Over-education in the Labour Market: Evidence from Australia

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ABSTRACT

This thesis follows a three essay approach to examine the impact of worker 'skill matching' on earnings and labour mobility. The analyses are at the individual level based on micro-panel-data in the Australian labour market.

The first essay explores the determinants of over-education and its impact on earnings in the Australian labour market by using both pooled and panel features of the data. Measurement error and unobserved heterogeneity are addressed. Alternative measures of over-education are evaluated. The trade-off between education and other types of human capital suggests that an excess of education may compensate for the other shortages in human capital, such as experience and the length of tenure. These relationships and the effects of over-education on earnings via qualification and occupation are examined.

The second essay extends the analyses in essay one to investigate the extent of matching between education and occupation and the resulting earnings effects on immigrants in Australia. Correlated random effects (CRE) logit results suggest that both English speaking background (ESB) and Non-English speaking background (NESB) immigrants have high rates of over-education. Age at migration and the year of arrival have significant effects on the incidence of over-education among NESB immigrants, but show no effects among ESB immigrants. The effects of age at migration, the year of arrival, and the country of qualification on earnings are examined based on longitudinal analyses.

The third essay addresses worker mobility resulting from skill under-utilisation in a dynamic setting. Wooldridge's (2005) Conditional Maximum Likelihood (CML) estimator is applied to control for the initial conditions problems. Mundlak's (1978) correction is used to solve the correlation between the explanatory variables and the error terms. These analyses are extended to examine the theory of career mobility among job mismatched workers from the perspective of both occupation moblity and wage growth, and also whether over-education is temporary or persistent.

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ABBREVIATIONS

ABS	Australian Bureau of Statistics
ANZSCO	Australia and New Zealand Standard Classification of Occupations
AQF	Australian Qualifications Framework
AUSEI06	Australian Socioeconomic Index 2006
CPS	Current Population Surveys in U.S.
DIMIA	Australian Department of Immigration, Multicultural and Indigenous Affairs
DOT	the Dictionary of Occupational Titles
ECHP	the European Community Household Panel
ESB	English speaking background
ESS	Earnings Structure Survey in Spain
ETS	the Australian Bureau of Statistics Education and Training Survey
GLS	Generalised Least Squares
GSOEP	German Socio-Economic Panel
HILDA	the Household, Income and Labour Dynamics in Australia Survey
JA	Job Analysis
LSIA	the Longitudinal Survey of Immigrants to Australia
NESB	Non-English speaking background
NLC	the Negotiating the Life Course (NLC) survey in Australia
OLS	Ordinary Least Squares
ORU	Over-education, Required education and Under-education
PSID	Panel Study of Income Dynamics
QLFS	the Quarterly Labour Force Survey (UK)
RM	Realised Match
SOCS	the Standard Occupational Classification System in the United Kingdom (UK)
SR	Self-Report
WA	Worker Self-Assessment
WES	Workplace and Employee Survey
YSM	Years Since Migration

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1. Introduction

This doctoral thesis consists of three self-contained essays on over-education.

Over-education is defined as the extent to which someone's actual education exceeds the educational requirement to perform his or her job. The earliest work on over-education (Freeman, 1976) was from a macro-economic perspective, and it concerned the excess of schooling attained by American youth in terms of labour market demand. Since then, a growing number of studies have examined the impact of over-education on earnings at an individual level; and the great majority of previous research has been based on cross-sectional data (Duncan & Hoffman, 1981; J. Hartog & Oosterbeek, 1988; Rumberger, 1987; Sicherman, 1991). While recent studies have incorporated panel analyses (Bauer (2001) and Tsai (2010)) of over-education and over-skilling (Mavromaras and McGuinness, 2012; Kostas Mavromaras, McGuinness, O'Leary, Sloane, & Fok, 2010a; Kostas Mavromaras, Sloane, & Wei, 2012; Mavromaras, Mahuteau, Sloane & Wei, 2013), there are a number of questions that remain.

Chevalier (2003), using cross-sectional data from the UK graduate market, distinguished over-education by dividing it into two categories, and evaluated the extent of workers' satisfaction with the match between education and work. One category used was 'apparent over-education', which was defined as a status where a graduate is in a non-graduate occupation but is satisfied with the match between his or her qualification and job. The second category was 'genuine over-education', which was defined as a status where the graduate is in a non-graduate occupation but is not satisfied with the match. Chevalier found that 'genuine over-education' results in a larger pay penalty (22%-26%) than does 'apparent over-education' (5%-11%).

Not only does over-education have a negative effect on an individual's earnings; it also reduces company revenue and it impedes potential economic growth (Séamus McGuinness, 2006; Tsang, Rumberger, & Levin, 1991).

For example, from the employees' perspective, over-education represents an inefficient allocation of human capital resources. If over-education produces psychological strain for over-educated workers, this, in turn, affects worker attitudes and behaviour, which indirectly reduces their productivity. This results in over-educated workers encountering larger wage penalties compared to their counterparts with the same educational attainments in a well-matched job (Tsang & Levin, 1985). From the employers' perspective, over-education involves a substantial cost due to reduced productivity by dis-satisfied workers, quit behaviour and hiring costs. With respect to the overall economy, a government has a considerable amount of expenditure in the subsidisation of a national education system. Over-education may reduce national productivity because of inefficiencies in the allocation of human resources; this may impact negatively on economic growth.

The recent changes to the structure of the economy and, in particular, technological advances demand new skills in the workplace. Higher education is associated with higher income. This significantly increases tertiary participation rates. Maani (1997) has shown that investing in post-compulsory education is associated with higher lifetime income levels and is worthwhile. However, if workers do not fully utilise their acquired skills, they earn less than workers who have the same level of years of education but work in matched jobs. This conclusion was drawn by Sicherman (1991) based on a cross-sectional study.

Based on cross-sectional data, Sicherman (1991) summarised the following stylised facts:

> *Over-educated workers earn higher wages than their adequately educated co-workers (holding other characteristics constant) but lower wages than workers with similar levels of schooling who work in jobs that demand the level of schooling they have acquired.*
>
> *Under-educated workers get lower wages than their adequately educated co-workers (i.e., those that have the required qualifications, and higher levels of schooling), but higher wages than workers with the same level of schooling who hold jobs which*

require their obtained schooling.

This thesis follows a three essay approach to examine the impact of over-education on earnings and labour mobility. The analyses are at the individual level based on micro-panel-data in the Australian labour market. The static and dynamic outcomes of over-education are examined. The key questions for this thesis are at the level of the individual and they are based on micro-data. They are: firstly to explore whether and to what extent unobserved individual heterogeneity explains earnings differential between over-educated and adequately educated workers among the male labour force in Australia; secondly to investigate the determinants of over-education among immigrants, and whether, and to what extent, over-education impacts immigrants' assimilation effects; and thirdly to evaluate dynamic mobility of education mismatch and skill mismatch.

The study considers the examination of the following questions in three essays:

Essay one: How is over-education defined? What is the extent of over-education and it's earning effect in the Australian labour market? Does unobserved heterogeneity have an impact on earnings?

Essay two: To what extent are immigrants and natives over-educated? Does the incidence of over-education among immigrants vary by country of origin, English proficiency, age on arrival and year of arrival? Are there impacts of over-education on earnings which differ between sub-groups based on country of origin and English proficiency? Are there impacts of over-education on earnings which differ between sub-groups based on age at arrival, year of arrival and country of qualification?

Essay three: To what extent do mismatches influence a worker's decision to quit (voluntary job leaving)? To what extent do mismatches influence workers' upward occupational mobility? To what extent do mismatches account for workers' upward wage growth? Does career mobility theory explain the education mismatch and skill mismatch in the Australian labour market? Are these mismatches temporary or persistent?

This study explores these questions using a sample of full-time male workers aged 23 to 64 years from the Household, Income and Labour Dynamics in Australia (HILDA)[1] Survey over the period 2001 to 2009. The HILDA Survey is a longitudinal panel data, with annual follow-up of individuals. It overcomes the weakness in cross-sectional data by addressing potential individual heterogeneity in empirical analyses. Specifically, when exploring the effects of over-education on earnings, the application of panel data could identify the extent of the causal effect of unobserved heterogeneity on earnings. In addition, in order to examine the effects of over-education and the dynamic effects of job mismatching on immigrant assimilation, the variables are required to change over time. The HILDA Survey is used in this study to reflect variation over time.

Longitudinal analyses allow controlling for unobserved heterogeneity based on panel techniques. This study, which is based on the nine years of longitudinal data, applies longitudinal analyses (fixed effects, random effects, correlated random effects and dynamic models), and it provides new evidence on the outcomes of over-education in the Australian labour market. It focuses on the performance of over-educated workers, and extends the existing literature in the methodology and the questions addressed using Australian data.

The thesis is structured as follows. Following this introduction, the first essay (Essay one) explores the determinants of over-education and its impacts on earnings in the Australian labour market by using both pooled and panel features of the data. Both measurement error and unobserved heterogeneity are addressed. Alternative measures of over-education are evaluated and the cross-wave mode is used to define over-education due to its advantages. The trade-off between education and other types of human capital suggests that an excess of education may compensate for the other shortages in human capital,

[1] "This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to either FaHCSIA or the Melbourne Institute." Detailed information about the HILDA Survey is , for example, available in Wooden and Watson (2007).

such as; experience, ability, on-the-job training and length of tenure. These relationships are examined. In addition, the effects of over-education on earnings via qualification and occupation are examined.

A growing number of international studies have examined the effects of over-education on earnings using panel data (Bauer (2001) and Tsai (2010)). The results from Essay one are in line with the findings of Bauer (2002) and Tsai (2010). Time-constant unobserved heterogeneity plays an important role in the return of over-education. Once this is controlled for, no earnings penalty is found for over-educated workers. The study also examined the over-education earnings effects in the levels of qualification and occupation and found that educational mismatch is serious among workers with lower levels of qualification and among those who are employed at lower levels of occupation.

The second essay (Essay two) extends the analyses in essay one to investigate the extent of matching between education and occupation and the resulting earnings effects on immigrants in Australia. Correlated random effects (CRE) logit results suggest that both English speaking background (ESB) and Non-English speaking background (NESB) immigrants have high incidence rates of over-education. Age at migration and year of arrival have significant effects on the incidence of over-education among NESB immigrants, but are found to show no effects among ESB immigrants. Age at migration, year of arrival, country of qualification and effects on earnings are examined based on longitudinal analyses.

Essay two extends Green, Kler and Leeves' (2007) work and it contributes to the Australian literature as follows: I extend the analysis to a different set of panel data; this covers 9 waves and a wide range of immigrants in comparison with short panel data (3 waves, two cohorts) and recently arrived immigrants (arrived after 1993) based on LSIA in Green, et al. (2007). I employ a correlated random effects (CRE) logit model to examine the incidence of over-education by focusing on the effects from years since migration, age at migration and year of arrival. I also employ a panel fixed effects (FE) model to examine the effects of over-education on earnings from years since migration and transferability of human capital by country of origin, age on arrival, year of arrival

and country of qualification, respectively. The latter aspect of my study on the effects of transferability of human capital on over-education and earnings and the panel feature of the analysis extend the international literature.

Because immigrants may have additional unobserved heterogeneity, when I examine the incidence of over-education among immigrants, I apply a correlated random effects (CRE) logit model with Mundlak (1978) correction to account for endogeneity. I also employ a random effects (RE) logit model as a benchmark to examine the effect due to heterogeneity. Results show that endogeneity should not be ignored when examining the determinants of over-education among immigrants.

The third essay (Essay three) addresses worker mobility resulting from skill under-utilisation in a dynamic setting. Wooldridge's (2005) Conditional Maximum Likelihood (CML) estimator is applied to control for the initial conditions problems. Mundlak's (1978) correction is used to solve the correlation between explanatory variables and error terms. These analyses are extended to examine the theory of career mobility among job mismatched workers from the perspective of both occupation moblity and wage growth, and also whether over-education is temporary or persistence.

Essay three is a dynamic study that extends the Australian literature as follows. In the international literature, Büchel and Mertens (2004) and Rubb (2006) examined career mobility theory from the perspectives of both upward occupational mobility and upward wage growth. This study examines career mobility theory from these two perspectives in the Australian labour market based on longitudinal data. It is the first study to examine career mobility theory directly in Australia. Consideration of over-education and over-skilling are also included in this study. The results of the study address the issue of heterogeneity and extend Linsley (2005a), Mavromaras, Sloane, & Wei, (2012) and Mavromaras, Mahuteau, Sloane & Wei, (2013) by examining career mobility theory.

Finally, the conclusions of the research findings are provided, followed by a complete list of references.

2. Essay One:

The Incidence of Over-education and its Earnings Effects

Abstract

Based on the HILDA Survey for years 2001 to 2009, this study explores the determinants of over-education and its impact on earnings in the Australian labour market using both pooled and panel data methods. Both measurement error and unobserved heterogeneity are addressed in this study.

Firstly, this essay evaluates four measures to define the required education to perform a job. Using the cross wave Mode measure, based on nine years of longitudinal HILDA data, after two steps sample selection correction, the incidence rate of over-education in Australia is found to be 29 per cent among full-time male workers aged between 23 and 64 years.

Secondly, unobserved heterogeneity is addressed, and its role is examined by comparisons of the estimator from both pooled OLS and panel fixed effects regression. Examination of the impact of education mismatch on earnings shows that unobserved heterogeneity plays an important role. Pooled OLS results are consistent with Sicherman's (1991) stylised facts. The returns to years of required education, over-education and under-education are 5.2 per cent, 4.3 per cent and -3.7 per cent respectively. Once unobserved heterogeneity (ability, motivation, etc.) is accounted for, the magnitude of the effects of required education, over-education and under-education declines and the effects become insignificant.

Moreover, pooled OLS estimation shows that younger workers are more likely to be over-educated due to lack of work experience. There is also a robust substitution relationship found between over-education and tenure in current occupation. However, these effects are not confirmed in a panel fixed effects regression. A complementary relationship is found between over-education and tenure in current employment for both pooled OLS and panel fixed effect regression. The education mismatch effect is serious among workers who have a low level of qualifications or are employed in a low level occupation.

Keywords: Over-education; earnings; fixed effects; qualification; occupation

2.1 Introduction

When workers' formal education is not fully utilised in their occupations, this under-utilisation is referred to as 'over-education', 'surplus schooling' or 'over-qualification'. In contrast, in instances in which workers work in employment positions requiring higher levels of education than those of their education attainment, 'under-education' occurs. 'Over-education' is a topic of international concern and numerous 'over-education' studies have been conducted in North America, Europe, and Australia.

There are two concerns involved in these over-education studies. One is the measurement error occurring in the evaluation of the required years of education to meet the requirements of an employment position; the other is individual unobserved heterogeneity which could bias the results upwards or downwards (Peter J Sloane, 2003).

When evaluating the educational qualifications necessary to meet the requirements of an employment position, avoiding or lessening measurement error has been an important issue. The validity and credibility of empirical results decrease with increasing measurement error. For example, years of over-education are defined as years of actual educational attainment minus the years of required education to do a job. Thus, if the years of required education are overstated, the incidence of over-education is downwardly biased, in that the truly over-educated workers may not be seen as over-educated due to upward bias in measuring required education.

Most of the previous literature is based on cross-sectional data, which assumes individuals are homogeneous, and leads to a significant earnings differential between matched and mismatched workers. Individuals' unobserved heterogeneity, such as variation in personal ability or the quality of education, cannot be examined by these cross-sectional studies; therefore, the results of cross-sectional analysis can potentially bias the effects of over-education.

A worker with insufficient personal ability or 'poor' quality of education might require

further education to perform the same job as a matched colleague. Thus the substitution between the components of human capital would overestimate the impacts of over-education. Therefore, a conclusion cannot be drawn as to whether a worker with surplus schooling required for a job is over-educated, or whether he or she has insufficient ability. Also, inappropriately assignment to different types of employment may classify someone inappropriately as being over-educated, since the qualification may not be fully transferable between different types of occupation. Thus, even though a worker may have more years of education than are required to perform his or her job, he or she may not be over-qualified for his or her job. Thus, if this aspect is ignored, regression results would overestimate the impact of over-education.

The individual's unobserved ability, motivation, or work efforts, would influence earnings, and also be correlated with observed education and skills. This problem could not be solved by cross-sectional data which only observes individuals at one point in time. Nonetheless, this problem of unobserved heterogeneity could be solved by panel data that follows individuals over time (Kostas Mavromaras & McGuinness, 2007).

Based on the HILDA Survey, this study provides a comprehensive analysis that explores the determinants of over-education and its impacts on earnings in the Australian labour market using both pooled and panel data methods.

As discussed previously, both measurement error and unobserved heterogeneity are addressed in this study. Firstly, I discuss and examine three empirical measures (cross-wave Mode and two versions of mean plus standard deviation) and one objective measure (Job Analysis). By doing so, I identify the cross-wave Mode as a relatively good measure to define 'over-education' that can reduce bias due to measurement error when I investigate the extent and effects of over-education on earnings. Secondly, I examine whether the over-education model is affected by sample selection bias using panel data. A double-probit selection model is applied to examine the incidence of over-education. Thirdly, I discuss alternative theories of over-education and their impact on earnings. I examine the effects of over-education on earnings using both pooled and panel techniques. The comparison of results from a pooled OLS and the panel fixed effects models reveals

whether unobserved heterogeneity affects the examination of the earnings of over-education.

This study extends the literature in three ways. (1) It evaluates the four conventional methods to measure over-education. The analysis shows that the incidence of over-education is influenced by which method is used in HILDA, and how belonging to the over-educated category is related to the choice of measurement variable; (2) it addresses the sample selection issue by applying the double probit model to estimate the incidence of over-education; (3) it studies the return to over-education and its impact on earnings through experience, tenure, qualification and occupations after controlling for unobserved heterogeneity.

This essay is structured as follows. It consists of seven sections. Section 2.2 covers measurement issues. Section 2.3 provides a brief overview of the literature. A discussion of data and variables is provided in Section 2.4. Sections 2.5 and 2.6 describe the methodology and the empirical results for incidence of over-education and impacts of over-education on earnings, respectively. The essay ends with a summary.

2.2 Measures of over-education

In the literature, there are three main measures that define required education in order to classify workers as being over-educated or not. They are Job Analysis (JA), Self-Report (SR) or Worker Self-Assessment (WA), and Realised Match (RM). Each measure has its own advantages and drawbacks.

The objective measure of Job Analysis (JA) is a systematic evaluation by professional job analysts who specify the level and type of education required based on grading the occupation; this is derived from information about respondents' occupations. For example, the *Dictionary of Occupational Titles* (DOT) (U.S. Department of Labour 1965) developed by the United States (U.S.) Employment Service, contains detailed descriptions of all occupations in the U.S. economy and information on a number of

occupational characteristics. Rumberger (1987) used DOT information in an over-education study (Rumberger, 1987). Such formal documents are also found for other countries, such as the Standard Occupational Classification System (SOCS) in the United Kingdom (UK), and the Australian and New Zealand Standard Classification of Occupation (ANZSCO) in Australia. In a number of studies the ANZSCO is referred to for defining the required education (Chiswick and Miller, 2006; Kler, 2007; Green, Kler and Leeves, 2007).

These documents include explicit definitions and comprehensive information generated by the professional job analysts on the qualifications required to undertake an employment position. The extent of substitution of various types of education can be exhibited by analysing the technology of the job and the type of activities to be performed (Joop Hartog, 2000).

Conceptually, JA is the most attractive measure to be found in the literature because it presents the core concept of over-education in which over-education is defined as under-utilisation of skills (Joop Hartog, 2000).

However, JA fails to account for the educational variations in jobs within occupations because of job aggregation, which is where the job analyst considers that the same job title requires the same educational requirement. The heterogeneity error is generated by aggregating error, where the heterogeneity within an occupation is ignored (Halaby, 1994). In addition, due to the large amount of expenditure required for updating codes, existing codes may lack depth and become out of date, which will bias the criteria of the required qualification. Furthermore, both the reliability and validity of JA are questioned by Verdugo and Verdugo (1992). They found that, based on the DOT Handbook, a single job analyst visits the employment site and discusses requirements with the employer. Thus, errors of judgment are generated by occupational analysts. Hartog (2000) pointed to the merits of available JA due to potential objectivity and standardisation, rather than WA (worker self-assessment) which could also reflect employee subjectivity. However, JA measurement also depends on the level of aggregation, the time lag in observations, and the care and precision of the measurement procedure. Thus, although JA is a general

method that is widely used in the literature, caution should be exercised when using this method.

Self-Report (SR) or Worker Self-Assessment (WA) is a subjective measure, which evaluates over-education by asking respondents the required educational level for their jobs. In general there are two types of question. The first type concerns the required level to do the job, for example "What kind of education does a person need in order to perform your job? " (Alba-Ramírez, 1993). The second type is based on the question of the required education level to get the job, for example "How much formal education do you require to get a job like yours?" (Duncan & Hoffman, 1981; Rumberger, 1987; Sicherman, 1991). These two types of questions reflect different standards. The required education to do the job is in line with the explanation of concept of over-education by considering skill utilisation to do the job (Green et al., 1999); therefore, this measure performs better than does the required education to get a job. The required level to get the job only considers the hiring standard below which educational level an employer will not employ job applicants (Dieter. Verhaest & Omey, 2004). Because this method measures required level of education based on the answers of workers, on the one hand, it "has the advantage of drawing on all local, up-to-date information. The assessment deals, in principle, precisely with the respondent's job, not with any kind of aggregate"; on the other hand, an SR measure could be biased due to classification error (Dieter Verhaest & Omey, 2006a), where workers might overstate job requirements or merely recite hiring practice standards (Joop Hartog, 2000; Kler, 2005).

