst these institutional groups, the Go8 universities stand out as the university group whose member universities consistently perform the best in international university rankings and league tables, which use an array of measures to assess university performance. However, graduates from the elite Go8 universities were found to be eight percentage points more likely to be overeducated, relative to graduates from Other universities. This, however, can likely be attributed to the higher amounts of postgraduates in the research intensive Go8 universities. When considering only undergraduates, Go8 and ATN graduates were seven and eight percentage points, respectively, less likely to be overeducated in comparison to Other university graduates. There are, therefore, differences across institutions in the determination of overeducation status.

The analysis of ORU earnings effects across institution type in Chapter 7, however, reveals that no university group comes across as a strong performer, and the relative performance of graduates from the various university groups differs by qualification type. Further, entering individual dummy variables for each institution into the estimating model reveals large differences in institution earnings effects, of up to around 30 percentage points. There are large differences even within each university group, including the elite Go8 universities, who dominate world university rankings. These factors, presumably, account for the weak aggregate-level institutional effects found in Chapter 4.

Further, across all institution types, penalties associated with overeducation were found, and these increased with the extent of overeducation. This reinforces the finding of Chapter 4 - that wages follows jobs - and the institution attended does not serve as a shield against the adverse labour market consequences of being overeducated. This is particularly true for graduates employed in higher level jobs that require a bachelor's pass degree. Relatively larger differences exist for graduates in certificate or diploma level jobs. On the whole, there appears to be no clear earnings advantage or disadvantage to attending universities from any group, and it is likely that each university has their own strength and differences across faculties or qualification levels.

These findings suggest that university rankings are poor indicators of graduate outcomes. It is acknowledged that there is no compelling reason to expect so, particularly when the measures used to assess university performances frequently relate to research performance.[88] Nevertheless, in the absence of better information, university rankings are a source which prospective students base their enrolment decisions on. At the same time, forming university groups, while ostensibly done to link common interests and focus across institutions, might be simply a branding exercise. Certainly, Australian universities are diverse in their graduates' outcomes. The recent release of the MyUniversity website in early 2012, which contains information on Australian universities, by the federal government may potentially aid in the release of more meaningful information to prospective students (MyUniversity 2012). This website contains information such as graduate outcomes, student satisfaction scores, staff-to-student ratios and qualifications of staff members, for individual institutions and courses. Prospective students may therefore make a more informed decision on which institution to enrol with, based, at the very least, on these indicators. The research in this thesis suggests that the information currently made available should be augmented through the provision of an index of overeducation, which could be quite easily generated. The annual GradStats and GradFiles publications by Graduate Careers Australia, which report on graduate outcomes and trends in the Australian labour market, and which are already in the public domain, will also add value to the MyUniversity website.

A separate issue that is related to the findings for institution type is with the call by the Go8 universities for autonomy in university fee setting. In their 'Submission to

[88] Whether or not research performance has positive effects on teaching quality is, by itself, a contentious topic. For instance, Hattie and Marsh (1996), in a meta-analysis of 28 studies, find no statistical relationship between measures of research performance and teaching quality, while Smeby (1998), drawing on surveys of academics and students, reports strong beliefs in the research-teaching nexus. Barrett and Milbourne (2011) analyse this issue in the Australian context.

the Review of Higher Education Base Funding', the Go8 universities argue that funding gaps of up to 30 percent exist, and that base funding provided by the government is not enough to cover the costs of the universities' core activities (Group of Eight 2011a). Further, it is argued that the funding shortfall will be exacerbated under the new demand-driven system, and that without additional funds being secured under increases in university tuition fees, teaching infrastructure will deteriorate and staff-to-student ratios will inevitably decrease. Given the large amounts of variability across institutions in graduate outcomes found in Chapters 3 and 7, a one-size-fits-all approach in regulating fees might not be ideal in the university sector.

The analysis by tenure groups suggests that the labour market is slow to move graduates into more suitable jobs when they become better qualified. This is reflected in the higher incidences of the overeducated among the groups with higher levels of tenure. Further, the estimated ORU effects across tenure groups lend credence to the screening hypothesis, out of the five labour market frameworks considered. Specifically, the stable earnings effects across tenure groups for graduates in lower level jobs, as well as the declining earnings premiums for the overeducated graduates in bachelor's degree level jobs, suggests that these graduates have been screened and are not getting rewarded for their higher qualification due to their 'lesser' ability. F-tests results for the estimated ORU earnings effects across tenure groups confirm that they are generally statistically the same, reinforcing the screening hypothesis and the point made above, that graduates of 'lesser' ability are getting left behind in their career. Where only graduates with positive levels of tenure are considered, nearly all estimated earnings effects were statistically similar across tenure groups. This once again highlights the perils of assuming that the attainment of a higher education qualification is a guaranteed ticket to greater earnings and success. The observed ORU earnings effects, specifically, that of stable earnings (or even decreasing earnings premiums) across tenure groups, might be indicative of a discerning labour market that looks beyond paper qualifications, and offers increased earnings only to individuals who have distinguished themselves while on-the-job. Thus, it might be prudent to abandon a blind chase for paper qualifications, and instead target areas of need or skill shortages, as stated above.