Realised Match (RM) includes the Mean measure and the Modal Education (Mode) measure. It is referred to as the empirical or the statistical measure of over-education. It was first introduced by Verdugo and Verdugo (1989) who considered that a worker is over-educated if his or her education is more than one standard deviation above the average for his or her 3-digit occupation code (in the 1980 census occupation). Conversely, a worker is under-educated if his or her education is less than one standard deviation below the average for his or her 1980 census occupation code. The advantage of this measure is that the mean is derived directly from the existing data, so it is always available. However, this measure also has its drawbacks. For example, RM assesses only frictional

mismatches, but fails to consider structural sources of over- and under-education (Kiker, Santos, & De Oliveira, 1997; Dieter Verhaest & Omey, 2006b). Kiker, et al. (1997) criticised this measure as being more sensitive to technological change and changes in workplace organisation than others. The measure is likely to be misinformed by the development of insufficient schooling over time. "One standard deviation away from the mean" implies symmetry between over-education and under-education, which is not rational. And the cut-off point is arbitrary. Moreover, as with JA, the mean method ignores job variations within occupations (Halaby, 1994).

The other Realised Match (RM) measure is the Modal method (Mode), which was proposed by Kiker, et al.(1997). The Mode measure estimates the level of required education by computing the amount of education that most commonly occurs within an occupational category (Stephen Rubb, 2003). The Mode measure proves more accurate than the Mean method because it considers the asymmetry between over-education and under-education, and is less sensitive to outliers or technological change. Kiker, Santos and Oliveira (1997) proved that the Mode criterion is preferred to Verdugo and Verdugo's Mean criterion by using a very simple example. They found that Verdugo and Verdugo's Mean criterion was changing gradually and that it could produce classification errors before correcting itself, but that the Mode changes more freely.

Verhaest and Omey (2010) supported the theory that measuring over-education is sensitive to the determinants of over-education, and that applying different measures of over-education would produce different results. Robst (1994) examined more than 200 individuals who were over-educated by one measure but under-educated by another measure, indicating that results may be seriously biased by measurement error. However, in other studies, scholars adopting different measures of over-education have found that over-education has similar effects on earnings (Cohn & Khan, 1995; Rumberger, 1987; Sicherman, 1991).

Furthermore, Hartog (2000) stated that although the returns to over-education (or under-education) are affected by the different measurements of required education, general conclusions are not sensitive to the application of different measures. For example, the

result that the return to over-education is lower than the return to required education is not sensitive to the different measures.

In the first part of this essay, the above measurements are evaluated, with the exception of Self-Report (SR) and Worker Self-Assessment (WA). This is due to lack of related information in the HILDA data.

2.3 An overview of the empirical literature

Alternative measurements have been applied in numerous 'over-education' studies based on cross-sectional analyses. Although the extent of over-education differs across countries, the effects of over-education on earnings are in line with stylised facts (Sicherman, 1991) based on cross-sectional analyses.

Sicherman (1991) summarised the following stylised facts: Over-educated workers earn higher wages than their adequately educated co-workers (holding other characteristics constant) but lower wages than workers with similar levels of schooling who work in jobs that demand the level of schooling they have acquired. Under-educated workers receive lower wages than their adequately educated co-workers (i.e., those that have the required, and higher, levels of schooling), but higher wages than workers with the same level of schooling who hold jobs which require their obtained level of schooling.

In the U.S., the incidence of over-education ranges from 11%, using RM (Verdugo & Verdugo, 1989), to over 50% using SR and JA (Tsang et al., 1991).

In Europe, Daly, Büchel, and Duncan (2000) used the 1984 survey of the German Socio-Economic Panel to find that approximately 14% of the population were over-educated. In the UK, Sloane, Battu, and Seaman(1999) reported that around 30% of workers had higher levels of educational attainment than was required in their occupations.

In Australia, based on the Negotiating the Life Course Survey, and a self-report (SR)

measure of required education, Linsley (2005b) found that 27% of individuals were over-educated and that younger workers, with pre-school aged children, working for large organisations, and with fewer years of tenure are more likely to be over-educated than older workers with a longer history of employment. Using data from the 1996 Census of Population and Housing and the Realised Match (RM) measure, Voon and Miller (2005) reported that about 16% (14%) of male (female) full-time workers aged 20-64 were over-educated. The returns to years of actual education, required education, over-education and under-education, for men and (women) respectively were 9.2% (8.0%), 18.2% (14.9%), 6.6% (5.3%) and -3.2% (-3.4%).

Groot and Maassen van den Brink (2000) summarised 25 studies of over-education by using a meta-analysis and found that the un-weighted average of the rates of return to required education, over-education, and under-education, were 7.8%, 3.0% and -1.5% respectively. The incidence of skill mismatch and the rate of return to education they obtained from five OLS estimations after addressing variation between studies due to sample composition, year of data sampling, inter-country variation, etc. are referred to as the 'true' rate of skill mismatch, and the 'true' rate of return. They reported that the 'true' or overall incidence of over-education in the labour market appeared to be about 26%; and that the rate had not changed significantly over the past decades; that the 'true' rate of return to a year of education required was 7.9% in the 1970s and 1980s increasing to about 12% in the 1990s; that the 'true' rate of return to a year of over-education was 2.6%, and that the rate of return to a year of under-education was -4.9%.

However, these results were challenged by Rubb (2003) who re-analysed over-education in the labour market using similar meta-analysis. Rubb (2003) argued that Groot and Maassen van den Brink's analyses were problematic because in their meta-analysis they did not separate the standard Over-education, Required education and Under-education (ORU) earning model studies (Duncan and Hoffman, (1981) from the earning model with dummy variables studies (Verdugo & Verdugo, (1989). These two earnings models control for different things, and mixed studies under these two models would potentially give rise to a downward bias in the return to over-education and an upward bias of the return to under-education. Rubb analysed 85 cases referring to ORU models. As expected,

the rates of return to a year of education, over-education and under-education were found to be 9.6%, 5.2% and -4.8% respectively (S. Rubb, 2003).

Prior literature on 'over-education' has consistently concluded that the return to over-education is lower (by about half to two-thirds) than the return to required education, but that there is a positive return in earnings (Cohn, 1992; Groot, 1996; Rumberger, 1987; Sicherman, 1991). The returns to years of required education are higher than the returns to years of actual education; the returns to years of under-education are negative, but the absolute values are smaller than the returns to years of over-education (Joop Hartog, 2000). This additional schooling beyond that required for the job is not always rewarded (Rumberger, 1987). It has a negative effect on job satisfaction, and turnover is more significant for workers with a higher level of surplus education (Tsang et al., 1991).

However, Verdugo and Verdugo (1989) stated that, if the Realised Match method is adopted to measure the required education to perform a job, over-educated workers are frequently found to earn less than their adequately educated and under-educated counterparts. Their empirical findings were disputed by Cohn (1992) and Gill and Solberg (1992) and examined by Cohn and Khan (1995) who explained that the negative sign does not imply that there is a negative return of over-education as long as the coefficient of over-education is significantly positive. Cohn and Khan (1995) considered that the negative coefficient of the Dummy variable for over-education means that workers achieve higher wages in occupations in which their educational level matches the required education level than in employment positions for which they are over-educated.

Disputing the assumption that all workers with a given educational level are perfect substitutes by ignoring their ability, Chevalier (2003) distinguished over-education by dividing it into two categories 'apparent over-education' and 'genuine over-education'; this was based on the evaluation of the extent, among graduates in the UK graduate market, of worker satisfaction with the match between their education and their actual employment. He found that 'genuine over-education' suffers a larger pay penalty of 22%-26% compared to that of (5%-11%) for 'apparent over-education'.

The above studies used cross-sectional data which assumes homogenous individuals and the random assignment of workers to jobs. Therefore, the question of unobserved heterogeneity of individuals and jobs is generally unresolved in cross-sectional studies.

In order to control for unobserved heterogeneity and to examine the wage effects of educational mismatch, Bauer (2002) and Tsai (2010) applied panel estimation techniques to longitudinal panel data sets.

Contrary to previous cross-sectional findings, based on a German panel data set (1984-1998), Bauer (2002) showed that after unobserved heterogeneity was controlled for the estimated wage differences between adequately and inadequately educated workers become smaller or disappear completely.

Using data from the Panel Study of Income Dynamics (1979-2005), Tsai (2010) also found that after conducting a fixed effects model to control for the non-random assignment of workers to jobs in the U.S. labour market, over-educated workers did not earn less than other workers. However, if there is insufficient within-panel variation of the education variables in a fixed effects model, coefficients for education may be very small. This is a challenge to the validity of estimators when conducting panel techniques.

Both pooled and panel regressions (fixed effects, random effects and pooled OLS) are applied in this study. The pooled OLS results are consistent with Sicherman's (1991) stylised facts. The Hausman test rejects that the random effects result is efficient and accepts that the fixed effects result is consistent. Panel fixed effects estimators are consistent with the findings in Bauer (2002) and Tsai (2010).

2.4 Data and variables

This section introduces data and variables in the research. There are three sub-sections. Firstly, data and sample in this essay are introduced in Section 2.4.1. Secondly, a number of variables are defined in Section 2.4.2. Finally, in Section 2.4.3, required years of

education is defined and the extent of over-education is evaluated.

2.4.1 Data

The data used in this research is taken from the first nine waves (2001-2009) in the responding person files of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Survey is Australia's first nationally representative household panel survey; and began in 2001. It was designed to support research in three topic areas: household and family dynamics; income and welfare dynamics; and labour market dynamics. The wave 1 panel consisted of 7,682 households and 19,914 individuals. Interviews are conducted annually with all adult household members (defined as persons aged 15 years or older on the June 30 preceding the interview date). In the data, 13,969 individuals completed the interviews. The balanced data set selected with respondents who had taken part in each year of the survey contains 7,721 individuals. After selecting the working-age male population and excluding self-employment, full-time students, the full size is composed of 15,915 observations (3,336 individuals). In this sample, 2,352 individuals have full-time jobs, 661 individuals have part-time jobs.

A major motivation for using this longitudinal survey is that it overcomes the weaknesses in cross-sectional data. The HILDA Survey is designed to follow the same units over time, and allows researchers to analyse the dynamics of change at the individual and household level. Specifically, when exploring the effects of over-education on earnings, the application of panel data could identify the extent of the causal effect of unobserved heterogeneity on earnings. Also, the HILDA Survey Re-interview rates are reasonably high, rising from 87 per cent in wave 2 to over 96.3 per cent in wave 9. This Survey reflects variations over time.

The focus of this study is on full-time male workers aged between 23 and 64 years old. In order to achieve a nationally representative estimation, I have created a balanced panel data weighted with responding person longitudinal weights variables.

Table 2.1 provides means and standard deviations for samples which are used in the estimation analyses. Definitions of variables are provided in Table 2A.1 in Appendix 2A. Based on the information in about country of birth, 76.8 per cent are Australian born, and 23.2 per cent are immigrants. Overall, among full-time workers, 25 per cent have degrees above Bachelor level, 31 per cent have Cert III or IV and 33 per cent have no qualifications. In contrast, unemployed workers have low educational attainment, that is, 12 per cent possess above Bachelor degree level and 49 per cent have no qualifications. The real hourly rate based on 2009 dollars for main job was $32.67 for part-time workers and $29.23 for full-time workers.

Among eight one-digit occupations, the largest proportion is accounted for by Professional occupations, which this account for 22 per cent of workers. Technicians, the second most observed occupation, employ 21 per cent of full-time workers. 17.3 per cent of workers are involved in Management, compared with 12.8 per cent of workers in the Operator category. 9.4 per cent are Clerical and Administrative workers, which contrasts with 7.9 per cent who are Labourers. Only 5.5 per cent are employed in Service occupations.

Workers are predominantly found in Manufacturing (17.3 per cent), Public Administration and Safety (9.8 per cent) and Construction (8.7 per cent) while they are less likely to work in the industries of Rental, Hiring and Real Estate Services (1.5 per cent) and of Administrative and Support Services (1.5 per cent).

Table 2. 1:Statistics of the Samples by Labour Force Status

VARIABLES	Full-time mean	Full-time sd	Part-time mean	Part-time sd	Unemployed mean	Unemployed sd
Personal Characteristics						
(1) General						
Age (years)	41.509	10.311	44.322	12.994	41.487	11.112
Year of birth	1962	10.398	1960	13.018	1962	11.381
Married*	0.682	0.466	0.569	0.495	0.382	0.486
Has children aged 14or less*	0.396	0.489	0.208	0.406	0.187	0.390
Disability or impairment*	0.131	0.337	0.257	0.437	0.402	0.490
Father working in professional occupations*	0.131	0.337	0.131	0.338	0.087	0.281
Mother working in professional occupations*	0.124	0.330	0.127	0.332	0.068	0.252
(2) Qualifications						
Years of education	13.688	2.445	13.338	2.642	12.601	2.520
Postgraduate*	0.111	0.314	0.112	0.315	0.049	0.217
Bachelor*	0.140	0.347	0.140	0.347	0.070	0.256
Advanced diploma*	0.107	0.309	0.118	0.323	0.093	0.290
Certificate*	0.313	0.464	0.208	0.406	0.296	0.456
No qualification*	0.329	0.470	0.422	0.494	0.491	0.500
(3) Country of Birth						
Australian*	0.768	0.422	0.757	0.429	0.670	0.470
ESB immigrant*	0.137	0.343	0.117	0.321	0.148	0.355
NESB immigrant*	0.095	0.293	0.127	0.333	0.182	0.386
(4) Region and States						
Urban*	0.873	0.333	0.844	0.363	0.872	0.334
NSW*	0.314	0.464	0.322	0.467	0.363	0.481
VIC*	0.259	0.438	0.250	0.433	0.292	0.455
QLD*	0.196	0.397	0.166	0.372	0.189	0.391
SA*	0.079	0.269	0.089	0.284	0.080	0.272
WA*	0.099	0.299	0.105	0.306	0.050	0.217
TAS*	0.024	0.152	0.039	0.195	0.018	0.132
NT*	0.010	0.102	0.017	0.131	0.004	0.063
ACT*	0.019	0.138	0.012	0.107	0.005	0.073
Job Characteristics						
(1) General						
Unemployment rate (ASB)	0.053	0.010	0.053	0.010	0.053	0.010
EXP	22.821	10.750	25.984	13.229	23.886	11.216
EXP^2	636.360	521.217	850.138	695.527	696.310	557.723
Job Tenure	8.562	8.711	5.835	8.343		
Job Tenure squared	149.195	267.881	103.656	296.948		
Occupation Tenure	11.308	10.030	9.006	11.155		
Occupation Tenure squared	228.458	348.134	205.542	425.467		
Weekly Hours worked in main job	45.815	9.710	21.001	8.645		
Weekly Hours worked in all job	46.708	9.820	21.697	8.441		
Weekly gross wages and salary from main job	1,325.793	750.938	585.188	480.366		
Hourly wage from main job	29.228	15.673	32.668	58.668		
Log hourly wage from main job	3.255	0.507	3.173	0.687		
Supervisory role*	0.592	0.491	0.278	0.448		
Union member*	0.323	0.468	0.207	0.405		
Small Sized Firm with less than 20 workers*	0.387	0.487	0.519	0.500		
Medium Sized Firm with 20 to 99*	0.276	0.447	0.255	0.436		
Medium-Large Sized Firm with 100 to 499*	0.210	0.407	0.135	0.341		
Large Sized Firm with 500 or more*	0.127	0.333	0.091	0.288		
jbmo6s-AUSEI06 occupational status scale	49.565	24.029	43.987	24.670		

Table 2. 1 *(Continued)*

VARIABLES	Full-time mean	Full-time sd	Part-time mean	Part-time sd	Unemployed mean	Unemployed sd
(2) **Occupations***						
Managerial	0.173	0.378	0.068	0.252		
Professional	0.218	0.413	0.221	0.415		
Technicians and Trades Workers	0.207	0.405	0.125	0.331		
Community and Personal Service Workers	0.055	0.228	0.104	0.305		
Clerical and Administrative Workers	0.094	0.291	0.069	0.254		
Sales Workers	0.047	0.212	0.073	0.260		
Machinery Operators and Drivers	0.128	0.334	0.110	0.312		
Labourers	0.079	0.269	0.230	0.421		
(3) **Industry Sectors***						
Agriculture, Forestry and Fishing	0.031	0.173	0.030	0.171		
Mining	0.031	0.173	0.006	0.080		
Manufacturing	0.173	0.378	0.070	0.256		
Electricity, Gas, Water and Waste	0.019	0.136	0.007	0.083		
Construction	0.087	0.282	0.067	0.251		
Wholesale Trade	0.049	0.215	0.025	0.155		
Retail Trade	0.064	0.245	0.116	0.320		
Accommodation and Food Services	0.030	0.171	0.094	0.291		
Transport, postal and ware housing	0.079	0.270	0.071	0.257		
Information, Media and Telecommunications	0.030	0.171	0.024	0.152		
Financial and Insurance services	0.039	0.193	0.011	0.104		
Rental, Hiring and Real Estate services	0.015	0.121	0.003	0.052		
Professional, Scientific and Technical services	0.076	0.265	0.076	0.265		
Administrative and Support Service	0.015	0.121	0.042	0.201		
Public Administration and Safety	0.098	0.297	0.046	0.210		
Education and Training	0.058	0.233	0.132	0.338		
Healthcare and Social Assistance	0.044	0.206	0.109	0.312		
Arts and Recreation services	0.018	0.135	0.046	0.209		
Other Services	0.045	0.206	0.025	0.155		
Individuals	2352		661		323	
Observations	13846		1551		518	

Notes:

Variables with * denote dummy variables.

Variables in Occupations and Industry Sectors are dummy variables.

Definition of variables is provided in Table 2A.1 in Appendix 2A.

Source: Derived based on HILDA, pooled sample for years 2001-2009 (15, 915 Observations)

2.4.2 Variables

HILDA does not provide direct information for variables of interest, thus they are derived from the relevant variables.

The earning variables used in this study are log hourly wage from main job. To derive the hourly wage for main jobs, the first step is to convert nominal earnings to real earnings. I use 2009 as a base year, reference ABS CateNo6345.0 labour price index, and generate real earnings for each year by using nominal earnings divided by the wage price index. To account for non-responding (in responding households) persons' wages which are presented as missing data, the variable I choose is imputed weekly gross wages and salary for the main job[2]. After converting the imputed nominal weekly gross wages and salary from the main job to real imputed weekly gross wages and salaries, the hourly wage from main job is derived by using imputed real weekly gross wages and salary from the main job divided by combined hours per week usually worked in the main job. Then I convert the hourly wage into log hourly wage.

The unemployment rate represents the percentage of the labour force that is currently unemployed and actively looking for work. It is also a common indicator of a country's economic conditions. It is used as a control for labour market conditions. I have collected the annual unemployment rate (years 2001 to 2009) from the Australian Bureau of Statistics (ABS)[3] as a reference.

The Australian Socioeconomic Index 2006 (AUSEI06) occupational status scale of current main occupation is used to control occupation level.

Years of education are derived from four variables from HILDA. Based on this derivation, the lowest number for years of education is 6. 21 years of education are required for a

[2] Imputation methods are used to deal with missing cases. Since income is a sensitive issue for some people who do not report their income in interview, thus missing data occurs. Nearest Neighbour Regression imputation and little and Su imputation are applied to the imputation of data for responding persons. A full description of the imputation process for the income variables is provided by Hayes and Watson (2009).
[3] It is referred to Cate No. 6202.0, ABS: Canberra.

Doctoral degree. 18 years for a Master's degree, 17 years for a Bachelor's honours degree, graduate Diploma or graduate Certificate, 16 years for a Bachelor's degree without honours, 15 years for an Advanced diploma or Diploma, 14 years for Certificate III or IV, and 13 years for Certificate I or II. To evaluate the effects of qualifications, the qualifications are categorised into five categories: Postgraduate, Bachelor's, Diploma, Certificate, and No qualification. Postgraduate includes Doctorate, Master's, graduate Diploma, graduate Certificate and Bachelor's with honours, which requires over 17 years of education. Bachelor's covers a Bachelor's degree without honours and takes 16 years of education to achieve. Advanced diploma includes Advanced Diploma and Diploma and requires 15 years of education. Certificate includes Certificate I, Certificate II, Certificate III and Certificate IV which all require over 13 years of education. 'No qualification' covers workers without qualifications, representing less than 13 years of education.

Eight states of living dummy variables are derived and NSW is a reference category. Married dummy variables include de facto relationships. The HILDA data provides current main job tenure and occupation tenure information. To control for occupation eight occupation dummy variables are constructed, which are derived by the Australian and New Zealand Standard Classification of Occupations (ANZSCO). To control for type of industry, nineteen industry dummy variables are derived by one digit industry (ANZSIC 2006 division).