8.2 Where Do We Go?

A number of limitations exist in the analyses contained in the thesis. As a result, a few issues remained unaddressed, and future research could be directed to the addressing of these issues. These limitations are primarily linked to the unavailability of information in the dataset used. The first relates to the fact that the GDS survey is conducted four months after graduation. Thus, a possible criticism of this study is that the time frame is too short for graduates to have found suitable employment. It can be argued, however, that the time frame is reasonable, given that 70 percent of employed graduates have found long-term employment at that stage. In addition, studies such as Battu, Belfield and Sloane (2000) that have examined issues pertaining to overeducation several years after graduation reveal a high level of persistence in both the incidence and earnings effects. Thus, the findings reported above should have considerable value.

Nevertheless, it would be of interest to extend the findings of this study using the Beyond Graduation Surveys (BGS) collected by Graduate Careers Australia. The Beyond Graduation Surveys follow up with graduates from the GDS three years after graduation. The analysis of ORU trends and effects in the longer-term would add value to the discussion in this thesis. Research using these alternative data will need to be mindful of the select nature of the follow-up surveys: the response rate to the 2010 BGS (which followed up on the 2007 GDS) was 15 percent, and not all institutions participated in the BGS (Carroll and Tani 2011). Further, the findings of this thesis would be well complemented by research which draws on demand-side perspectives of the labour market, such as surveys of employers. These employer-based surveys will give valuable insights into the reasons behind hiring decisions, as well as other issues which will help shed more light on the issue of education-job mismatch and the pathways by which it affects outcomes in the labour market.[89] However, it is recognised that such research would be better done using linked employer-employee datasets, which would be expensive to obtain. An alternative would be to conduct case studies with firms which employ large numbers of graduates, and focus on specific universities or local labour markets.

[89] For example, it would be interesting to know why graduates are hired, even if they are overeducated for the job.

As mentioned earlier in this concluding chapter, non-monetary outcomes of ORU in the graduate labour market are not addressed. However, this is due to data availability, and most studies on ORU express outcomes in monetary terms. Exceptions do exist, such as Fleming and Kler's (2008) study, which also looks at job satisfaction amongst the overeducated. This study found that overeducated workers tend to report lower levels of work satisfaction relative to their non-overeducated peers. Other studies in the economics of happiness literature indicate that the university educated report lower levels of happiness or well-being, compared to their peers with lower levels of education (see, for example, Hickson and Dockery 2008; Dockery 2010). There is thus some evidence to suggest that some externalities associated with (over)education are negative. The inclusion of a question in the GDS and BGS asking respondents to report their state of well-being and job satisfaction would be of use in future research in this area.

There have also been other studies which assess the monetary externalities associated with a higher education degree in Australia (Department of Education, Employment and Workplace Relations 2012a). This report, written by Bruce Chapman and Kiatanantha Lounkaew from the Australian National University, found that the average public benefit from each year of a university degree ranges from \$6,000 to \$10,000.[90] Note, however, that the upper bound of \$10,000 is equivalent to only 60 percent of the average expenditure that goes into a Commonwealth Supported Place at university (Department of Education, Employment and Workplace Relations 2012d). In another study by Andrew Norton, presented at a seminar held by The University of Melbourne's Centre for the Study of Higher Education (and aimed at discussing the results of the Base Funding Review for higher education in Australia), it was found that from a tax revenue perspective, funding of university places should not be open to all fields, as a number of graduates in certain fields of study, such as humanities or creative arts, decreased rather than increased fiscal revenue, compared to the median individual who entered the workforce with a Year 12 education.[91, 92] The results of the studies by Chapman and Lounkaew, as well as Norton, indicate that the benefits associated with the positive externalities of higher education are

[90] The main externality used in the analysis by Chapman and Lounkaew is that of fiscal revenue generated due to increases in the graduates' earnings.
[91] This was observed even for male humanities graduates at the 40th percentile of earnings.
[92] The author is grateful to Andrew Norton for the provision of figures from this research.

insufficient to offset the public costs. Certainly, Norton's findings appear to be in line with those of the present thesis, and advocate the restriction of higher education subsidies to fields in demand rather than all higher degree courses. Note, however, that this view arises on purely monetary grounds. As stated earlier, non-monetary public benefits can and may arise from higher education. While these are beyond the scope of the present thesis, accounting for non-monetary public benefits may prove that subsidising higher education is a worthwhile exercise, even if poorer employment outcomes are experienced by some graduates.