Six interaction terms are produced by the over-educated and under-educated dummy variables interacting with the potential experience, current job tenure, and current occupation tenure variables. Ten interaction terms are produced by over-educated and under-educated dummy variables interacting with five qualification category dummy variables. Sixteen interaction terms are produced by over-educated and under-educated, dummy variables interacting with eight occupational category dummy variables. Interaction terms between Education match and experience, tenure, qualification or occupation are referred to as reference categories.

2.4.3 How is the term 'required years of education' defined?

Because the HILDA data does not provide any information on over-education, worker's self-report (SR) is not applicable. Thus, I define the 'adequate education for performing the job' using the Realised Match (RM) method (cross-wave Mode measure and Verdugo and Verdugo' Mean measure), and Job Analysis (JA).

Based on Verdugo and Verdugo's (1989) Realised Match (RM) method, two range measures are used in this study. Since, under this measure, the required education to do a job is a range, I call this method a 'range measure'. Range-one measures over-education by comparing each individual's actual years of education to a mean plus one standard deviation within occupations. Over-education is defined as the actual years of education exceeding one standard deviation above mean education; under-education is defined as the actual years of education those are one standard deviation below the mean education within the occupation. Range-half measures of over-education in turn replace one standard deviation with half a standard deviation in the Range-one measure to evaluate the required education to perform a job. As a complementary method, the mean plus one and mean plus a half standard deviations are adopted in this study.

The Job Analysis (JA) measure is obtained based on the Australian and New Zealand Standard Classification of Occupations (ANZSCO2006) and Australian Qualifications Framework (AQF). ANZSCO2006 provides qualifications and skill level requirements to work in specific occupations. In HILDA, Variable jbmo62 provides 2-digit ANZSCO2006 occupations categories for employed workers for each wave. Thus, each occupation in HILDA has its qualification and skill requirements indicated in ANZSCO2006. The Australian Qualifications Framework (AQF) is the national policy for regulated qualifications in Australian education and training. Each qualification type describes its purpose, knowledge, skills and volume of learning. I compare each qualification type in the AQF with matched qualifications required in ANZSCO2006 at the two digit occupation code level, then convert qualification to required years of education.

The cross-wave Mode measures the required years of education to take on an employment position varying by waves. I construct this measure for each of the occupational categories and for each wave. In HILDA, Variable jbmo62 provides 2-digit ANZSCO 2006 occupations category for employed workers for each wave. Within each occupational category and wave, I calculate the modal number of years of education for individuals working in that occupational category. This figure is my measure of the required years of education. Because of the required years of education is generated for each wave separately, I call this the cross-wave Mode measure. Years of over-education and years of under-education are obtained by comparing the actual years of education with the required years of education.

For full-time workers, the extent of educational mismatching under four measures is reported in Table 2.2. In Australia, among full-time male workers aged 23 to 64 years old, there exists a high incidence rate of over-education following JA; this is 32.6 per cent. The incidence rate of over-education varies with different measures, ranging from 11.4 per cent based on the Range-one measure, to 32.6 per cent under JA. The percentage of adequately educated workers is higher under the Range-one measure (71.3 per cent) than the other three measures. JA reports the lowest rate of adequate matches (23.9 per cent) and the highest rate of under-education (43.5 per cent). Moreover, under all measures the extent of over-education is higher among part-time workers than among full-time workers.

With the Mode measure, there is no uniformity between full-time and part-time workers. Part-time workers are more likely to be over-educated compared with full-time workers (33.9 per cent as opposed to 27.2 per cent). On average, full-time workers have a higher average of years of education (13.688) than part-time workers (13.338). The required years of education to perform a job for full-time workers (14.112) are also slightly higher than those (13.599) for part-time workers. This may imply that part-time workers are more likely to perform lower level tasks compared to full-time workers. This is consistent with respective job occupational scale variable jbmo6s (49.565 to 43.987) in Table 2.1.

Table 2.2 further reports that 11.4 per cent of full-time workers, 3.7 per cent less than for part-time workers, are over-educated in their current jobs, 71.3 per cent of full-time

workers and 67.3 per cent of part-time workers are working in matched occupations according to the Range-one measure. These mismatches are fairly consistent with the findings in Voon and Miller (2005) who use the same measure to define the level of education required. In their study, the incidence of over-education and adequate education are about 16% and 71% respectively among full-time male workers aged between 20 and 64 years.

After comparing the four conventional methods to measure over-education, the evidence indicates that the incidence of over-education is influenced by which method is used in HILDA, and how belonging to over-educated category is related to the choice of measurement variable.

For simplicity and clarity, the four measures are called Mode, Range-one, Range-half, and JA.

Table 2. 2: Statistics for Educational Mismatches under Four Measures

VARIABLES	Full-time mean	sd	Part-time mean	sd
Actual years of education	13.688	2.445	13.338	2.642
(1)Under Cross-wave Mode measure (Mode)				
Incidence of over-education				
Over-educated	0.272	0.445	0.339	0.473
Under-educated	0.362	0.481	0.364	0.481
Adequately educated	0.366	0.482	0.297	0.457
Average years of education				
Years of over-education	0.670	1.458	0.873	1.650
Years of under-education	1.094	1.729	1.133	1.777
Years of required education	14.112	2.080	13.599	2.310
(2)Under Job Analysis measure (JA)				
Incidence of over-education				
Over-educated	0.326	0.469	0.349	0.477
Under-educated	0.435	0.496	0.442	0.497
Adequately educated	0.239	0.427	0.209	0.407
Average years of education				
Years of over-education	0.571	0.971	0.795	1.286
Years of under-education	1.091	1.594	1.034	1.518
Years of required education	14.208	1.474	13.578	1.624
(3) Under range measure				
[31] Under mean plus one standard deviation measure (Range-one)				
Incidence of over-education				
Over-educated	0.114	0.318	0.151	0.358
Under-educated	0.172	0.378	0.176	0.381
Adequately educated	0.713	0.452	0.673	0.469
Average years of education				
Years of over-education	0.083	0.323	0.146	0.476
Years of under-education	0.924	2.085	0.939	2.089
Years of required education	13.952	1.728	13.468	1.941
[32]Under mean plus half standard deviation measure (Range-half)				
Incidence of over-education				
Over-educated	0.277	0.447	0.305	0.460
Under-educated	0.301	0.459	0.342	0.474
Adequately educated	0.422	0.494	0.353	0.478
Average years of education				
Years of over-education	0.300	0.623	0.389	0.791
Years of under-education	1.094	1.797	1.209	1.813
Years of required education	13.886	1.487	13.490	1.620
Observations	13846		1551	
Individuals	2532		661	

Source: HILDA-Release 9 (Wave 1-Wave 9).

Correlations between measures are given in Table 2.3. The correlations range from 50 per cent for Mode and Range-one to 71 per cent for Range-half and JA, which indicates that the same individual is over-educated for one measure but may be adequately educated for the other measure. This is consistent with the results of Verhaest and Omey (2010) who demonstrated that measures are sensitive to the determinants of over-education.

Table 2. 3: Correlations between Measures (Years 2001 to 2009)

	Mode	**Job Analysis (JA)**	**Range-one**	**Range-half**
Mode	1.0000			
Job Analysis (JA)	0.5405	1.000		
Range-one [a]	0.4994	0.4991	1.000	
Range-half [b]	0.5823	0.7148	0.5795	1.000

[a] Mean plus one standard deviation [b] Mean plus half standard deviation

Source: HILDA-Release 9 (Wave 1-Wave 9).

Based on Figures 2.1 and 2.2, educational mismatch status differs from other measures among qualifications groups. In Figure 2.1 we see that for workers who have qualifications, on average, the actual years of education are greater than the requirements of the job the worker is in. Both the years of education and the required years of education increase with the qualification level in the expected way. The difference between the required level and the actual years of education also increases in the same way. For the workers with no qualifications, the actual years of education are, on average; less than all measures of the requirements of the job the worker is in.

In Figure 2.2 we see that, as expected, workers with the highest qualifications are most likely to be over-educated and workers with no qualifications are least likely to be over-educated. For intermediate levels of qualification the dependence of the incidence of over-education on the level of qualification is less clear and depends on the particular method

of defining the educational requirements of the job. Using the JA or Range-one method leads to a monotonic pattern while using the Mode and Range-half method gives an incidence of over-education for the Advanced diploma group that is substantially greater than for the Bachelor group.

In this study, all measures of required education are defined according to two-digit occupations. Based on the extent of over-education for full-time workers in eight occupations (ANZSCO-one digit) for pooled nine waves' data, Figure 2.3 describes required and actual years of education, and Figure 2.4 indicates the extent of over-education among eight occupations based on four measures. In Figure 2.3, under Mode and JA, the required education changes abruptly, but under Range-one and Range-half, required education changes gradually around the average actual years of education. Professionals have the highest levels of required education for all measures. For Mode, at least 16.044 years of education is required to enter a Professional occupation. The occupation of labourer requires the lowest level of education except when the Range-half measure is used.

To investigate the extent of over-education over time under different measures, I use cross-sectional data with three-year intervals (2003-2006-2009), named as Year 2003, Year 2006 and Year 2009. Since the required years of education are likely to change over time, Figures 2.5 and 2.6 further present the means for education related variables by occupation for specific time periods (Year 2003, Year 2006 and Year 2009).

Based on Figures 2.5 and 2.6, compared to the other three measures, Mode is the more appropriate measure in this study, for the following reasons: First, the JA measure has not been updated over time. For Year 2003 (wave3), Year 2006 (wave6) and Year 2009 (wave9), the required years of education for the JA measure remain the same within each occupation; this is shown in Figure 2.5 in purple with a triangle marked line for three waves within occupations. This necessarily implies that the extent of over-education has not changed over the years, and this is further shown in Figure 2.6. JA also ignores the heterogeneity of jobs within occupations due to job aggregation. Moreover, JA overestimates the required education for Managers, Technicians, Operators Drivers and

Labourers, and thus underestimates the extent of over-education. Secondly, and differing from Mode and JA, both Range-one and Range-half define required education as a range about the mean of actual years of education. This implies symmetry between over-education and under-education, which can be seen through three lines (Range-one, Range-half, and Actual years of education) in Figures 2.3 and 2.5. In addition, both Range-one and Range-half lines change gradually, which implies classification errors. In particular, Figure 2.6 clearly displays symmetry for Range-one and Range-half, that is, the proportions of those who are over-educated and those who are under-educated are quite similar, as is represented by the light grey and dark grey areas. This means that Range one is more conservative in determining over-education. We can see that the size for these two areas is the same under Range-one and Range-half. The middle area in Figure 2.6 represents adequate education matches, and represents a large proportion for Range-one and a small proportion for JA. This indicates that workers match less well for JA, and match well for Range-one, thus implying that workers who are over-educated based on JA, may be adequately educated based on Range-one.

Some features are worth noting. In general, the average actual years of education are increasing over time except in the case of Technicians and Sales workers. The incidence of over-education varies through occupations and time trends. Under the Mode measure, large fluctuations over time are found in the occupations of Management, Sales workers, Machinery Operators and Drivers, and Labourers. For example, within Machinery Operators and Drivers, the over-education rate was 13 per cent in 2003, but it increased to 52 per cent in 2006, and then decreased to 14 in 2009. Overall, among the four measures, the variation in mismatches is largest for Mode. Mode overcomes the drawbacks of Range measures, and changes more freely. It considers the asymmetry between over-education and under-education, and is less sensitive to outliers or technological change when compared to Range. Similar results were found in Kiker, Santos and Oliveira (1997)'s study.

The returns to over-education are examined by alternative measures across studies and in

my sensitivity test[4] analyses (Wen & Maani, 2012). The pooled OLS results indicate a consistent conclusion with stylised facts (Sicherman, 1991) although the magnitude of mismatch coefficients across studies varies with different measures except Range-one. Over-educated workers earn more than their adequately educated colleagues, but they earn less than do workers with the same level of education who work in a matched job (Daly et al., 2000; Hartog, 2000; Rumberger, 1987; Cohn and Kahn, 1995). Based on the Mode measure, earnings penalties disappear in fixed effects, indicating that individual heterogeneity plays an important role. In contrast, when results from pooled OLS and fixed effects estimation based on Range-half and JA measures, the penalty of over-education reduces a little (from 62 per cent to 60 per cent for Range-half and 76 per cent to 64 per cent for JA). This reveals that individual heterogeneity does not play a role in earnings. In addition, the results across fixed effects and random effects are very consistent based on the Mode method. They are significantly different across fixed effects and random effects for the Range-one, Range-half and JA measures, which present inconsistent estimations.

In summary, each of the four methods to measure over-education has advantages and disadvantages. The Mode measure is used in the rest of analyses incorporating over-education and under-education due to its several advantages. These are: objective and statistically based; the most common method used across studies for comparison; readily available in data sets; it allows frequent change in the measure as technology and markets change.

[4] Wen, L., & Maani, S. (2012). 'Over-education Impacts on Earnings: A comparison of Alternative Measures', Paper Presented at the UABS PhD Conference, The University of Auckland, Auckland, 26 October. The results are available upon request.

Figure 2. 1: Required Years of Education based on Four Measures by Qualifications (Years 2001 to 2009)

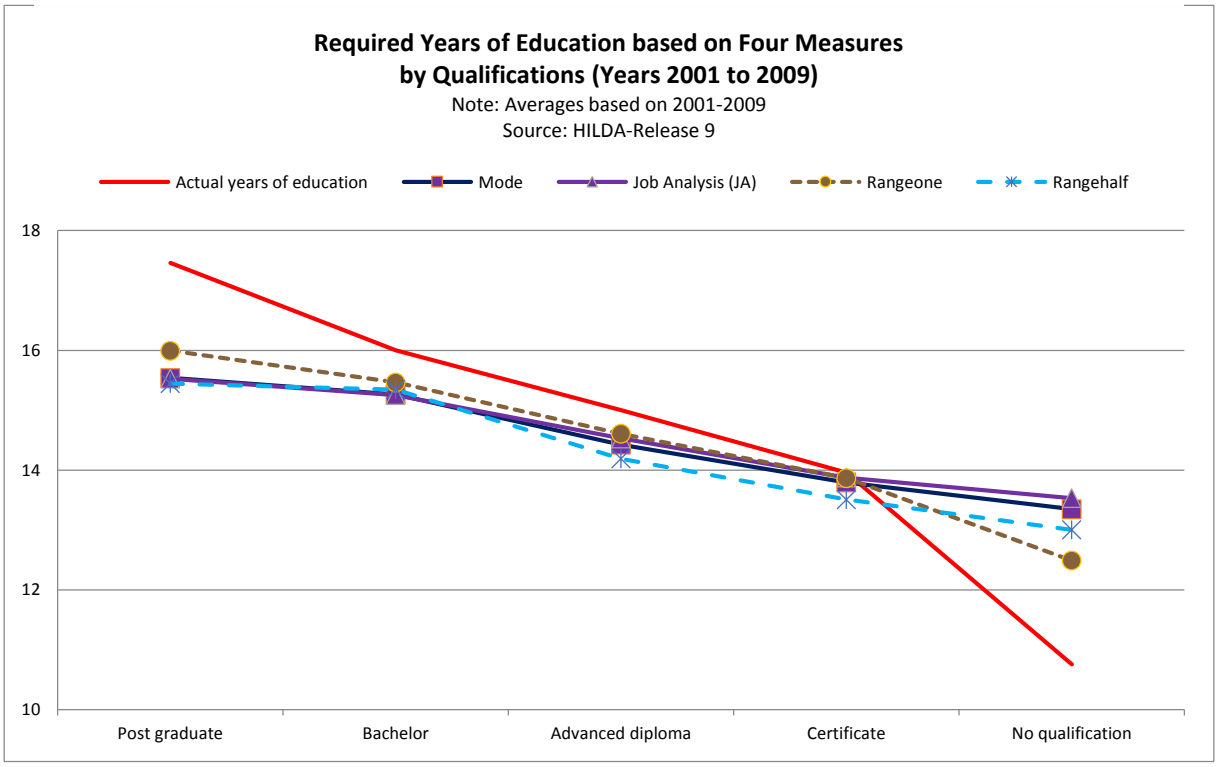
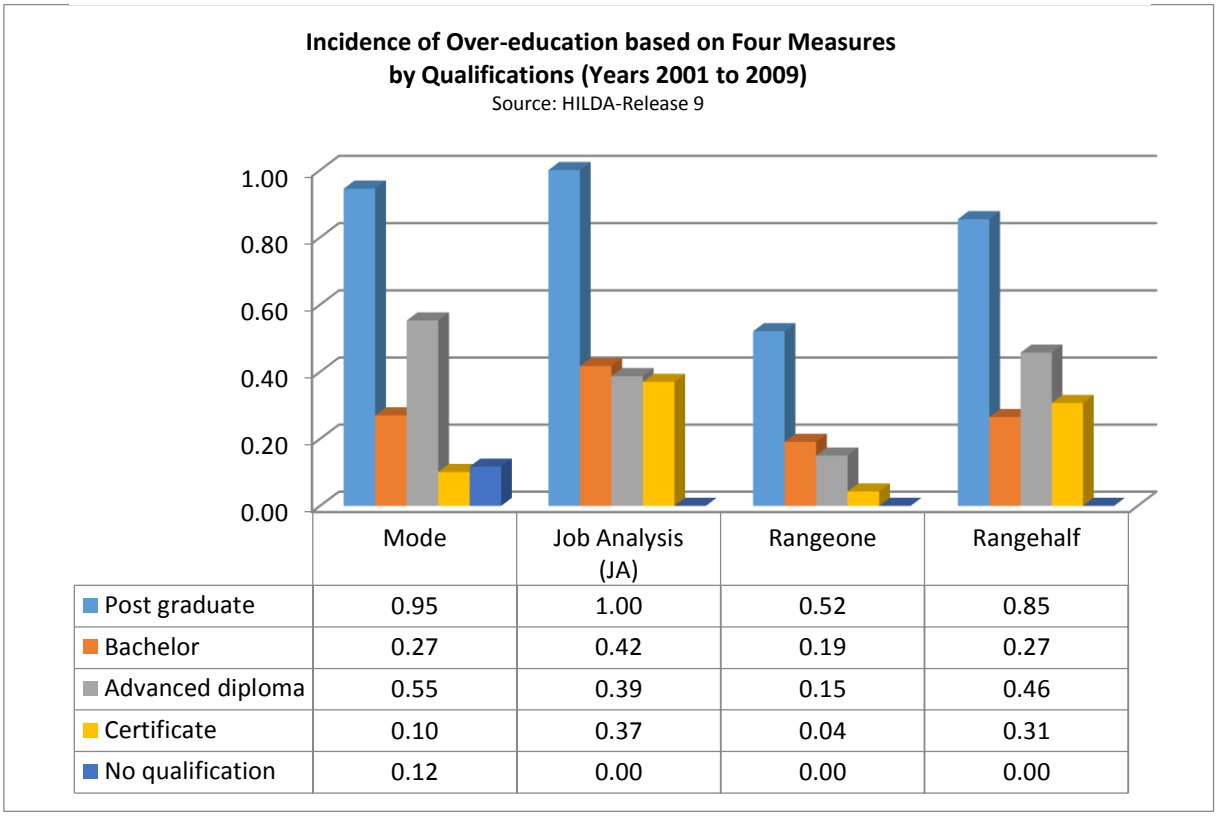


Figure 2. 2: Incidence of Over-education based on Four Measures by Qualifications (Years 2001 to 2009)



	Mode	Job Analysis (JA)	Rangeone	Rangehalf
Post graduate	0.95	1.00	0.52	0.85
Bachelor	0.27	0.42	0.19	0.27
Advanced diploma	0.55	0.39	0.15	0.46
Certificate	0.10	0.37	0.04	0.31
No qualification	0.12	0.00	0.00	0.00

Figure 2. 3: Required Years of Education by Occupations
(Years 2001 to 2009)

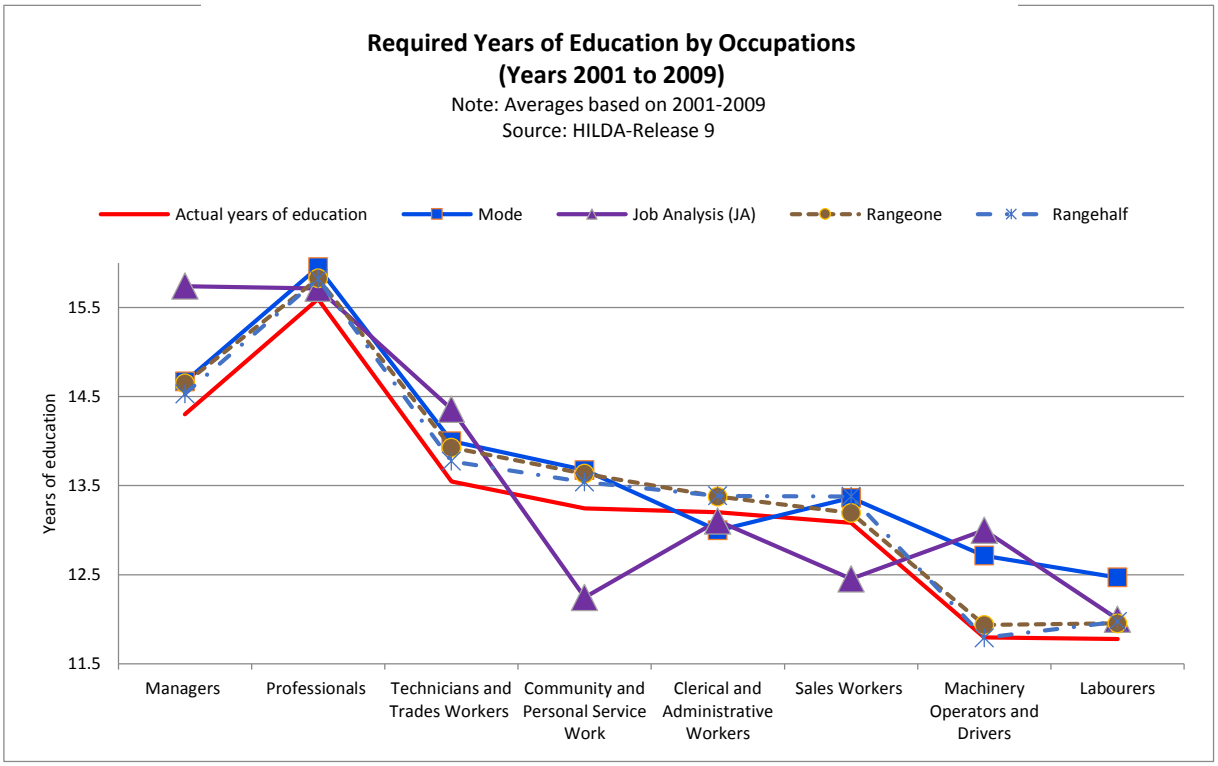
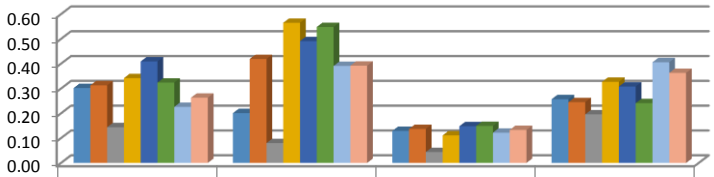


Figure 2. 4: Incidence of Over-education based on Four Measures by Occupations
(Years 2001 to 2009)

Incidence of Over-education based on Four Measures by Occupations (Years 2001 to 2009)

Source: HILDA-Release 9



	Mode	Job Analysis (JA)	Rangeone	Rangehalf
Managers	0.30	0.20	0.13	0.26
Professionals	0.31	0.42	0.14	0.25
Technicians and Trades Workers	0.14	0.08	0.04	0.20
Community and Personal Service Work	0.34	0.57	0.11	0.33
Clerical and Administrative Workers	0.41	0.49	0.15	0.31
Sales Workers	0.32	0.55	0.15	0.24
Machinery Operators and Drivers	0.23	0.39	0.12	0.41
Labourers	0.26	0.39	0.13	0.36

Figure 2. 5: Required Years of Education based on Four Measures by Occupations and Years (Year 2003, Year 2006 and Year 2009)

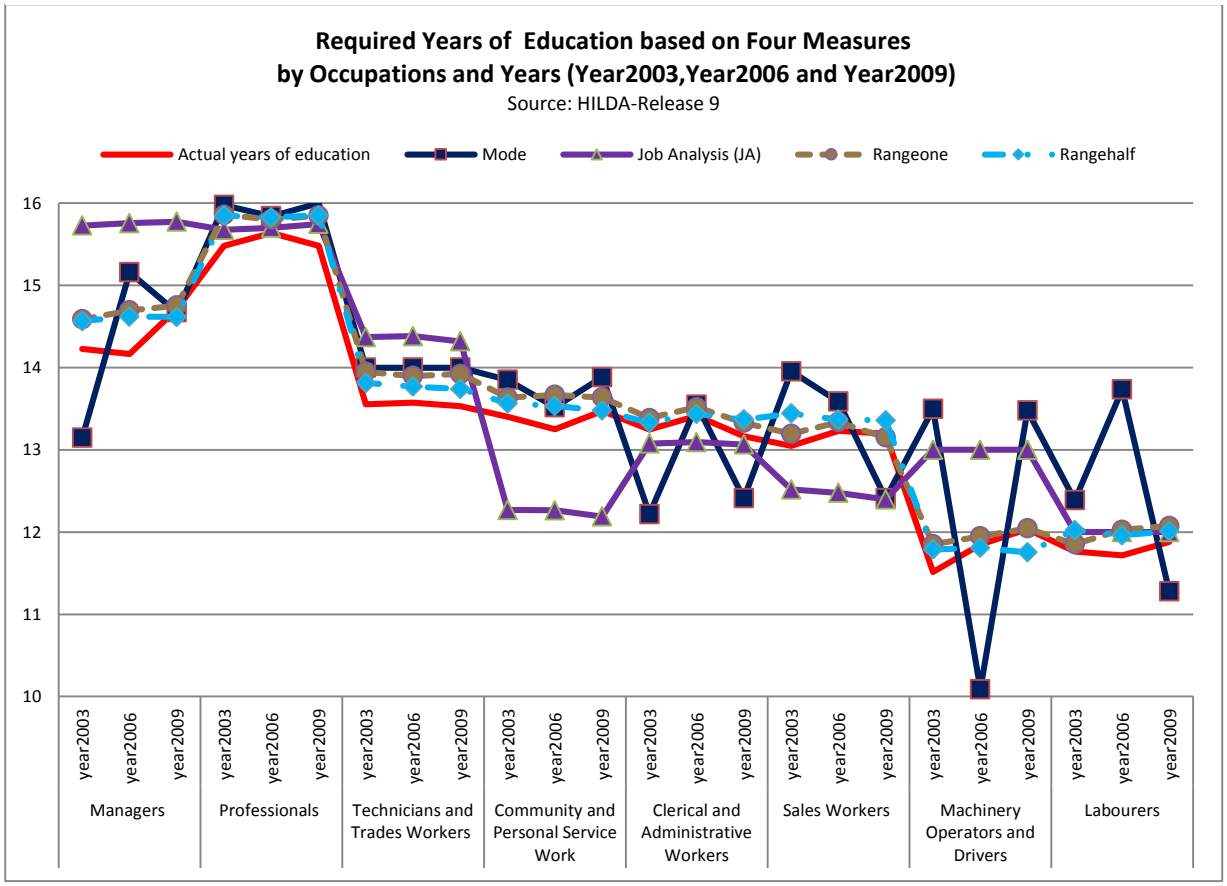
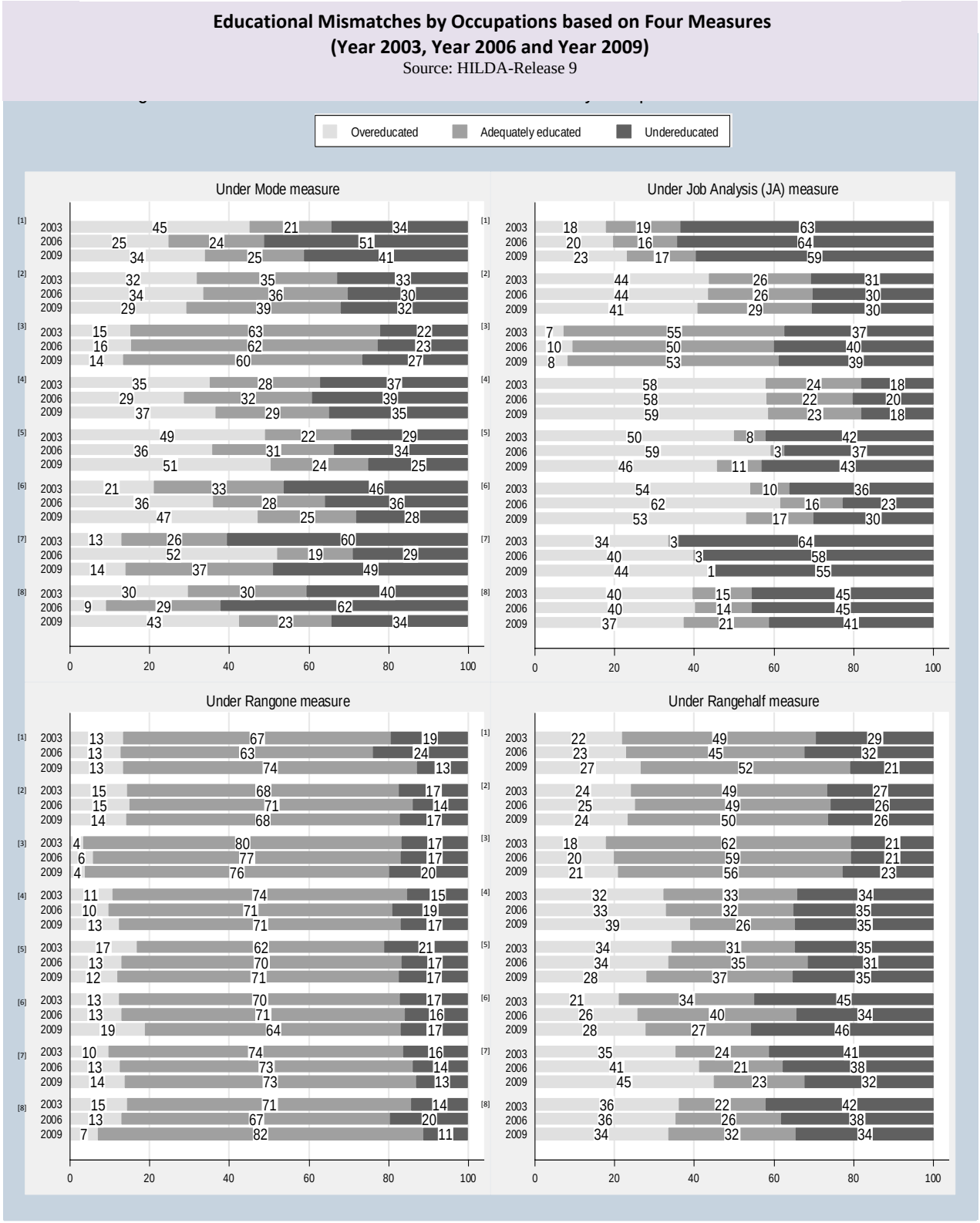


Figure 2. 6: Educational Mismatches by Occupations based on Four Measures (Year 2003, Year 2006 and Year 2009)



[1]Managers [2] Professionals [3] Technicians and Trades Workers [4] Community and Personal Service Work [5]Clerical and Administrative Workers [6] Sales Workers [7] Machinery Operators and Drivers [8] Labourers

2.5 Incidence of over-education

This section aims to examine the incidence of over-education among male full-time workers aged 23 to 64. The structure of this section is as follows. Section 2.5.1 provides the econometric framework. Section 2.5.2 lists the hypotheses, and empirical results are presented in Section 2.5.3.

2.5.1 Econometric framework

Following Maani & Maloney (2004), Cutillo & Di Pietro (2006) and Green, et al. (2007), sample selection bias would occur when estimating the incidence of over-education for full-time workers without considering non-full-time workers. Because these coefficients come from regressions which restrict the relevant sample to those who are full-time employed and over-educated, and are not randomly drawn from the population, using coefficients based on this sample to represent the overall rates of incidence of over-education for population may produce sample selection bias.

To avoid potential selection biases, a double selection probit model is adopted to estimate the incidence of over-education for full-time male workers.

The following steps represent a double selection probit model to estimate the incidence of over-education.

The first step, estimate of the latent probability of employment in full-time work for individual i is

(2.1) $$FT_i^* = \beta_1 X_i + \nu_i$$

X_i denotes a set of personal characteristics and job characteristics. The dependent variable FT_i^* is a latent value and unobserved, depicting the probability of being employed in full-

time work for individual i. Its observed counterpart FT_i is a dummy variable that takes a value of 1 if the individual is employed in full-time work; zero otherwise. This can be expressed as: $FT_i = 1$ if $FT_i^* > 0$; $FT_i = 0$ otherwise.

Similarly, the second step estimate of the probability of being over-educated for individual i is

$$O_i^* = \delta_1 Z_i + \varepsilon_i \tag{2.2}$$

Where Z_i denotes a set of personal characteristics, job characteristics; O_i^* denotes the propensity of being over-educated, O_i^* is the latent propensity of over-education and it is unobservable, but we observe the outcome denoted by a dummy variable (O_i) defined as: $O_i = 1$ if $O_i^* > 0$; $O_i = 0$ otherwise.

Here, to estimate the incidence of over-education for full-time workers, the double selection process is that first individuals are selected into employment, then employed workers are selected into full-time employment.

The equation is:

$$P_r(O_i | FT_i = 1) = P_r(\varepsilon_i > -\delta_1 Z_i | \nu_i > -\beta_1 X_i) \tag{2.3}$$

Where the disturbance terms ν_i and ε_i are bivariate, normally distributed, and assumed to have zero mean and constant variance.

The covariance between error terms is estimated by the correlation coefficient ρ. If parameter ρ is significant, then it provides evidence that these two equations are correlated. If the selection is relevant, the act of not considering selection would bias the coefficient in estimating the incidence of over-education. Coefficients β_1 and δ_1 denote vectors of coefficients of Equations (2.1) and (2.2) respectively, while X_i and Z_i stand for the matrices of explanatory variables which contain each of the following variables:

qualification categories, immigrants, regional variables, urban, years of birth categories, experience, tenure, supervisory role, union membership, firm size categories, occupations and industries. Based on the Heckman procedure (1979), in Equation (2.1), X_i should include only characteristics of the individual that explain the decision to work in a full-time job, but are not correlated with the probability of over-education. After testing the correlation between variables, it was found that being the parent of a young child correlates highly with the decision to do a full-time job but not with the propensity of being over-educated. Thus, additionally, matrix X_i contains the variable of being, or not being, the parent of a child/children aged 14 or less.

It is plausible to consider that both of the above equations are also needed to address workers' self-selectivity in employment (Heckman, 1979). Only employed workers have the probability of working for a full-time job and being over-educated, therefore, this first step is called, sample selection into employment. The following selection probit model is used to obtain selection hazard variables (inverse Mills' ratio).

(2.4) $$E_i^* = \beta_2 X_i + \beta_3 C_i + u_i$$

(2.5) $$Prob[E_i^* | E_i = 1] = \Phi(E_i \gamma)$$

Where E_i^* is the latent variable, and Ei is the vector of variables explaining the selection to work and γ is a vector of selection probit parameters.

In this case, explanatory vector X_i contains a disability and impairment variable, mother or father has a professional job, married, children aged 14 or less, qualification categories, immigrants, regional or urban, and years of birth categories. C_i in Equation (2.4) is labour market conditions. In this study, the unemployment rate is based on the Australian Bureau of Statistics (ABS), to control for labour market conditions. From Equation (2.4), the inverse Mill's ratio is obtained:

(2.6) $$\lambda_i = \frac{\Phi(E_i\,\gamma)}{\Psi(E_i\,\gamma)}$$

Taking all of the relevant decision combinations into consideration, Equation (2.1) and Equation (2.2) can be written as follows:

(2.7) $$FT_i^* = \beta_1 X_i + a_1\,\lambda_{1i} + \nu_i$$

(2.8) $$O_i^* = \delta_1 Z_i + a_2\,\lambda_{2i} + a_3\lambda_{3i} + \varepsilon_i$$

Equation (2.7) and Equation (2.8) are estimated with a full information maximum likelihood function which generates consistent estimates of β_1 , δ_1 and ρ.

2.5.2 Hypotheses

According to the previous stylised facts (Sicherman, 1991), HILDA data is used to test the following hypotheses:

a) The potential trade-off between schooling and other components of human capital (ability and experience) imply that over-educated workers may use their surplus schooling to compensate for their shortage of other types of human capital. Therefore, workers with less market experience are more likely to be over-educated.

b) Jobs in a higher occupational scale require higher specific skills. This implies that the extent of educational match is larger in higher than in lower occupational ranks. Thus, combining the concept of over-education it is expected that the incidence of over-education is more likely to increase with education level, and to decrease with occupation level.

c) Immigrants are more likely to be over-educated than native Australians due to language proficiency, cultural barriers, or qualifications un-recognised by

Australian employers.

2.5.3 Empirical analysis

Based on Equations (2.7) and (2.8), using bi-probit models, the results are reported in Table 2.4. The difference between Model H 2-1 and Model H 2-2 is that Model H 2-2 has the first step employment selection control: this is represented by variable Invmills_E[5]. Invmills_E is derived from the probability of being employed after controlling for a number of personal variables (see Appendix 2A.2). The Wald test of independent equations is rejected in Models H2-1 and H2-2. Columns (1) and (3) report marginal effects, using mean characteristics. These marginal effects are very similar even with some restrictions. A significant negative relationship[6] is found between the probability of filling a full-time position and the probability of being over-educated. This implies that workers who are selected for their full-time employment positions have less probability of being over-educated compared to part-time counterparts. It means that the incidence of over-education is higher among part-time workers. Also, the first step selection variable is negative and significant for selection for a full-time job. However, in the probability of being over-educated equation this effect is not significant. This implies that selection into employment does not by itself have a significant impact on the incidence of over-education. However, it does have a negative impact on the probability of working in a full-time position. Overall, this double selection procedure shows that, in Australia, about 29 per cent of full-time workers are over-educated. If we ignore sample-selection adjustment, we will underestimate the incidence of over-education.

From Column (3), as expected, non-English speaking background immigrants (NESB) are more likely to be over-educated than native Australians. Workers who hold post

[5] It is calculated by the following steps. Firstly, calculate predicted value (p1) from employment probit regression. Secondly, generate the normal distribution function phi=(1/sqrt(2*_pi)*exp(-(p1^2/2)), and phi is equivalent to $\Phi(E_i\,\gamma)$. Then, generate the cumulative density function: capphi=normal (p1) and capphi is equivalent to$\Psi(E_i\,\gamma)$. This calculates inverse Mill's ratio lambda $\lambda_i = \frac{\Phi(E_i\,\gamma)}{\Psi(E_i\,\gamma)}$ in Equation (2.6).

[6] It is represented by /athrho. The relation between /athrho and rho is: /athrho=$\frac{1}{2}$ln ($\frac{1+rho}{1-rho}$).

graduate degrees have 78 per cent more chance of being over-educated compared to workers with diplomas; however, workers with Certificates are more likely to get matched jobs. Compared with Sales workers, workers in three occupations (Professional occupation, Technician and Trades Worker, Management) have less likelihood of being over-educated. In contrast, there is an 11 per cent greater likelihood to be over-educated among workers in Clerical and Administrative occupations. Having high level occupations helps workers to have a lower likelihood of over-education. These results support the original hypotheses.

By using a double selection adjustment procedure, it was found that 29 per cent of full-time workers are over-educated in Australia. Full-time workers are less likely to be over-educated than part-time workers. The incidence of over-education decreases with occupational level and it increases with educational level. Compared with Australians, NESB immigrants are more likely to be over-educated. Workers in Clerical and Administrative occupations have 11 per cent more likelihood of being over-educated than those who work in a position in Sales.

Different selection methods have been applied to over-education studies. Based on a survey carried out in 2001 by the Italian national statistics authority, Cutillo and Di Pietro (2006) employed a double selection probit model to examine the effects of over-education on wages in Italy. They considered two basic individual decisions. 'The decision to work' could create a problem of sample selection bias, whereas 'the choice of occupation' could generate an endogeneity bias. In addition, Green, et al. (2007) applied a bivariate probits approach to examine the determinants of over-education among employed immigrants based on the Longitudinal Survey of Immigrants to Australia (LSIA). They found that there are unobservable factors that increase the likelihood of both employment and over-education. These studies addressed sample selection issues based on cross-sectional data. The heterogeneity is controlled for in a panel fixed effects model based on longitudinal data: the selection issue due to heterogeneity may be solved in a fixed effected model. I will examine this effect in the next section.