Finally, the use of the Vahey (2000) model in this thesis has shown that this model is useful in the analysis of ORU, particularly in the study of graduate outcomes, where the years of schooling measure is not meaningful. Further, the Vahey (2000) model captures more detail relating to ORU earnings effects, compared to the Verdugo and Verdugo (1989) specification. Where the dataset supports the use of the Vahey (2000) model, it should be utilised, and support the building up of a comparable literature over time.

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Appendix A: Occupation Categories in the Study

No.	Occupation	No.	Occupation
1	Managers and Admin/General	43	Chiropractor/Osteopath
2	Specialist Manager	44	Podiatrist
3	Chemist	45	Medical Imaging Prof.
4	Geologists/Geophysicist	46	Veterinarian
5	Life Scientist	47	Dietician
6	Environment/Agriculture/Science Prof.	48	Natural Therapist
7	Medical Science Prof.	49	Audiologist
8	Other Natural/Physical Science Prof.	50	Other Health Prof.
9	Architect/Landscape	51	Pre-primary School Teacher
10	Quantitative Surveyor	52	Primary School Teacher
11	Cartographer/Surveyor	53	Sec School Teacher
12	Chemical Engineer	54	Spec Ed Teacher
13	Civil Engineer	55	University Lecturer/Tutor
14	Electrical/Electronic Engineer	56	Vocational Education Teacher
15	Mechanical/Production/Plant Engineer	57	Extra-Systemic Teacher
16	Mining Engineer/Metallurgist/Material Surveyor	58	Education Officer/other Education Professional
17	Other Engineer or Related	59	Social/Community Worker
18	Accountants/Auditors	60	Counsellor
19	Sales Specialist	61	Psychologist
20	Marketing Specialist	62	Lawyer/Legal Prof.
21	Advertising Specialist	63	Minister of Religion
22	Market Research Specialist	64	Urban/Regional Planner
23	Technical Sales Representative	65	Economist
24	Computing Professional	66	Interpreter/Translator
25	Personnel Specialist	67	Other Social Prof.
26	Training Officer	68	Visual Arts/Crafts Prof.
27	Librarian/Archivist	69	Photographer
28	Mathematician/Statistician	70	Designer/Illustrator
29	Actuary	71	Journalist/Related Prof.
30	Business Organisations Analyst	72	Author/Related Prof.
31	Policy Analyst	73	Film/TV/Radio/Stage Director
32	Medical Record Administrator	74	Musician/Composer/Related Prof.
33	Other Business/IT Prof.	75	Actor/Dancer/Related Prof.
34	General Medical Practitioner	76	Media Presenter/Announcer/Commentator
35	Specialist Medical Practitioner	77	Air/Sea Transport Prof.
36	Registered Nurse	78	Occupational Safety Prof.
37	Dental Practitioner	79	Recreation Officer
38	Pharmacist	80	Other Prof.
39	Occupational/Recreation Therapist	81	Medical Technical Officer
40	Optometrist	82	Science Technical Officer
41	Physiotherapist	83	Electrical/Electronic Technician
42	Speech Pathologist	84	Civil Engineering Technician

Appendix A: Occupation Categories in the Study (cont.)

No.	Occupation
85	Mechanical Technician
86	Building/Architectural Technician
87	Other Technician
88	Admin Associate Prof.
89	Finance Associate Prof.
90	Biz/Admin Associate Prof.
91	Farm Manager
92	Managing Supervisor/Sales/Service
93	Police
94	Ambulance Officer
95	Fire Fighter/Defence
96	Other Health/Welfare Associate Prof.
97	Other Tech/ Associate Prof.
98	Tradesperson
99	Advanced Clerical/Service Worker
100	Intermediate/Elementary Clerical Worker
101	Intermediate /Elementary Sales Worker
102	Intermediate /Elementary Service Worker
103	Production/Transport/Labourer