Table 2. 4: Determinants of Over-education

	Model H2-1 No first step selection Dependent variables		Model H2-2 With first step selection Dependent variables	
	Probability of over-education Pr(over-education=1) =27%	Probability of full-time	Probability of over-education Pr(over-education=1) =29%	Probability of full-time
Explanatory Variables	Marginal effects	Coefficients	Marginal effects	Coefficients
Personal Characteristics				
Postgraduate	0.780***	-0.0112	0.780***	-0.0504
	(0.0116)	(0.0719)	(0.0115)	(0.0724)
Bachelor	-0.0879***	0.0937	-0.0865***	0.0593
	(0.0156)	(0.0660)	(0.0157)	(0.0665)
Certificate	-0.492***	0.314***	-0.493***	0.321***
	(0.00958)	(0.0603)	(0.00957)	(0.0603)
No qualification	-0.509***	0.281***	-0.510***	0.321***
	(0.00975)	(0.0608)	(0.00985)	(0.0616)
ESB immigrant	-0.00144	0.0715	-0.00253	0.0982**
	(0.0142)	(0.0487)	(0.0143)	(0.0492)
NESB immigrant	0.0513***	-0.0575	0.0486**	0.00979
	(0.0192)	(0.0571)	(0.0198)	(0.0593)
Has children aged 14 or less	/	0.177***	/	0.124***
Job characteristics	/	(0.0368)	/	(0.0388)
jbmo6s	-0.00738***	0.00528***	-0.00737***	0.00484***
	(0.000542)	(0.00186)	(0.000544)	(0.00186)
EXP	-0.00111	0.0116	-0.000871	0.00987
	(0.00315)	(0.00993)	(0.00315)	(0.00995)
EXP^2	3.95e-05	-0.000819***	3.62e-05	-0.000812***
	(6.00e-05)	(0.000172)	(5.98e-05)	(0.000173)
Job Tenure	-0.00334*	0.0369***	-0.00331*	0.0366***
	(0.00193)	(0.00638)	(0.00192)	(0.00638)
Job Tenure squared	0.000110*	-0.000704***	0.000109*	-0.000691***
	(5.89e-05)	(0.000180)	(5.89e-05)	(0.000180)
Occupation Tenure	-0.00238	0.0407***	-0.00242	0.0414***
	(0.00175)	(0.00548)	(0.00175)	(0.00549)

Table 2.4 *(Continued)*

	Model H2-1 No first step selection Dependent variables		Model H2-2 With first step selection Dependent variables	
	Probability of over-education Pr(over-education=1) =27%	Probability of full-time	Probability of over-education Pr(over-education=1) =29%	Probability of full-time
Explanatory Variables	Marginal effects	Coefficients	Marginal effects	Coefficients
Occupation Tenure squared	1.85e-05	-0.00101***	1.95e-05	-0.00103***
Occupations	(5.08e-05)	(0.000142)	(5.08e-05)	(0.000142)
Managers	-0.151***	0.545***	-0.151***	0.544***
	(0.0206)	(0.0996)	(0.0206)	(0.0997)
Professionals	-0.294***	0.00117	-0.294***	0.00981
	(0.0182)	(0.110)	(0.0182)	(0.110)
Technicians and Trades Workers	-0.123***	0.0821	-0.123***	0.0815
	(0.0220)	(0.0877)	(0.0220)	(0.0879)
Community & Personal Service Workers	0.0200	-0.138	0.0197	-0.145
	(0.0333)	(0.100)	(0.0333)	(0.101)
Clerical & Administrative Workers	0.112***	0.163*	0.111***	0.160*
	(0.0313)	(0.0945)	(0.0313)	(0.0947)
Machinery Operators and Drivers	-0.0339	0.216**	-0.0345	0.201**
	(0.0269)	(0.0947)	(0.0269)	(0.0948)
Labourers	0.0513	-0.344***	0.0503	-0.339***
Selection control	(0.0321)	(0.0922)	(0.0320)	(0.0923)
+Invmills_E	/	/	0.0627	-1.104***
	/	/	(0.0801)	(0.256)
Constant	/	0.556**	/	0.720***
	/	(0.222)	/	(0.226)
++Invmills_FT	-0.896***		-0.901***	
	(0.117)		(0.117)	
rho	-0.714		-0.717	
Observations	15,397	15,397	15,397	15,397

Notes: Wald test of independent equations is rejected in Models H2-1 and H2-2. Robust standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively. Base-categories are Advanced diploma, Australian, Not domiciled within a major city, NSW, Born in the 1950s, No supervisory role, Not Union member, Medium sized firms with 20 to 99 workers, Sales workers and Public administration and safety. The models include States dummy variables (QLD, VIC, SA, WA, TAS, NT, and ACT), Urbanization variables, Years of birth categories, Supervisory role, Union membership, Company size categories, Industry sectors, Unemployment, and time dummy variables. + Selection into employment (inverse of Mill's ratio); ++ Selection into full-time employment (inverse of Mill's ratio). Source: HILDA-Release 9.

2.6 Impacts of over-education on earnings

The purpose of this section is to examine the return to over-education and seek the explanation of over-education in relation to theory. It highlights the importance of taking into account unobserved heterogeneity when estimating the impacts of over-education on earnings.

This section is organised as follows. Firstly, in Section 2.6.1, I introduce three important theories based on the ORU earnings model. Then the econometric framework is discussed in Section 2.6.2. Hypotheses are outlined in Section 2.6.3, and empirical results are presented in Section 2.6.4.

2.6.1 Theoretical consideration

What is the reason for the existence of over-education, and why do over-educated workers accept jobs below their educational attainment and with a lower pay rate than they should achieve? Why do employers employ these over-educated workers who might not be satisfied with their circumstances and are more likely to leave? There is no unique theory of over-education. The following broad overview theories explain the existence of over-education from both the demand and the supply side, separately or jointly.

2.6.1.1 Human capital theory (HCT) (Becker, 1964)

The standard human capital earnings equation runs:

$$(2.9) \qquad lny = \alpha_1 + \beta_a S_a + \delta_1 X \quad + \varepsilon$$

Where lny is the natural logarithm of earnings, X is a vector of a variety of other control variables that generally includes personal characteristics and job characteristics, α_1 is the intercept term, and ε is an error term. (S_a) denotes years of education actually attained.

Human capital theory assumes that earnings do not depend on the job characteristics; they depend on the worker's educational attainment. This theory explains the existence of over-education based on the supply-side theory and the assumption that productivity is an increasing function of the human capital level of the worker (Linsley, 2005a). Human capital includes formal education, experience and on-the-job training. Ignoring the other human capital factors such as experience and on-the-job training, workers with the same education are paid equally. The return to over-education is the same amount as the return to adequate education.

Over-educated workers substitute weaknesses in other factors (experience, ability, quality of schooling, on-the-job training) of human capital by having a higher education than required. In contrast, under-educated workers substitute their shortage of education with strengths in other factors of human capital.

An extension of human capital theory is occupational mobility theory (or career mobility theory) which supports that over-education is a temporary, short-term mismatch phenomenon. This theory suggests that an over-educated worker would accept low-level jobs to gain the work experience and training in an effort to move to higher levels on the occupational ladder (Rubb, 2006). An over-educated worker gets more chances to be promoted to a higher level occupation matching his or her qualifications (Hersch, 1995; Rosen, 1976). Over-educated workers would change their status from being over-educated and underutilizing their skills to fully using their qualifications and skills.

Human capital theory can be rationalised by allowing for the existence of short-run disequilibria but does not explain the long-run phenomenon (Séamus McGuinness, 2006).

2.6.1.2 Job competition theory (Thurow, 1975)

The standard Job competition equation runs:

$$(2.10) \qquad lny = \alpha_1 + \beta_r S_r + \delta_1 X \quad + \varepsilon$$

Where (Sr) denote years of education required for the job. The other variables are defined as in Equation (2.9).

Job competition theory interprets the existence of over-education based on demand-side theory. Marginal productivity depends on job characteristics and the individual's earnings depend on his or her job's characteristics rather than his or her own personal characteristics. Any qualifications beyond those required to perform a job are not rewarded because workers are paid equally for a given job (Peter.J Sloane, 2002).

Thurow's (1975) job competition model characterises a market within which individuals compete for job opportunities based on their relative training costs, as opposed to competition based on the wages individuals are willing to accept given their human capital (Séamus McGuinness, 2006).

In general, job competition assumes there are two queues created: a job queue ranked by earnings because of workers' competition for high wage jobs, and a labour queue ranked by workers' educational level which saves training costs for firms. Job competition assumes that formal education and on-the-job training are substituted. Firms would like to hire workers with higher education to reduce training costs, and workers would like to have higher wage jobs. Thus, highly educated individuals are matched to higher paying jobs.

The increase in the educational attainment of workers causes a shift in the distribution of workers in the labour queue: firms will pick up people with higher education which forces low-skilled workers into low-paid jobs or out of the labour market. People with higher education pay a penalty since they are forced to accept jobs lower in the job queue. Even over-educated workers have lower returns on their educational investment; for securing a job or keeping that position, rational individuals still will invest in education. Job competition theory explains that over-education is a suboptimal investment in education, a form of allocation inefficiency.

Using Negotiating the Life Course Survey data, Linsley (2005a) studied the causes of over-education in Australia. After testing four key theories (human capital, job competition, assignment and career mobility theories) which have been used to explain over-education Linsley showed that the job competition model was the best model to explain the over-education phenomenon in the Australian labour market.

2.6.1.3 Assignment theory (Sattinger, 1993)

The standard assignment theory earning equation runs:

$$(2.11) \qquad lny = \alpha_1 + \beta_r S_r + \beta_o S_o + \beta_u S_u + \delta_1 X \quad + \varepsilon$$

This is the standard ORU (Over-education, Required education and Under-education) earnings model. It is widely used in 'over-education' empirical research. It was proposed by Duncan and Hoffman (1981) and it is the predominant approach in the recent literature.

lny is the natural logarithm of earnings, X is a vector of a variety of other control variables that generally includes personal characteristics and job characteristics, α_1 is the intercept term, and ε is an error term.

This model decomposes actual years of education (S_a) into required years of education (S_r), years of over-education (S_o), and years of under-education (S_u), that is $S_a = S_r + S_o - S_u$, where $S_o = S_a - S_r$ if $S_a > S_r$, and 0 otherwise. Similarly, $S_u = S_r - S_a$ if $S_r > S_a$, and 0 otherwise.

Equation (2.11) estimates β_r, β_o, β_u continuously, and β_r, β_o, β_u are the rates of returns to required education, over-education and under-education respectively.

Equations (2.9) and (2.10) can be special cases of Equation (2.11). Then human capital theory plays the role if $\beta_r = \beta_o = -\beta_u$ and job competition theory plays the role if $\beta_o = \beta_u = 0$. Therefore, human capital theory and job competition theory are two extreme cases of

assignment theory. Hartog and Oosterbeek (1988) tested these two conditions and the results did not support either, which means that the extended Equation (2.11) including both supply and demand side parameters is superior to Equations (2.9) and (2.10). Their results supported that the assignment model is superior to both the human capital model and the job-competition model.

Assignment theory derives from allocation theory which states that wages are instrumental in allocating heterogeneous workers to heterogeneous jobs. Assignment theory is used to explain the phenomenon of over-education according to the job and the worker's characteristics (J. Hartog & Oosterbeek, 1988).

Under this theory, the allocation is optimal when the workers' skill level matches their job level. Over-education represents allocation inefficiency in which Over-educated workers are under-utilising their education and skills by working at jobs beneath their level. Educational mismatches imply skill mismatches which in turn have a strong negative effect on productivity and wages. Over-education is a persistent phenomenon requiring matching processes and government policies to improve an efficient allocation of individuals to jobs.

Using data from the Netherlands, Allen and Velden (2001) tested assignment theory among a representative sample of graduates in the academic year 1994-95 by examining the relationship between educational mismatches and skill mismatches. Their findings shed light on the distinction between skills and schooling. Compared with assignment theory, their findings are mixed. In line with the predictions of assignment theory, educational mismatch has significant effects on wages, but inconsistently with the assumptions of assignment theory, educational mismatches are neither a necessary nor a sufficient condition for skill mismatches, and only a small proportion of the wage effects of educational mismatches are accounted for by skill mismatches. But after controlling for job quality, skill mismatches do have a significant effect on job satisfaction and on job search, whereas educational mismatches do not have a significant impact on these outcomes. In addition, their findings supported human capital theory by explaining that the graduates who are most competent attain higher level jobs and rewards more

frequently than those who are least competent even with the same educational level.

According to human capital theory, occupational mobility theory and job searching theory, 'over-education' is only a temporary period for workers who would get promoted within the firms or change a matching job across the firms. Job competition theory and screening theory explain that 'over-education' is a persistent phenomenon and brings inefficient resource allocation which should be researched seriously.

2.6.2 Econometric framework

I will follow the standard ORU (Over-education, Required education and Under-education) earnings model based on Equation (2.11).

The majority of previous studies (Allen and Velden, 2001; Cohn & Khan, 1995; Rumberger, 1987; Sicherman, 1991)) have supported assignment theory (Sattinger, 1993), whereas they reject human capital theory and job competition theory as indicated by the omitted variables in the earnings equation. Assignment theory proposes that the earnings function is a hedonic price equation with both supply and demand side parameters (J. Hartog & Oosterbeek, 1988).

Previous studies (Hartog, 2000; J. Hartog & Oosterbeek, 1988; Sicherman, 1991) consistently found that $\beta_r > \beta_o$ and $\beta_o > 0$, in which the return of over-education is lower than the return of required education, and the return of over-education is positive. In contrast, they also found that $\beta_u < \beta_r$ and $\beta_u < 0$, which means the return of under-education is lower than the return of required education, and that it is a negative return. These findings are found after controlling for the required years of education. This implies that the workers examined have remained in the same occupations with different level of education.

In this section, the analysis focuses on the link between over-education and earnings. A number of questions are to be answered. How does over-education impact, directly or

indirectly, on earnings via experience, tenure, and qualification category? Is the impact of over-education on earnings affected by factors of selection and unobserved heterogeneity, such as personal ability or 'poor' quality of qualification? Based on the standard ORU earnings model, several earnings models are applied in this study for issues of interest.

The first earnings model is based on a Heckman sample selection adjustment model. Model 2 uses basic ORU earnings model by applying panel fixed effects and random effects to examine the return to over-education. Model 3 provides an expanded earnings model to examine the impacts of over-education on earnings via experience, tenure, qualification and occupation).

Model 1: Heckman earnings correction

Similarly to the analysis of the incidence of over-education, sample selection bias would occur when estimating the return to over-education, because coefficients based on regressions which are restricted to the full-time sample would ignore part-time and unemployed workers. This is especially true if those who are in full-time employment are not randomly drawn from the working population. As a result, using coefficients based on this sample to represent the overall return to over-education for the population could produce sample selection bias.

To avoid potential selection bias while estimating the return to over-education, a two-step Heckman (1979) selection model is adopted. The same procedure is employed as in the analysis of the incidence of over-education. The difference is that, in this case, the latent over-education outcome equation is replaced by the continuous earnings equation. Thus, the first step estimates the probability of full-time employment for individual i, as in Equation (2.1). The second step estimates the return to over-education for individual i following the extended ORU (Over-education, Required education and Under-education)

earnings model (Equation (2.11)) under the condition of full-time employment.

Decisions to take full-time or part-time employment are quite different after becoming a parent. The financial responsibility may push male workers to undertake full-time, rather than part-time work if their partners take time off from work.

In addition, the double selection procedure is applied here as well. Both equations are adjusted for selection into employment; this is presented by variable Invmills_E.

An alternative approach to the sample selection adjustment is fixed effects. The fixed effects estimation method is applied to Models 2 and 3.

Model 2: Panel fixed effects (FE) and random effects (RE) model (unobserved heterogeneity)

(2.12)

$$lny_{i,t} = \beta_r S_{i,t}^r + \beta_o\left(S_{i,t}^a - S_{i,t}^r\right) + \beta_u\left(S_{i,t}^r - S_{i,t}^a\right) + \delta X_{i,t} + \alpha_i + \varepsilon_{i,t}$$

$$i = 1, \dots, N;\ t = 1, \dots, T$$

Where $lny_{i,t}$ denotes the hourly wage from the main job of individual i at year t; $X_{i,t}$ is personal characteristics and job characteristics of individual i at year t; α_i denotes the unobservable individual-specific effects and $\varepsilon_{i,t}$ denotes the remainder disturbance assumed independent and identically distributed i.i.d (0, σ_ε^2). $S_{i,t}^a$ denotes years of actual education and $S_{i,t}^r$ is the years of required education for individual i at year t. Thus, ($S_{i,t}^a - S_{i,t}^r$) is years of over-education when $S_{i,t}^a > S_{i,t}^r$; 0, otherwise. In contrast,

$(S_{i,t}^{r} - S_{i,t}^{a})$ is years of under-education when $S_{i,t}^{r} > S_{i,t}^{a}$; 0 otherwise. β_r is the rate of return to required education, β_o is the rate of return to over-education and β_u is the rate of penalty to under-education.

When conducting a fixed effects model, extra care needs to be taken because the coefficients may be biased if there is small within-group variation. An extended panel model was employed by adding interaction terms to Equation (2.12) to examine the impacts of educational mismatch, experience, tenure and qualifications on the return to over-education after controlling for the individual effects. The extended ORU earnings model is built by adding the experience-mismatch, tenure-mismatch and qualifications-mismatch, and occupation-mismatch variables into the basic ORU model. By doing so, I can examine the educational mismatch impacts on earnings via work experience, job tenure, occupation tenure, qualification categories and occupation. These results reveal further explanation regarding over-education earnings effects in the Australian labour market.

The extended model takes the following form:

Model 3: The extended ORU earnings model (over-education earnings impact via experience, tenure, qualification and occupation)

$$(2.13) \qquad lny_{i,t} = \beta_r S_{i,t}^{r} + \beta_o(S_{i,t}^{a} - S_{i,t}^{r}) + \beta_u(S_{i,t}^{r} - S_{i,t}^{a}) + \sum_{k=1}^{3}[\beta_{ke}\,(TYP_k \times \mathrm{EXP}) + \beta_{kt}(TYP_k \times \mathrm{Tenure})] + \sum_{k=1}^{3}\sum_{q=1}^{5}\beta_{kq}\,(TYP_k \times Qua_q) + \sum_{k=1}^{3}\sum_{o=1}^{5}\beta_{ko}\,(TYP_k \times Occup_o) + \delta X_{i,t} + \alpha_i + \varepsilon_{i,t}$$

$i = 1, \dots, N;\ t = 1, \dots, T; k = 1,2,3;\ q = 1, \dots ,5; O = 1, \dots ,8$

TYP_k is a dummy variable[7], which corresponds to the three types of educational mismatch. k takes the value of 1 if individual i is over-educated at time period t, and 0 otherwise. k takes the value of 2 if individual i at time t is under-educated, 0 otherwise. Education matched is the reference category.

EXP denotes the number of years of actual work experience. Tenure denotes the number of years of tenure in the current occupation or in the current job. Qua is a dummy variable and it denotes one of five qualifications categories. Occup is a dummy variable which represents one of the eight occupation categories.

The coefficient of interaction terms, β_{ke} and β_{kt} evaluate the earnings impacts of educational mismatch via experience and tenure. β_{kq} estimates the earnings impacts of educational mismatch via qualifications. β_{ko} examines the earnings effects of educational mismatch via occupations. These coefficients indicate whether over-education is a complement or a substitute for other types of human capital. The coefficient of these interaction terms between educational mismatch and qualifications or occupations indicates the extent of earnings penalty between over-education and required education with different levels of qualifications or in different occupations.

2.6.3 Hypotheses

a) When the ORU model is given by Equation (2.11):

$$lny = \alpha_1 + \beta_r S_r + \beta_o S_o + \beta_u S_u + \delta_1 \Phi_1 + \varepsilon$$

[7] See Verdugo and Verdugo (1989) for the applications of these dummy variables specifications in cross-sectional data.

β_r, β_o and β_u are the returns to required education, over-education and under-education, respectively. According to the previous stylised facts (Sicherman, 1991), the HILDA data is used to examine the following hypotheses:

(1) At any point in time over-educated workers would earn more than their matched co-workers; that is, $\beta_r > \beta_o$ and $\beta_o > 0$.

(2) Under-educated workers would receive lower wages than their matched co-workers, that is, $\beta_u < \beta_r$ and $\beta_u < 0$.

(3) To test the human capital, job competition and assignment theories, the following hypotheses could be constructed:

H1: $\beta_r = \beta_o = -\beta_u$

H2: $\beta_o = \beta_u = 0$

H3: $\beta_r = \beta_o = \beta_u = 0$

The first hypothesis H1 implies that earnings are only determined by educational attainment, If H1 is not rejected, the human capital theory holds.

The second hypothesis H2 implies that earnings are only determined by the educational requirements of the job. The failure to reject H2 indicates that job competition theory holds. If the third hypothesis H3 is rejected, then assignment theory holds.

b) The potential trade-off between education and other components of human capital (ability, experience, tenure, types of qualification and on-job-training) implies that over-educated workers may use their surplus years of education to compensate for their shortage of other types of human capital. Therefore, on average, over-educated workers are more likely to have less experience relative to adequately educated workers. It is hypothesised that there is a substitution relationship between over-education and experience. The signs of the coefficients of the interaction terms for experience, tenure and qualification and education variables imply the substitution or complementary

relationship between educational mismatch and the other components of human capital. For example, if the coefficients β_{ke} and β_{kt} are negative; this means that surplus education could compensate for lack of experience and tenure.

2.6.4 Empirical analysis

Based on three models previously discussed in Section 2.6.2, I examine earnings in three sub-sections. First, I use a double selection model to examine earnings by addressing selection issues: the results are presented in 2.6.4.1. Second, in Section 2.6.4.2, unobserved heterogeneity is accounted for in a panel fixed effects model. The three hypotheses H1, H2 and H3 are also examined by pooled OLS and panel fixed effects models. Third, the effects of over-education on earnings via experience, qualifications and occupation are examined in Section 2.6.4.3.

2.6.4.1 Heckman sample selection adjustment

With respect to the sample selection, I consider two specifications based on the first step selection (select into employment) control. Estimation results are shown in Table 2.5. The first model specification (Model 1A) presents no first step selection variable Invmills_E in both, outcome equation (Column (1)) and selection equation (Column (2)). In contrast, the second specification Model 1B is given by adding the selection variable, and the results are reported in Columns (3) and (4).

As anticipated, in Columns (2) and (4), male workers with children aged 14 or younger are more likely to be employed full-time. When the selection variable Invmills_E is not included, there is a significant negative effect, as shown by the second step selection variable (Invmills_FT) in Column (1), Table 2.5. However, once the selection variable Invmills_E is included in the earnings equation, there is no significant effect between the outcome equation and the selection equation. This implies that when examining return to over-education, the first step selection should be included. Without it, omitted variable bias will occur. However, the second step, selection into full-time employment does not have a significant effect on the earnings equation, which implies that the full-time

selection issue can be ignored when estimating earnings effects. After adjustments for sample selection have been made, return to over-education and return to required education are both moderately decreased from 4.6 per cent to 4.3 per cent and 5.4 per cent to 5.2 per cent. Without considering sample selection issue, the return to over-education and required-education are being slightly overestimated.

Comparing results in Column (1) with those in Column (3) in Table 2.5, the magnitude of coefficients slightly changes after adding the first step selection control variables. However, the significance of coefficients on years of over-education, under-education and required education does not change.

In summary, I use two steps selection to examine the incidence of over-education and its impact on earnings. The first step selection is for being selected from the labour force into employment. Results show that without this selection the result is an underestimation of the incidence of over-education, and the over-estimation of the return to over-education. The second step selection is from employment into full-time employment. This selection does not cause biases when estimating the incidence of over-education or return to over-education when the first step selection variable is added into the Heckman selection model. Without the first selection control, the Heckman selection result tells us that the incidence of over-education is more among part-time workers, and also part-time workers earn more than full-time workers per hour.

There are two motivations for using selection controls: one aims at examining whether or not the selection changes the overall results. The other aims at finding which selection correction is needed when examining earnings effects. Table 2.5 results show that after adding the first step selection control for employment, selection into full-time employment does not change the results for earnings.

Table 2. 5: Heckman Sample Selection Adjustment (Model1)

	Model 1A No first step selection		**Model 1B** With first step selection	
	(1)	(2)	(3)	(4)
Explanatory Variables	The Natural Logarithm of main job hourly wage in 2009 Dollars	Probability of full-time	The Natural Logarithm of main job hourly wage in 2009 Dollars	Probability of full-time
Years of over-education	0.0447**	/	0.0420**	/
	[0.019]	/	[0.019]	/
Years of under-education	-0.0405***	/	-0.0380**	/
	[0.016]	/	[0.016]	/
Years of required education	0.0527***	/	0.0505***	/
	[0.018]	/	[0.019]	/
Personal Characteristics				
ESB	-0.0117	0.1673*	0.0107	0.1825*
	[0.023]	[0.091]	[0.023]	[0.096]
NESB	-0.0564*	-0.0550	-0.0251	-0.0074
	[0.029]	[0.111]	[0.030]	[0.121]
Has Children aged 14 or less	/	0.3022***	/	0.2280***
	/	[0.064]	/	[0.074]
Job characteristics				
jbmo6s	0.0083***	0.0019	0.0081***	0.0019
	[0.001]	[0.003]	[0.001]	[0.003]
EXP	0.0233***	0.0093	0.0242***	0.0144
	[0.004]	[0.015]	[0.004]	[0.016]
EXP^2	-0.0003***	-0.0006**	-0.0004***	-0.0008***
	[0.000]	[0.000]	[0.000]	[0.000]
Job Tenure	-0.0056*	0.0344***	-0.0039	0.0357***
	[0.003]	[0.010]	[0.003]	[0.011]
Job Tenure squared	0.0001	-0.0007**	0.0000	-0.0007**
	[0.000]	[0.000]	[0.000]	[0.000]
Occupation Tenure	0.0041*	0.0432***	0.0075***	0.0439***
	[0.002]	[0.007]	[0.002]	[0.008]
Occupation Tenure squared	-0.0001	-0.0010***	-0.0002**	-0.0011***
	[0.000]	[0.000]	[0.000]	[0.000]
Selection control				
+Invmills_E	/	/	-0.5625***	-0.9817**
	/	/	[0.150]	[0.431]
Constant	1.7205***	0.4280	1.7183***	0.6685*
	[0.300]	[0.348]	[0.305]	[0.379]
++Invmills_FT	-0.315***		-0.0141	
	[0.0271]		[0.0515]	
rho	-0.725		-0.0344	
Censored observations	1551		1551	
Observations	15397		15397	

Notes:
Wald test of independent equations is rejected in Model 1A and is not rejected in Model 1B.
Robust standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are Advanced diploma, Australian, Not domiciled within a major city, NSW, Born in the 1950s, No supervisory role, Not Union member, Medium sized firms with 20 to 99 workers, Sales workers and Public administration and safety.
The models include qualifications dummy variables, States dummy variables (QLD, VIC, SA, WA, TAS, NT, and ACT), Urbanization variables, Years of birth categories, Supervisory role, Union membership, Company size categories, Industry sectors, Unemployment, and time dummy variables.
+ Selection into employment (inverse of Mill's ratio)
++ Selection into full-time employment (inverse of Mill's ratio)
Source: HILDA-Release 9.

2.6.4.2 Pooled ordinary least square regressions, panel fixed effects (FE) and random effects (RE)

Following the Heckman sample selection adjustment, controlling for selection into full-time employment shows no impact on earnings. Thus, the estimation of return to over-education can ignore the, second step, full-time selection issue. The first time employment selection variable needs to be added in both pooled OLS and panel fixed effects (FE) and random effects (RE) models.

Pooled OLS estimations:

Pooled OLS estimations of earnings effects may suffer from unobserved heterogeneity due to the assumption of homogeneous workers who are randomly assigned into jobs. In pooled OLS regression unobserved heterogeneity, such as ability, motivation, luck, or quality of qualification, etc. is not considered, but in panel regression it is controlled for. Thus, pooled OLS estimations are used as a benchmark in this study, for comparison with the panel regressions which examine the role of unobserved heterogeneity. Estimation results are reported in Table 2.6, Columns (1) to (3).

Following the standard ORU earnings model in Equation (2.11), OLS results are listed in Column (1) of Table 2.6, which is virtually the same as the results from Model 1B in Table 2.5. This confirms that results are not sensitive to the second step full-time selection. The return to over-education is 4.3 per cent and the return to under-education is -3.7 per cent. The return to required education is 5.2 Per cent. Potential work experience has a return of 2.5 per cent and tenure in current occupation has a relatively small return of 0.8 per cent.

These pooled OLS estimations are consistent with those from Rubb (2003) in which, the rates of return to a year of education, over-education and under-education are 9.6%, 5.2% and -4.8% respectively (S. Rubb, 2003). However, it is lower than the results from Voon and Miller (2005) who, based on the data from the 1996 Census of Population and Housing in Australia, reported the returns to years of actual education, required education,

over-education and under-education are 9.2% (8.0%), 18.2% (14.9%), 6.6% (5.3%) and -3.2% (-3.4%) for men (women), respectively. The researchers (Voon and Miller) used the Realised Match method (mean plus one standard deviation) to define the required years of education. They found that the years of attained education, if correctly matched, were 12.76 years for both men and women. The incidence of over-education is about 16% (14%) for male and female full-time workers aged 20 to 64. 71% of males and 68% of females had matched jobs. In the current study, based on the cross-wave Mode method, as shown in Table 2.2, 27.2 per cent of full-time workers are over-educated. Only 36.6 per cent of workers have educationally matched employment. Most workers cited in Voon and Miller (2005) were in matched employment, and a higher rate of the return to required education and actual education was found in their study.

Addressing potential endogeneity:

Fixed effects and random effects models are applied to evaluate the impact of unobserved heterogeneity on the earnings and estimation; the results are reported in Columns (2) and (3) of Table 2.6, respectively.

The Hausman test rejects the null hypothesis that individual-specific error is uncorrelated with the explanatory variables of the wage equation. Therefore, in the context of over-education, fixed effects estimates are preferred to random effects. The fixed effects results support the hypothesis that individual heterogeneity plays an important role in the return to over-education.

Comparing results in Column (1) with those in Column (2), Table 2.6, the first step selection variable becomes insignificant with panel fixed effects, which indicates that selection is not an issue when applying fixed effects to adjust for individual heterogeneity. In addition, the magnitude of over-education effects in a fixed effects model declines dramatically from 4.3 per cent to 1.9 per cent and the effects become insignificant. Similar effects are found in the return to required education, which decreases from 5.2 per cent to 1.5 per cent in fixed effects. The magnitude of the effects of under-education also becomes smaller. Notably, none of the above has a significant effect in fixed effects

estimations. This is evidence that after accounting for unobserved heterogeneity, educational mismatch does not have a significant effect on earnings.

Work experience has a stronger positive effect on earnings in panel fixed effects estimation (4 per cent) than in pooled OLS estimation (2 per cent). There is a 0.8 per cent return to each year of occupation tenure in pooled OLS; this return disappears in panel fixed effect regression.

As discussed previously in Section 2.6.3, three hypotheses tests H1, H2 and H3 are examined and results are presented in Table 2.6. The results indicate the explanation of over-education based on theoretical considerations.

Based on pooled OLS estimations, hypothesis tests H1, H2 and H3 are rejected. These results are consistent with those in a cross-sectional study (J. Hartog & Oosterbeek, 1988). They imply that assignment theory is superior to both human capital and job competition theory to explain the phenomenon of over-education according to worker and job characteristics.

In contrast, after controlling for unobserved heterogeneity, empirical results in a panel fixed effects model for hypotheses tests H1, H2, and H3 differ from pooled OLS regressions. Results from Column (2) in Table 2.6 show that H1 is not rejected. It indicates that the earnings model is determined by the supply side (worker characteristics). Human capital theory is applied to explain the existence of over-education. The more earnings workers get, the more years of education they obtain. After workers unobserved heterogeneity, such as ability, quality of qualification, and motivation is accounted for, Over-education is not a penalty.

Table 2. 6: Return to Over-education (Model 2)

Explanatory Variables	Dependent Variables: The Natural Logarithm of Hourly Wage from Main Job in 2009 Dollars		
	(1) Pooled OLS	(2) Panel-FE	(3) Panel-RE
Selection Variable: +Invmills_E	-0.5680***	0.0128	-0.1386**
	[0.145]	[0.067]	[0.064]
Years of over-education	0.0420**	0.0186	0.0543***
	[0.019]	[0.015]	[0.009]
Years of under-education	-0.0381**	-0.0063	-0.0485***
	[0.016]	[0.015]	[0.009]
Years of required education	0.0505***	0.0153	0.0547***
	[0.019]	[0.015]	[0.009]
ESB	0.0113	/	0.0064
	[0.023]	/	[0.024]
NESB	-0.0249	/	-0.0931***
	[0.030]	/	[0.031]
jbmo6s	0.0081***	0.0014***	0.0032***
	[0.001]	[0.000]	[0.000]
EXP	0.0243***	0.0398***	0.0355***
	[0.004]	[0.003]	[0.002]
EXP^2	-0.0004***	-0.0005***	-0.0005***
	[0.000]	[0.000]	[0.000]
Job Tenure	-0.0038	0.0017	0.0003
	[0.003]	[0.001]	[0.001]
Job Tenure squared	0.0000	-0.0001	-0.0000
	[0.000]	[0.000]	[0.000]
Occupation Tenure	0.0076***	0.0012	0.0026**
	[0.002]	[0.001]	[0.001]
Occupation Tenure squared	-0.0002***	-0.0001	-0.0001**
	[0.000]	[0.000]	[0.000]
Constant	1.7135***	2.4011***	1.6625***
	[0.300]	[0.231]	[0.142]
F-test	34.43	13.18	/
H1: ßr = ßo = -ßu	5.469***	4.604	4.190
H2: ßo = ßu =0	2.830*	4.890***	37.59***
H3: ßr = ßo = ßu=0	4.420***	3.344*	39.59***
R2	0.339	0.0575	0.0481
rho	/	0.777	0.654
Individuals	2352	2352	2352
Observations	13846	13846	13846

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result.
+ Selection into employment (inverse of Mill's ratio)
Robust standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are Advanced diploma, Australian, Not domiciled within a major city, NSW, Born in the 1950s, No supervisory role, Not Union member, Medium sized firms with 20 to 99 workers, Sales workers and Public administration and safety.
The models include qualifications dummy variables, States dummy variables (QLD, VIC, SA, WA, TAS, NT, and ACT), Urbanization variables, Years of birth categories, Supervisory role, Union membership, Company size categories, Industry sectors, Unemployment, and time dummy variables.
Source: HILDA-Release 9.

As noted earlier, in fixed effects models sufficient 'within' variation is required for achieving unbiased coefficients. The overall, 'between' and 'within' variations, for education mismatches related variables are presented in Table 2.7. In this study, for the full-time sample, the 'within variations' for continuous variables could explain around 57 and 22 per cent respectively of the general variation in years of over-education and under-education; these are slightly larger than those 'within variations' in Bauer (2002) and Tsai (2010). These estimations from panel fixed effects regression in this study still face a challenge related to the low 'within group' variations; and these may underestimate the effects of educational mismatch on earnings.

Table 2. 7: Standard Deviations of Education Mismatched Variables under Mode Measure

Continuous variables	Years of over-education	Years of under-education	Years of required education
Overall	1.46 [1.74]	1.69 [1.85]	2.05 [1.89]
Between	1.04 [1.79]	1.59 [1.89]	1.56 [1.65]
Within	1.10 [0.41]	0.79 [0.80]	1.45 [1.02]

Note: Numbers in [] are the respective standard deviations in Bauer (2002).
Source: HILDA-Release 9

2.6.4.3 Over-education interaction effects on wages

According to human capital theory, over-educated workers are more likely to substitute their education for lack of work experience. To test this hypothesis, two interactive products are added into the basic ORU model. Tenure in current employment and in current occupation are interacted with educational mismatch. In addition, ten interaction terms of educational mismatch and type of qualifications are used to estimate the mismatch effect on the various qualifications groups. Furthermore, terms for mismatch interaction with occupations are added to examine the mismatch effect in different

occupations (see Equation (2.13)).

Based on Model 3 in Equation (2.13), Tables 2.8 to 2.10 report the results of interaction terms after adding the interaction terms into Equations (2.11) and (2.12). The Hausman test rejects that random effects results are efficient and accepts that fixed effects results are consistent.

1. The impacts of over-education on earnings via experience and tenure

The results of education mismatch on earnings via experience and tenure are reported in Table 2.8.

Table 2. 8: Interaction with Experience, Job Tenure and Occupation Tenure (Model 3)

	Dependent Variable: The Natural Logarithm of Hourly Wage from Main Job in 2009 Dollars		
	(1)	(2)	(3)
Explanatory Variables	Pooled OLS	Panel-FE	Panel-RE
over-educated × Potential years of work experience	-0.0024**	-0.0009	-0.0002
	[0.001]	[0.001]	[0.001]
under-educated × Potential years of work experience	-0.0001	0.0000	0.0007
	[0.001]	[0.001]	[0.001]
over-educated × Tenure in the current occupation	-0.0011	0.0003	-0.0009
	[0.002]	[0.001]	[0.001]
under-educated × Tenure in the current occupation	-0.0010	-0.0007	-0.0012
	[0.001]	[0.001]	[0.001]
over-educated × Tenure in the current job	0.0056***	0.0025**	0.0018*
	[0.002]	[0.001]	[0.001]
under-educated × Tenure in the current job	0.0029	0.0004	-0.0004
	[0.002]	[0.001]	[0.001]
Individuals	2352	2352	2352
Observations	13846	13846	13846

Notes:

These models are based on models in Table 2.6 by adding interaction terms.
The Hausman test rejects the random effects result and accepts the fixed effects result.
Robust standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are Advanced diploma, Australian, Not domiciled within a major city, NSW, Born in the 1950s, No supervisory role, Not Union member, Medium sized firms with 20 to 99 workers, Sales workers and Public administration and safety.

The models include qualifications dummy variables, States dummy variables (QLD, VIC, SA, WA, TAS, NT, and ACT), Urbanization variables, Years of birth categories, Supervisory role, Union membership, Company size categories, Industry sectors, Unemployment, and time dummy variables.

Source: HILDA-Release 9

Firstly, even though the negative relationship is maintained between potential years of work experience, and over-education, it is not significant under fixed effects regression. The negative sign may imply that young workers use their excess education to substitute for their lack of work experience, as explained by human capital theory. The robust positive sign for tenure in current job does not change, but the magnitude of coefficient reduces from 0.6 per cent to 0.3 per cent between years of tenure in current employment position and over-education. This implies that once workers are allocated to their employment tasks, the over-educated workers earn more the longer they stay in their work place in comparison to workers who are in education-matched positions. Employers seemingly value over-educated workers with longer tenures more than they value matched workers with the same characteristics. There is no significant effect found between 'education mismatch' and 'occupation tenure'.

2. The impact of over-education on earnings via qualifications

The impact of education-occupation mismatch on earnings varies with the level of qualifications. The extent of the effects of education mismatch on earnings by qualifications is shown in Table 2.9.

Pooled OLS estimations show that over-educated workers holding a Bachelor degree earn 10.5 per cent less than matched workers holding a similar level of qualification. Among workers who hold other types of qualification, a negative, though insignificant, effect on earnings is found for over-educated workers compared with matched workers. This indicates that workers holding a Bachelor degree suffer most from educational mismatch compared to workers with other types of qualification. However, once unobserved heterogeneity is controlled for, workers with higher levels of qualification suffer lower earnings penalties than workers with lower levels of qualification or those without qualifications. This indicates that workers with a lower standard of education are more vulnerable to suffering an earnings loss from being educationally mismatched.

Table 2. 9: Interaction with Qualification Categories (Model 3)

Explanatory Variables	Dependent Variable: The Natural Logarithm of Hourly Wage from Main Job in 2009 Dollars (1) Pooled OLS	(2) Panel-FE	(3) Panel-RE
over-educated × Post graduate	-0.0171	-0.0042	-0.0030
	[0.077]	[0.034]	[0.031]
over-educated × Bachelor	-0.1048***	0.0131	-0.0030
	[0.039]	[0.024]	[0.022]
under-educated × Bachelor	0.0416	0.0352	0.0016
	[0.068]	[0.037]	[0.033]
over-educated × Diploma	-0.0605	0.0347	-0.0136
	[0.095]	[0.036]	[0.036]
under-educated × Diploma	-0.0022	-0.0095	-0.0223
	[0.089]	[0.036]	[0.036]
over-educated × Certificate	-0.0588	-0.0234	-0.0368*
	[0.041]	[0.022]	[0.021]
under-educated × Certificate	-0.0724*	-0.0300	-0.0269
	[0.043]	[0.021]	[0.019]
over-educated × No qualification	-0.0388	-0.0474**	-0.0174
	[0.040]	[0.023]	[0.023]
under-educated × No qualification	-0.1305***	-0.0586**	-0.0422
	[0.046]	[0.027]	[0.027]
Individuals	2352	2352	2352
Observations	13846	13846	13846

Notes: These models are based on models in Table 2.6 by adding interaction terms.
The Hausman test rejects the random effects result and accepts the fixed effects result.
Robust standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are Advanced diploma, Australian, Not domiciled within a major city, NSW, Born in the 1950s, No supervisory role, Not Union member, Medium sized firms with 20 to 99 workers, Sales workers and Public administration and safety.

The models include qualifications dummy variables, States dummy variables (QLD, VIC, SA, WA, TAS, NT, and ACT), Urbanization variables, Years of birth categories, Supervisory role, Union membership, Company size categories, Industry sectors, Unemployment, and time dummy variables.

Source: HILDA-Release 9

3. The impact of over-education on earnings via occupations

The earnings' effects of educational mismatch in occupations are also examined and the results are given in Table 2.10. It is found that the impact of education mismatch on earnings varies between different occupations. In addition, pooled OLS and panel estimations differ within occupations. In general, the higher the occupation level, the smaller the earnings penalty found between over-education and required education after

controlling for unobserved heterogeneity. For example, on results in Column (1) from pooled OLS estimations holding other factors constant, an over-educated manager earns less than a manager who works in a matched job; in contrast, based on the results in Column (2) from panel fixed effects regression, this person earns 4 per cent more than a manager in a matched job. Moreover, contrasting with results from pooled OLS regressions, over-educated Sales Workers earn 10 per cent less than other workers in jobs better matching their education. Similar evidence is also found among clerical and administrative workers who are found to have relatively 4 per cent less earnings than comparative workers. This further shows that educational mismatches are more serious at lower levels of skill or occupational scale levels, which should be a matter of concern.

In summary, pooled OLS results are consistent with previous stylised facts (Sicherman, 1991). The return to over-education is 4.3 per cent, the return to under-education is -3.7 per cent, and the return to adequate education is 5.2 per cent. However, the Panel fixed effects results are contrary to stylised facts, but they are consistent with the findings in Bauer (2002) and Tsai (2010). Over-educated workers do not earn less compared to matched workers after accounting for unobserved heterogeneity. Over-educated workers earn 3 per cent more than matched workers for each additional year of job tenure. The impacts of 'education mismatch' on earnings vary with the levels of qualifications and occupation. Clerical and Administrative workers, and Sales workers earn 4 per cent and 11 per cent less than comparable matched workers within occupations, respectively.