Appendix B: Occupational Categories and Required Level of Qualifications

Requires Certificates	Requires Diplomas	Requires Bachelor's Pass Degree
Civil Eng Tech	Other Technician Associate Professional	Medical Imaging Professional
Tradesperson	Building or Architectural Technician	Secondary School Teacher
Intermediate or Elementary Service Worker	Business or Administrative Associate Professional	Architect or Landscape Professional
Mechanical Engineering Technician	Medical Technician or Technical Officer	Speech Pathologist
Intermediate or Elementary Sales Worker	Police	Occupational or Recreation Therapist
Intermediate or Elementary Clerical Worker	Finance Associate Professional	Audiologist
Advanced Clerical or Service Worker	Other Health Welfare Associate Professional	Special Education Teacher
Fire Fighter or Defence Worker	Managing or Sales or Service Supervisor	Training Officer
Farm Manager	Administrative Associate Professional	Accountants or Auditors
Production or Transport Labourer	Science Technician or Technician Officer	Electrical or Electronic Engineer
Other Technician	Air or Sea Transport Professional	Specialist Medical Practitioner
Electrical or Electronic Engineering Technician	Ambulance Officer	Occupational Safety Professional
		Policy Analyst
		Urban or Regional Planner
		Media Presenter or Announcer or Commentator
		Quantity Surveyor
		Journalist or Related Professional
		Medical Science Professional
		Education Officer or other Education Professional
		Designer or Illustrator
		Extra-Systemic Teacher
		Medical Record Administrator
		Life Scientists
		Mechanical or Production or Plant Engineer
		Computing Professional
		Primary School Teacher
		Specialist Managers
		Pre-primary School Teacher
		Mathematician or Statistician or Actuary
		Other Health Professional
		Pharmacist
		Psychologist

Appendix B: Occupational Categories and Required Level of Qualifications (cont.)

Requires Certificates	Requires Diplomas	Requires Bachelor's Pass Degree
		Photographer
		Librarian or Archivist
		Other Professional
		Actor or Dancer or Related Professional
		Natural Therapist
		Environment or Agriculture or Science Professional
		Musician or Composer or Related Professional
		Interpreter or Translator
		Podiatrist
		General Medical Practitioner
		Personnel Specialist
		Vocational Education Teacher
		Other Business or IT Professional
		Other Engineer or Related
		Physiotherapist
		Recreation Officer
		Registered Nurse
		Author or Related Professional
		Counsellor
		Visual Arts or Crafts Professional
		Civil Engineer
		Chemist
		Cartographer or Surveyor
		Geologist or Geophysicist
		Dietician
		Minister of Religion
		University Lecturer or Tutor
		Mining Engineer or Metallurgist or Material Specialist
		Sales or Marketing or Advertising Specialist
		Other Social Professional
		Economist
		Optometrist
		Managers and Administrative or General
		Lawyer or Legal Professional
		Business Organisations Analyst
		Social or Community Worker

Appendix B: Occupational Categories and Required Level of Qualifications (cont.)

Requires Certificates	Requires Diplomas	Requires Bachelor's Pass Degree
		Dental Practitioner
		Veterinarian
		Other Natural or Physical Science Professional
		Chiropractor or Osteopath
		Film or TV or Radio or Stage Director
		Chemical Engineer

Appendix C: Australian Universities and Groups

Group of Eight	The University of Adelaide The Australian National University The University of Melbourne Monash University The University of New South Wales The University of Queensland The University of Sydney The University of Western Australia
Australian Technology Network	Curtin University University of South Australia RMIT University University of Technology Sydney Queensland University of Technology
Innovative Research Universities Australia	Flinders University Griffith University La Trobe University Murdoch University University of Newcastle James Cook University Charles Darwin University
Other Universities	Australian Catholic University Bond University Central Queensland University Charles Sturt University Deakin University Edith Cowan University Macquarie University Southern Cross University Swinburne University of Technology The University of New England The University of Newcastle The University of Notre Dame Australia University of Ballarat University of Canberra University of Southern Queensland University of Tasmania University of the Sunshine Coast University of Western Sydney University of Wollongong Victoria University

Appendix D

To Whom It May Concern,

I, Ian W. Li, contributed 80 to 90 percent to each component of the research reported in the following papers, which have been accepted for publication in academic journals.

Li, I.W. and Miller, P.W. (forthcoming), "Overeducation in the Australian Graduate Labour Market: An Application of the Vahey Model", in *Education Economics*

Li, I.W. and Miller, P.W. (forthcoming), "Gender Discrimination in the Australian Graduate Labour Market", in *The Australian Journal of Labour Economics*

Li, I.W. and Miller, P.W. (forthcoming), "The Absorption of Recent Graduates in the Australian Labour Market: Variations by University Attended and Field of Study", in *The Australian Economic Review*

The original material for these papers stemmed from Ian Li's thesis research, where Ian's contribution was 90 percent or more. In the crafting of the papers for journal submission, the co-author Paul Miller contributed more, and the overall contribution from Ian Li to the papers would thus fall within 80 to 90 percent.

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Ian W. Li

I, as a Co-Author, endorse that this level of contribution by the candidate indicated above is appropriate.

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Paul W. Miller