Table 2. 10: Interaction with Occupation Categories (Model 3)

	Dependent Variable: The Natural

Explanatory Variables	Logarithm of Hourly Wage from Main Job in 2009 Dollars (1) Pooled OLS	(2) Panel-FE	(3) Panel-RE
over-educated × **Managers**	-0.0395	0.0416*	0.0085
	[0.047]	[0.022]	[0.021]
under-educated × Managers	-0.0185	0.0226	-0.0025
	[0.047]	[0.022]	[0.021]
over-educated × Professionals	-0.0034	0.0093	0.0003
	[0.050]	[0.025]	[0.023]
under-educated × Professionals	0.0265	0.0423*	0.0339
	[0.050]	[0.025]	[0.023]
over-educated × **Technicians**	-0.2091***	-0.0487	-0.0573**
	[0.050]	[0.030]	[0.027]
under-educated × Technicians	-0.1650***	-0.1254***	-0.1093***
	[0.050]	[0.028]	[0.026]
over-educated × Service workers	-0.0641	0.0304	0.0046
	[0.046]	[0.042]	[0.039]
under-educated × Service workers	-0.0429	-0.0279	-0.0052
	[0.061]	[0.043]	[0.040]
over-educated × **Clerical and Administrative workers**	-0.0396	-0.0436*	-0.0329
	[0.045]	[0.025]	[0.025]
under-educated × Clerical and Administrative workers	-0.0626	-0.0434*	-0.0482*
	[0.042]	[0.026]	[0.026]
over-educated × **Sales workers**	-0.0467	-0.1095***	-0.0681*
	[0.073]	[0.038]	[0.037]
under-educated × Sales workers	-0.0702	-0.1084***	-0.0778**
	[0.059]	[0.037]	[0.037]
over-educated × **Operators and Drivers**	-0.0799**	-0.0130	-0.0160
	[0.039]	[0.025]	[0.025]
under-educated × Operators and Drivers	-0.0142	0.0015	0.0054
	[0.046]	[0.026]	[0.025]
over-educated × Labourers	-0.0437	-0.0129	-0.0005
	[0.059]	[0.029]	[0.029]
under-educated × Labourers	-0.0709	-0.0573*	-0.0313
	[0.061]	[0.030]	[0.029]
Individuals	2352	2352	2352
Observations	13846	13846	13846

Notes: These models are based on models in Table 2.6 by adding interaction terms.
The Hausman test rejects the random effects result and accepts the fixed effects result.
Robust standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are Advanced diploma, Australian, Not domiciled within a major city, NSW, Born in the 1950s, No supervisory role, Not Union member, Medium sized firms with 20 to 99 workers, Sales workers and Public administration and safety.

The models include qualifications dummy variables, States dummy variables (QLD, VIC, SA, WA, TAS, NT, and ACT), Urbanization variables, Years of birth categories, Supervisory role, Union membership, Company size categories, Industry sectors, Unemployment, and time dummy variables.

Source: HILDA-Release 9

2.7 Summary

This essay evaluates four alternative measures of over-education based on nine years of longitudinal HILDA data, examines the extent and determinants of over-education, and its impacts on earnings for full-time male workers aged 23 to 64 years old.

Four measures are based on cross-wave Mode (Mode), mean plus one standard deviation (Range-one), mean plus half standard deviation (Range-half) and Job Analysis (JA). Analyses show that the incidence of over-education is influenced by which method is used and how in HILDA belonging to the over-educated category is related to the choice of measurement variable. Job Analysis (JA) is not updated over time, and there is lack of consideration for the heterogeneity of jobs. Range-one (mean plus one standard deviation) and Range-half (mean plus half standard deviation) represent the symmetry between over-education and under-education; and the cut-off points of one standard and half standard deviation are arbitrary. The choice of the Mode measure is used to define the required years of education in the rest of thesis due to its several advantages.

Under the cross-wave Mode measure, after sample selection correction, approximately 29 per cent of full-time workers are found to be over-educated in Australia. Non-English speaking background Immigrants are more likely to be over-educated than native Australians. Workers with a post graduate degree have 78 per cent more chance of being over-educated, compared to workers with Advanced diploma qualifications. However, workers with a subject specific certificate qualification are more likely to work in jobs better matched to their education. Compared with Sales workers, workers in three types of occupations (Professional, Technical and Trades, Management) seemingly have less likelihood of being over-educated. In contrast, there is 11 per cent more likelihood of being over-educated in Clerical and Administrative occupations. Having a higher occupational level position assists workers in having less risk of being over-educated.

Without controlling for unobserved heterogeneity, the pooled OLS results are consistent with stylised facts (Sicherman, 1991). The returns to years of required education, over-education and under-education are 5.2 per cent, 4.3 per cent and -3.7 per cent, respectively.

27 per cent of workers with Bachelor's degrees are over-educated and earning 9.9 per cent less than their matched colleagues at the same educational level. A substitution relationship is found between over-education and potential years of work experience. A complementary relationship is found between educational mismatch and current employment tenure. Technicians are less likely to be over-educated, but once they are classified as being over-educated, they suffer a 19 per cent earnings loss compared with matched workers in the same occupation.

Once unobserved heterogeneity (ability, motivation, etc.) is accounted for, the effects of required education, over-education and under-education drop and become insignificant. There are no significant effects on the terms of interaction between educational mismatch and qualification categories. The substitution relationship between over-education and potential work experience no longer exists. However, a positive sign is still maintained between over-education and current job tenure, even with smaller effects than those in the pooled OLS estimations. This implies that over-educated workers may benefit from staying in their current positions or, employers may value over-educated workers if they stay in their firms longer. With respect to educational effects on different occupations, panel fixed effects results contrast with results drawn from OLS regression. Technicians do not suffer a wage penalty from educational mismatch. Within occupations, over-educated Sales Workers and over-educated Clerical and Administrative Workers earn 10 per cent and 4 per cent less, respectively, than other workers who work in jobs which require education equal to their educational attainments. In contrast, over-educated managers earn 4 per cent more than matched managers with the other similar characteristics. This evidence indicates that educational mismatch is serious among workers with lower levels of qualification who have been allocated to lower level occupations. This fact requires attention.

Appendix 2A

Table 2A. 1: Definition of Variables

Personal Characteristics	
(1) General	
Age	Continuous age variable, expressed in years
Years of birth	Years of birth variable, expressed in years
Married	Dummy variable, 1 if married(or de facto), zero otherwise
Has Children aged 14 or Less	Dummy variable, 1 if has any children aged 14 or less, zero otherwise
Disability or impairment	Dummy variable, 1 if has Long term health condition, disability or impairment, zero otherwise
Father working in professional occupation	Dummy variable, 1 if father working in professional occupations, zero otherwise
Mother working in professional occupation	Dummy variable, 1 if mother working in professional occupations, zero otherwise
(2) Qualifications	
Years of education	Continuous educational attainment variable, expressed in years
Postgraduate	Dummy variable, 1 if highest qualification is Doctorate, Masters, grad diploma, grad certificate or Bachelor with honours, zero otherwise
Bachelor	Dummy variable, 1 if highest qualification is Bachelor without honours, zero otherwise
Advanced diploma	Dummy variable, 1 if highest qualification is Advanced diploma or diploma, zero otherwise
Certificate	Dummy variable, 1 if highest qualification is certificate I II III or IV, zero otherwise
No qualification	Dummy variable, 1 if highest qualification is year12 or below, zero otherwise
(3)Country of birth	
Native	Dummy variable,1 if born in Australia, zero otherwise
ESB immigrant	Dummy variable,1 if born in an English speaking country, zero otherwise
NESB immigrant	Dummy variable,1 if born in an non-English speaking country, zero otherwise
(4)Region and States	
Urban	Dummy variable,1 if domiciled within a major city, zero otherwise
NSW	Dummy variable, 1 if living in NSW, zero otherwise
VIC	Dummy variable, 1 if living in VIC, zero otherwise
QLD	Dummy variable, 1 if living in QLD, zero otherwise
SA	Dummy variable, 1 if living in SA, zero otherwise

Table 2A.1 *(Continued)*

WA	Dummy variable, 1 if living in WA, zero otherwise
TAS	Dummy variable, 1 if living in TAS, zero otherwise
NT	Dummy variable, 1 if living in NT, zero otherwise
ACT	Dummy variable, 1 if living in ACT, zero otherwise
Job characteristics	
(1) General	
Employed	Dummy variable,1 if employed, zero otherwise
Unemployed	Dummy variable,1 if unemployed, zero otherwise
Unemployment	Unemployment rate annually, refer to 6202.0 - Labour Force, Australia, Australian Bureau of Statistics
FT	Dummy variable,1 if full-time employed, zero otherwise
PT	Dummy variable,1 if part-time employed, zero otherwise
EXP	Continuous variable, expressed in potential years of work experience, calculated by hgage-edhighy-5.
EXP^2	Continuous variable, experience square
Job Tenure	Continuous variable, expressed in year's tenure in the current job.
Job Tenure squared	Continuous variable, expressed in year's tenure square in the current job.
Occupation Tenure	Continuous variable, expressed in year's tenure in the current occupations.
Occupation Tenure squared	Continuous variable, expressed in year's tenure square in the current occupations.
Weekly Hours worked in main job	Continuous variable, expressed in hours per week usually worked in main job
Weekly gross wages and salary from main job	Continuous variable, expressed in current weekly gross wages and salary from main job
Hourly wages from main job	Continuous variable, expressed in current weekly gross wages and salary from main job divided by combined hours per week usually worked in main job 2009$
Log hourly wage from main job	Continuous variable, expressed in the natural logarithm of hourly wage from main job in 2009 dollars
Supervisory role	Dummy variable,1 if supervise work of other employees, zero otherwise
Union member	Dummy variable,1 if union member, zero otherwise
Small Sized Firm with less than 20 workers	Dummy variable,1 if employed in a firm with less than 20 employees, zero otherwise
Medium Sized Firm with 20 to 99 workers	Dummy variable,1 if employed in a firm with 20 to 99 employees, zero otherwise
Medium Large Sized Firm with 100 to 499 workers	Dummy variable,1 if employed in a firm with 100 to 499 employees, zero otherwise
Large Sized Firm with 500 or more workers	Dummy variable,1 if employed in a firm with 500 or more employees, zero otherwise
Jbmo6s	AUSEI06 occupational status scale, current main job
(2) Occupations	
Managers	Dummy variable, takes the value 1 if working in the occupation of managers, zero otherwise
Professionals	Dummy variable, takes the value 1 if working in the occupation of professionals, zero otherwise
Technicians and Trades workers	Dummy variable, takes the value 1 if working in the occupation of technicians and trades workers, zero otherwise
Community and Personal Service Workers	Dummy variable, takes the value 1 if working in the occupation of community and personal service work, zero otherwise

Table 2A.1 *(Continued)*

Clerical and Administrative Workers	Dummy variable, takes the value 1 if working in the occupation of clerical and administrative workers, zero otherwise
Sales Workers	Dummy variable, takes the value 1 if working in the occupation of sales workers, zero otherwise
Machinery Operators and Drivers	Dummy variable, takes the value 1 if working in the occupation of machinery operators and drivers, zero otherwise
Labourers	Dummy variable, takes the value 1 if working in the occupation of labourers, zero otherwise
(3) Industry Sectors	
Agriculture, Forestry and Fishing	Dummy variable, takes the value 1 if working in the industry of agriculture, forestry and fishing, zero otherwise.
Mining	Dummy variable, takes the value 1 if working in the industry of mining, zero otherwise.
Manufacturing	Dummy variable, takes the value 1 if working in the industry of Manufacturing, zero otherwise.
Electricity, Gas, Water and Waste	Dummy variable, takes the value 1 if working in the industry of electricity, gas, water and waste services, zero otherwise.
Construction	Dummy variable, takes the value 1 if working in the industry of construction, zero otherwise.
Wholesale Trade	Dummy variable, takes the value 1 if working in the industry of wholesale trade, zero otherwise.
Retail Trade	Dummy variable, takes the value 1 if working in the industry of retail trade, zero otherwise.
Accommodation and Food Services	Dummy variable, takes the value 1 if working in the industry of accommodation and food services, zero otherwise.
Transport, postal and ware housing	Dummy variable, takes the value 1 if working in the industry of transport, postal and warehousing, zero otherwise.
Information, Media and Telecommunications	Dummy variable, takes the value 1 if working in the industry of information media and telecommunications, zero otherwise.
Financial and Insurance services	Dummy variable, takes the value 1 if working in the industry of financial and insurance services, zero otherwise.
Rental, Hiring and Real Estate services	Dummy variable, takes the value 1 if working in the industry of rental, hiring and real estate services, zero otherwise.
Professional, Scientific and Technical services	Dummy variable, takes the value 1 if working in the industry of professional, scientific and technical services, zero otherwise.
Administrative and Support Service	Dummy variable, takes the value 1 if working in the industry of administrative and support services, zero otherwise.
Public Administration and Safety	Dummy variable, takes the value 1 if working in the industry of public administration and safety, zero otherwise.
Education and Training	Dummy variable, takes the value 1 if working in the industry of education and training, zero otherwise.
Healthcare and Social Assistance	Dummy variable, takes the value 1 if working in the industry of health care and social assistance, zero otherwise.
Arts and Recreation services	Dummy variable, takes the value 1 if working in the industry of arts and recreation services, zero otherwise.
Other Services	Dummy variable, takes the value 1 if working in the industry of other services, zero otherwise.
Mismatched status	
Over-educated	Dummy variable, takes the value 1 if over-educated, zero otherwise.
Under-educated	Dummy variable, takes the value 1 if under-educated, zero otherwise.
Adequately educated	Dummy variable, takes the value 1 if adequately educated, zero otherwise.
Years of over-education	Continuous variable, the years of over-education.
Years of under-education	Continuous variable, the years of under-education.
Years of required education	Continuous variable, the years of adequate education.

Table 2A. 2: Sample Selection for Employed Category

Explanatory Variables	Dependent Variable The Probability of being Employed
Disability or impairment	-0.0531***
	(0.00858)
Mather working in professional occupations	0.00809*
	(0.00462)
Father working in professional occupations	0.00490
	(0.00479)
Married	0.0359***
	(0.00779)
Has Children aged 14 or Less	0.00579
	(0.00466)
Postgraduate	0.0124*
	(0.00691)
Bachelor	0.0125**
	(0.00487)
Certificate	-8.66e-05
	(0.00676)
No qualification	-0.00766
	(0.00693)
ESB	-0.0137
	(0.00953)
NESB	-0.0362**
	(0.0153)
Urban	0.00230
	(0.00601)
VIC	-0.00548
	(0.00637)
QLD	-0.00236
	(0.00621)
SA	0.000434
	(0.00748)
WA	0.0131***
	(0.00463)
TAS	0.00868
	(0.00882)
NT	0.0162**
	(0.00755)
ACT	0.0154**
	(0.00777)
Unemployment rate	-0.724***
	(0.130)
Control for time periods	YES
Observations	15,915
Individuals	2578

Notes: Robust standard errors in parentheses;
***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively

3. Essay Two:

A Longitudinal Analysis on the Incidence of Over-education among Immigrants and its Impacts on Earnings

Abstract

This essay uses longitudinal analyses based on the Household, Income and Labour Dynamics in Australia (HILDA) Survey to investigate the extent of matching between education and occupation and resulting effects on earnings among immigrants in Australia. The panel approach based on nine years of longitudinal data addresses individual heterogeneity effects that are important to over-education analysis, and thereby extends the international literature. Correlated random effects (CRE) logit with Mundlak (1978) correction results suggest that both ESB (English speaking background) and NESB (Non-English speaking background) immigrants have high incidence rates of over-education. Age at migration and year of arrival have significant effects on the incidence of over-education among NESB immigrants, on the other hand, this appears to have no effects among ESB immigrants. Longitudinal analyses show an assimilation effect among both NESB and ESB immigrants, with ESB immigrants experiencing faster assimilation rates than NESB immigrants. Over-education has been shown to slow down assimilation for NESB immigrants. Pre-migration education obtained abroad is valued in Australia for ESB immigrants; although this is not the case for NESB immigrants. Current Australian immigration policy favours skilled migrants. However, if their skills are not fully used in their jobs, the under-utilisation of skills impedes their assimilation process.

Keywords: over-education, years since migration, age on arrival, year of arrival, country of qualification, earnings

3.1 Introduction

It is a commonplace occurrence to hear of immigrants being employed in occupations that are below the level of their educational attainment; such as those from professional occupations driving taxis or working as kitchen hands. What is the extent of this phenomenon across host countries? What are the determinants of this disadvantageous situation among immigrants? How can immigrants' skills be used to full advantage? A topic of significant debate among researchers and policy makers has been immigrants' adjustment, assimilation, and success in their new labour market.

This study uses longitudinal data to examine labour market outcomes for immigrants in the Australian labour market.

During a two-year period (2005-2006), about 48,865 skilled migrants, 45,290 family migrants and 14,140 humanitarian migrants arrived in Australia. The number of skilled migrant visas issued in 1998-99 was 35,000, which increased to 97,340 in 2005-06. Of these, 17% permanent arrivals came from the United Kingdom and 11% came from New Zealand.

> "Skilled visa holders were the most likely to be employed after arriving in Australia. Humanitarian visa holders were the least likely to be employed. However, the longer an immigrant remained in Australia, no matter what their visa class, the more likely they were to be in employment." (DIMA 2007)

The evidence shows that Australian immigration policy has placed greater emphasis on skill based immigration because skilled immigrants are more employable and more productive than their unskilled counterparts. Thus, they are therefore likely to increase Australia's productive capacity. However, if immigrants cannot work in occupations that fully utilise their skills, this productivity gain is reduced. The cause of "the unrecognised skills of immigrants" is the mismatching of educational attainment and the educational requirements for migrants prospective occupations in the host country, generally referred to as over-education. When compared to native-born, immigrants are more likely to be

over-educated and to suffer an earnings loss and therefore explicit individual earnings disadvantage (See for example, Chiswick and Miller, 2008). Moreover, a potential loss to the economy as well as a significant burden on new arrivals may be caused (Ferrer & Riddell, 2008).

Over-education[8] is defined as the extent of someone's actual education exceeding the educational requirement to perform his or her job. Because the HILDA data does not provide any questions on over-education, workers' self-reports (SR) are not applicable. Thus, the required years of education to do a job for a particular occupation can be defined by using a cross-wave Mode measure; this measures the number years of education required to undertake a position of employment; the number varies between waves. The amount of education that most commonly occurs within an occupational category is calculated for each wave. The required years of education for all nine waves, are derived by combining the Mode education of all waves; next, the years of over-education and years of under-education are obtained by comparing the actual years of education with the required years of education.

By employing the procedure described, it was found that the incidence of over-education differed considerably between the native born population and the immigrants. In particular, immigrants were shown to have a higher probability of being over-educated than natives[9]. Non-English-Speaking background (NESB) immigrants were found to suffer especially from extremely high levels of educational mismatch. For example, the incidence of over-education ranged from 24 per cent to 28 per cent among natives. However, among English-Speaking background (ESB) immigrants it was 3 to 10 per cent higher, ranging from 28 per cent to 36 per cent; the incidence of over-education was 36 per cent to 48 per cent among NESB immigrants. This is 17 per cent to 21 per cent higher than for the native born population, depending upon the specific year of assessment. It was also found that ESB immigrants earn a premium wage and NESB immigrants suffer

[8] Over-education is defined and calculated based on cross-wave mode method which can be referred to essay one.

[9] Natives in this paper refer to people who were born in Australia, and this applies to the entire study.

loss of earnings when compared to natives.

A number of questions arise from these findings. Why is it that immigrants have a higher incidence of over-education than natives? What are the determinants of educational mismatch? What is the relationship between earnings and over-education? Does over-education have a negative effect on earnings? Why do NESB immigrants earn less than natives? Can NESB immigrants reduce their earnings disadvantage with years since migration? These questions have motivated the research reported in this paper.

To date, immigrants' over-education is under-researched in Australia. This study makes the following contributions to the international literature: It investigates the determinants of over-education among immigrants in Australia, and the extent of the impact of over-education on earnings after accounting for individual heterogeneity. I use the correlated random effects (CRE) logit model, and fixed effects earnings models to address endogeneity and individual heterogeneity. To the best of our knowledge, it is the first examination of the determinants of over-education and its impact on earnings among immigrants using longitudinal techniques based on panel data. In addition, specific sub-group effects, such as, age at migration, year of arrival and country of qualification effects are examined among ESB and NESB immigrants respectively. This study also examines new evidence based on panel data on the transferability of experience and education abroad for immigrants.

The over-education of immigrants is examined from the following perspectives:

Country of origin and language proficiency

In the study of immigrants 'assimilation, country of origin is of importance. Immigrants from different countries have differing assimilation rates in the host country. Immigrants from a background that is similar to that of the host country are more likely to have similar incidence rates of over-education due to the higher transferability of human capital. However, those from a non-English speaking background may find it more difficult to

settle down, which could produce serious over-education rates. The over-education rate of immigrants may not converge with the rate of natives, even after a lengthy period of residence.

As English is the main language in Australia, the English proficiency of immigrants may help them to obtain education-occupation matched jobs. Compared to NESB immigrants, in the host country, ESB immigrants would expect to face similar labour market conditions to those of their country of origin. Their prior migration experience and education may be portable to the host countries. As a result, relative to NESB immigrants, ESB immigrants may adapt to new environments quickly, and be more likely to find a matched job.

In this study, an immigrant is defined as a person who was born overseas. Base on the English proficiency and country of origin, I differentiate immigrants between ESB immigrants and NESB immigrants. People born overseas are asked whether English is the first language they learned to speak as child[10]. If English was the first language learned, the immigrant is defined as an ESB immigrant, otherwise, as a NESB immigrant. Thus, the sample is divided into three subsamples: Natives, ESB immigrants and NESB immigrants.

Chiswick and Miller (2009b) provided evidence of strong positive relationships between English speaking proficiency and occupational attainment.

Transferability of human capital

Human capital acquired both abroad and domestically may have a variety of effects on the rates of over-education. Since transferability of human capital is limited, education and experience obtained abroad are discounted in the host country (Friedberg, 2000).

[10] This variable is constructed for the population born overseas. The survey asked: Is English the first language you learned to speak as a child? Answer 1-English was first language learned; 2- English was not first language learned.

Immigrants generally demonstrate high rates of over-education due to the imperfect transferability of human capital in the host country. Thus, the over-education rates of immigrants signify education-occupation matching difficulties in the host countries' labour market, and they reflect an important dimension of immigrants assimilation (Friedberg, 2000).

Therefore, to analyse the impact of over-education on transferability of human capital, I distinguish human capital between human capital obtained abroad and that obtained domestically. I examine the impacts of both experience and education acquired abroad on the incidence of over-education.

Furthermore, based on the country where qualifications are obtained, two types of qualification are defined among immigrants: Qualifications obtained domestically (in Australia) and abroad (overseas qualifications). The differing incidence of the rates of over-education among these two groups may reflect the transferability of human capital.

With time, gaining local experience or investing in local education may help immigrants to improve educational and job matches, reduce the rates of over-education, and decrease the earnings penalty.

Age at migration

Migrating as a child or as an adult may give rise to differing effects on the incidence of over-education. Young immigrants are more likely than adults to adapt to their new country of residence and to achieve qualifications in the host country. Thus, they behave similarly to a member of the local population even though they may still face a certain amount of discrimination.

Year of arrival

Immigrants 'quality' affect them to allocate at matched position, in particular,

immigration policy has favoured skilled immigrants in recent years. Thus, this implies that recent cohort 'quality' is increasing compared to the earlier cohort. However, the earlier entrants have acquired the domestic experience and are expected to less likely to be over-educated than the recent entrants.

The following questions are addressed in this study:

> *To what extent are immigrants and natives over-educated? Does the incidence of over-education among immigrants vary by country of origin, English proficiency, age on arrival and year of arrival?*
>
> *Are there differing impacts of over-education on earnings between sub-groups based on country of origin and English proficiency?*
>
> *Are there differing impacts of over-education on earnings between sub-groups based on age on arrival, year of arrival and country of qualification?*

To estimate the effects of over-education on immigrants' assimilation effects, I examine the following hypotheses.

1. NESB Immigrants are more likely to be over-educated in relation to ESB immigrants at the time of arrival.
2. As time passes, by gaining local experience or investing in local education, the over-education rates of immigrants converge to the rates of the native born population, and the immigrant earnings differential relative to that of the native born decreases. Therefore, the coefficients of YSM (years since migrating to Australia) are predicted to be negative when examining the incidence of with over-education, and positive with earnings.
3. Immigrants' experience and education are divided into pre-migration experience and pre-migration education, and post-migration experience and post-migration education. ESB immigrants are predicted to have pre-migration human capital transferable to the host country and can thereby enhance the match of their education and occupation.
4. Younger labour market entrants are less likely to be over-educated compared to the older entrants because they are likely to gain more education and experience

in host country than older entrants.

5. Over-education is more likely among the recent labour market entrants compared to the earlier entrants.

The remainder of this essay is organised as follows. Section 3.2 provides an overview of recent immigrants' over-education literature, and it identifies the main factors affecting immigrants mismatch and labour market outcome in the host country. Section 3.3 develops the econometric framework. Section 3.4 outlines the data and variables. The results are presented in Section 3.5 to Section 3.6, followed by a summary in Section 3.7.

3.2 Review of the literature

A number of studies have examined over-education among immigrants in different countries, and reviews of the literature are presented in Table 3.1. Regardless of host country and official language, these studies have shown that immigrants have a high incidence rate of over-education, ranging, from 16 per cent (Kler, 2007) in Australia to 96 per cent (Aringa and Pagani, 2010) in Italy. And immigrants suffer an earnings loss from education-occupation mismatches (Chiswick and Miller, 2006; Kler, 2007; Green, Kler and Leeves, 2007; Lindley, 2009; Wald and Fang, 2008).

To date few studies have been conducted on immigrant assimilation in the Australian labour market. Based on the 2001 Census of Population and Housing, Chiswick and Miller (2006) reported that NESB immigrants have a lower rate of return to schooling accompanied by over-education and under-education. The payoff to years of schooling for Australian-born males is 8.8 percent. For ESB immigrants and NESB immigrants, it is 8 percent and 5.9 percent, respectively. However, there is the same payoff to required years of schooling of 15.2 percent for these three groups. The earning effects of over-education (under-education) is 5 to 6 (-3 to -4) percent for the Australian-born and ESB immigrants, and it is about 3 (-1) percent for NESB immigrants.

Based on longitudinal data for immigrants to Australia (LSIA), Green, Kler and Leeves (2007) examined the determinants of employment and over-education. They also studied

the return to required schooling and surplus schooling by two cohorts among male immigrants aged 15-64. They found that immigrants, even those with skill-assessed visas are more vulnerable to over-education than natives. NESB immigrants are more likely to be over-educated, with the incidence of over-education between 32% and 49%. NESB immigrants also have lower returns to required and surplus education than do natives. Tighter welfare and support policies[11] for immigrants may increase the employment at the expense of under-utilising their skills. However, their sample is limited to recent immigrants in their sample (arriving in 1993, 1995, 1999, and 2000). The analysis employed OLS estimation.

Using the same LSIA dataset with the addition of the inclusion of both genders, Kler (2007) examined the effects of over-education among tertiary educated immigrants. The evidence is in line with Green, Kler and Leeves (2007). The incidence of over-education is similar between ESB immigrants and natives, and is higher among Asian NESB immigrants. The rate of over-education is around 16% for ESB immigrants. Among Asian immigrants, approximately 50% are over-educated. Among other NESB immigrants, the rate of over-education is close to 40%. The payoff to over-education is much smaller than the payoff to required education. There is no significant effect of over-education on earnings among Asian immigrants.

Green, Kler and Leeves (2007) and Kler (2007) used a bivariate probit model to examine the incidence of over-education, and an augmented human capital earnings model (Frenette,2004) to examine earning effects in the Australian labour market. They focused on the effects of visa category and labour market conditions.

This study extends Green, Kler and Leeves' (2007) work and it contributes to the Australian literature as follows. I extend the analysis to panel data, and I employ a correlated random effects (CRE) logit model with Mundlak (1978) correction to examine the incidence of over-education by focusing on the effects from years since migration,

[11] For example, stringent entry standards were applied to skill and English language ability test scores and eligibility to claim welfare and unemployment benefits was extended from 6 to 24 months (except for humanitarian visa holders).

age at migration and year of arrival. The endogeneity due to the correlation between explanatory variables and error terms is addressed by Mundlak correction. I also employ both panel fixed effects (FE) and random effects (RE) models to examine the effects of over-education on earnings from years since migration and transferability of human capital by country of origin, age on arrival, year of arrival and qualification type respectively. The latter aspect of my study on the effects of transferability of human capital on over-education and earnings and the panel feature of the analysis extend the international literature.

In Spain, the effects of years since migration effects have been examined by Fernández and Ortega (2008). They used data from the Spanish Labour Force Survey for the period 1996-2006, and showed that compared to the rates for the native-born, immigrants experience initially higher participation and unemployment rates, and have a higher incidence of over-education and temporary contracts. Over a five-year period, immigrants' participation rate was shown to be reduced to that of those who are native-born and unemployment rates to levels even lower than those of the native-born. The incidence of over-education and temporary contracts however remained constant.

Moreover, the portability of immigrants' human capital into the Spanish job market has been studied by Sanroma, Ramos, and Simon (2008). They suggested that geographic origin has an influence on transferability of human capital. Immigrants from countries that are highly developed, or have a similar culture or language to that of the host countries, have higher transferability levels. This indicates their human capital acquired from abroad is portable to the host countries. The researchers' empirical results were consistent with those of previous studies (Friedberg, 2000); schooling acquired abroad has a significant effect on earnings in the host country, whereas, seemingly, experience gained elsewhere has no such effect.

Similar evidence is also found in the study of the Italian labour market by Aringa and Pagani (2010). Based on data from the Italian Labour Force Survey for the years between 2005 and 2007, Aringa and Pagani found that foreigners arriving in Italy are much more likely to be over-educated than are the natives, and that work experience acquired in

countries of origin is not valued in the Italian labour market. Furthermore, experience acquired in Italy did not help to improve their education-occupation match. The researchers suggested that foreigners struggle to catch up with natives even if they adapt their skills to the host countries.

Age at arrival is expected to have a negative effect on immigrant earnings. This was shown by Friedberg (1992), who found that there was an 11.6 per cent earnings disadvantage between an immigrant who arrived in the United States at age 30 and a comparable immigrant who had migrated at age 10.

Reference to Table 3.1 here. Table 3.1 provides a succinct summary of the studies reviewed in this section.

Table 3. 1: Review of Recent Literature on Over-education among Immigrants

Study **Year Measure** **Country of study**	**Data** **Sample**	**Incidence of over-education**	**Earning consequence or others**
Chiswick and Miller 2006 JA RM Australia	2001 Australian Census of Population and Housing NESB: Immigrants from non-English speaking countries; ESB: immigrants from English speaking countries.	n/a	Actual Education: 8.8 % for Australian-born males; 8% for ESB and 5.9% for NESB. Required education (RM): 15.2% for all. (11.2,12.7,9.6 with JA) Over-education (RM): 6-5.6% for Australian-born and ESB; 3.2% for NESB. (5.3,5.3,3.5with JA) Under-education (RM): -3 .7to -2.7% for the Australian-born and ESB;-1.4% for NESB. (-8.3,-6,-5.2 with JA)
Kler 2007 JA Australia	The Longitudinal Survey of Immigrants to Australia (LSIA) Estimates Impacts from visa classes and prior employment type prior to immigration. Male and female graduates aged 20-64 who obtained their tertiary qualification abroad.	16% for ESB close to 50% for Asian immigrants and close to 40% for NESB respectively.	Results Indicate the payoff to required schooling was positive (modest for Asian immigrants) and the payoff to surplus schooling was much smaller than the payoff to required schooling (insignificant among Asian immigrants)
Green, Kler and Leeves 2007 JA Australia	The Longitudinal Survey of Immigrants to Australia (LSIA) Address the issue of the apparent lack of recognition of qualification obtained abroad among foreign-born. Including all levels of schooling, but only for males aged 15-64 full-time employed.	Ranged from 20% in 1996 to 22% in 2001 for Native graduates; from 15% in cohort 1 to 21% in cohort 2 for ESB; from 33% in cohort 1 and 49% in cohort 2 for Asian NESB;from35% in cohort 1 and 31% in cohort 2 for other NESB.	Asian immigrants were broadly the same as those for other immigrants when all schooling levels were included in the analysis. Return to years of required education and surplus education are 0.14, 0.08 for ESB, 0.09, 0.05 for Asian NESB and 0.08, 0.03 for other NESB.
Sanroma, Ramos and Simon 2008 RM-Mode and Mean Spain	2001 Spanish Census data; 2002 Earnings Structure Survey (ESS); The European Community Household Panel (ECHP). Individuals aged 16-65 years; immigrants with a minimum age of 16 years upon arrival in Spain as a way of ensuring that they had undertaken studies in their country of origin.	The incidence of over-education, Properly educated and under-education are 28.2%, 42.6% and 29.2% for Spaniards and 35.5%, 33.2% and 31.3% for immigrants respectively under Mode measure.	Studies obtained in Sub-Saharan Africa, Eastern Europe, Asia and Latin America has a limited transferability, in contrast, studies undertaken in developed countries are totally transferable. Experience acquired in Southern Cone, Latin America and the Maghreb is favourable for the portability.

Table 3.1 *(Continued)*

Study **Year Measure** **Country of study**	**Data** **Sample**	**Incidence of over-education**	**Earning consequence or others**
Cristina Fernandez and Carolina Ortega 2008 RM- mean plus one standard deviation Spain	The Spanish Labour Force Survey for the period 1996-2006 Aged 20-45; Immigrants from three localized areas: Eastern Europe, Latin America, and Africa; Restrict the sample to those immigrants who migrated at age 18 or older in order to minimize the effect of arriving at early age	Male (Female) : Over-education: 17.65% (16.66%) for Natives; 51.83% (50.55%) for East Europe; 40.81% (37.39%)for Latin America; 19.94 %(17.83%) for Africa.	Five years after arrival immigrants participation rates start to converge slightly to natives' rates, unemployment rates decrease to levels even lower than those of natives, while the incidence of the over-education and temporary contracts remains roughly constant. It shows that the Spanish labour market is managing to absorb the immigration flows but at the expense of allocating immigrants in temporary jobs for which they are overqualified.
Chiswick and Miller 2009 RM -Modal Schooling US	2000 US Census Males aged 25-64	32.07 % are over-educated, 24.55% under and 43.38% are matched for Native born; 27.45% are over-educated, 44.73% are under-educated and 27.82% are correctly matched for Foreign born	There is a slight U-shaped relationship between the incidence of over-education and of being correctly matched to the requirements of jobs and duration of residence; conversely, an inverted-U-shaped relationship between the incidence of under-education and duration of residence in the United States.
Lindley 2009 RM* UK	The Quarterly Labour Force Survey (QLFS) Pooled cross-sections over the period 1993-2003; Immigrants is restricted to those with UK highest qualifications, Aged 16-65 by controlling for ethnic difference	Male(female) Immigrants are more likely to be over-educated (27.29% to 22.51% for men; 32.77 % to 28.73% for women) and less likely to have the required highest qualification or be under-educated compared to white natives.	Over-education penalty is largest for South Asian natives (19.7%), followed by South Asian immigrants (13.2%), white immigrants (10.4%), white natives (5.5%), and Black immigrants(4.3%) ; the smallest for Black natives(3.7%)
Steven Wald and Tony Fang 2008 WA Canada	1999 Workplace and Employee Survey (WES) Aged 18-64	Over-education(under-education) 31.3 % (17.2%) for Canadian-born; 34.6% (14.6%) for Non-recent immigrants 47.8% (11%) for Recent immigrants.	Actual Education: 8.3 % for Canadian-born; 6.7 % for Recent Immigrants. Return to Required education, over-education and under-education are 10.2% , 7.6 % -2.8% for Canadian-born and 8.7%, 5.3% and -0.2 %(not significant) for Recent Immigrants.
Aringa and Pagani 2010+ RM Italy	The Italian Labour Force Survey for the years 2005-2007 Male workers with at least vocational education (10 years of education)	96% of immigrants are over-educated; 41% of natives are over-educated	No assimilations are found among Immigrants incorrectly matched with the educational requirement of their job even their residency in Italy is lengthening.

* A comparison between the occupational Mode highest NVQ to that highest NVQ (National Vocational Qualification) held by the respondent; + Working paper series;
The RM, JA and WA indicate Realised Matches, Job Analysis measure and Workers' Self-Assessment respectively to define the required education for measuring years of over-education.

3.3 Econometric framework

A longitudinal analysis is applied in this study to address the potential problem of "omitted unobservable bias" from cross-sectional analysis, which is important to examine both the incidence and potential earnings penalty to over-education. Therefore, both the determinants of over-education and the impact of over-education on earnings are examined with panel techniques.

In order to obtain the estimates for comparison between the Australian-born and immigrants, two samples are examined in this study. One sample consists of the Australian-born (natives) and ESB immigrants, and the other sample is natives and NESB immigrants.

This approach allows me to examine results for each immigrant group compared to the same base category of the Australian-born.

Part 1: Determinants of over-education

I apply the correlated random effects logit model to examine the likelihood of over-education with panel data. In this model a number of important variables, such as immigrant status, are time-invariant. A conditional logit (or fixed effects logit) model which was also considered, sacrifices time-invariant but potentially important information on any individual who presents no change in dependent variables by eliminating time-invariant variables. However, this model benefits from controlling for the endogeneity from individual effects. The random effects logit model, is in comparison able to estimate the coefficient of time invariant variables whilst also allowing for dynamic adjustment. Thus, based on these considerations, I have chosen the random

effects logit model to examine the determinants of over-education.[12]

A potential problem arises from the biases occurring in the correlation between explanatory variables and error terms in random effects models. I address this problem by using the Mundlak (1978) correction.

In the following latent model, β is unbiased if explanatory variables x_{it} and individual specific effects μ_i are independent, that is

(3.1) $$y_{it}^{*} = x_{it}\,\beta + \mu_i + \varepsilon_{it}\text{ , Where } E[\mu_i|X_i] = 0, and\ \varepsilon_i|\ X_i \sim \mathrm{N}\ (0,\sigma_{\varepsilon}^{2}).$$

To relax this assumption, the Mundlak (1978) model proposes individual effects μ_i as a function of individual means, that is $\mu_i = \bar{X}_\iota\ \delta + \eta_i$, where $\eta_i|\ X_i \sim \mathrm{N}(0,\sigma_{\eta}^{2})$. It assumes zero correlation between $\bar{X}_\iota$ and η_i.

Thus, we have $E[\mu_i|X_i] = \bar{X}_\iota\delta$, where $\bar{X}_\iota$ is an average of x_{it} over time for individual i, and it is time invariant.

We rewrite the above latent model as

(3.2) $$y_{it}^{*} = x_{it}\,\beta + \bar{X}_\iota\delta + \left[\varepsilon_{it} + \mu_i - E[\mu_i|X_i]\right] = x_{it}\,\beta + \bar{X}_\iota\delta + u_{it}\ ,$$

where

u_{it} is the new error term. By this construction, we have

[12] Chamberlain (Chamberlain, 2010) has shown that 'logit' rather than 'probit' can achieve root and consistency in a fixed effects model. In other words, the probit setup is not available in a fixed effects model, and would not allow the test of fixed-effects versus random-effects.

(3.3) $$E[u_{it}|X_i] = E[\varepsilon_{it} + \mu_i - E[\mu_i|X_i] \quad |X_i] = 0$$

Mundlak's approach is used to control for endogeneity effects due to unobserved individual effects. It is considered as a compromise between the fixed and random effects models. It also provides a test for adjustment for endogeneity as an alternative to the Hausman test--If the coefficient on group mean δ is non-zero, that suggests that individual effects are not to be ignored (Greene, 2010).

Applying the Mundlak (1978) correction, the unobserved individual effect μ_i is conditional on the means of time varying explanatory variables.

(3.4) $$\mu_i = \overline{X}_\iota \delta + \eta_i \;\; where\; \eta_i|X_i \sim \mathrm{N}\left(0, \sigma_\eta^2\right)$$

Thus, the model is written as:

(3.5) $$y_{it}^* = x_{it}\,\beta + \overline{X}_\iota \delta + \eta_i + \varepsilon_{it}$$

It is noted that coefficients δ will differ between panels of different lengths *T* and they are specific to the particular sample. The estimates of β approximate the fixed effects estimators, as shown by Wooldridge (2009).

In this study, I employed both a random effects logit model and a correlated random effects logit model with Mundlak (1978) correction to estimate the determinants of over-education. As noted earlier, I consider effects for natives and ESB immigrants, and among natives and NESB immigrants, respectively. The random effects logit model is applied as a benchmark. The endogeneity issue due to the individual effects is corrected by the correlated random effects logit model with Mundlak correction. If the results from these two models are significantly different, then endogeneity is addressed by the correlated random effects logit model.

I examine the hypothesis that the incidence of over-education for immigrants may decrease with their duration of stay (YSM) in Australia. This less-examined hypothesis has important implications for understanding the labour market assimilation of immigrants in earnings models.

Model 1: Determinants of over-education

The functional form of logit model is written as:

$$(3.6) \qquad ln\left(\frac{Pr(overeducation_{it})}{1-Pr(overeducation_{it})}\right) = \delta_0 + \delta_1 Z_{it} + \delta_2 M_i + \delta_3 ED_{it} + \delta_4 DQUA_{it} + \delta_5 (DQUA_{it} * M_i) + \delta_6 YSM_{it} + \delta_7 YSM_{it}^2 + \delta_8 EXP_{it} + \delta_9 EXP_{it}^2 + \sum_{j=1}^{m} [\bar{X}_\iota \ \delta_j] + \eta_i + \varepsilon_{it} \ ,$$

$$\eta_i \sim N(0, \sigma_\eta^2); \qquad \varepsilon_i \sim N(0, \sigma_\varepsilon^2)$$

$$i = 1, \dots, N; \ t = 1, \dots, T; j = 1, .., m$$

By this logit model setup, the natural log of the odds ratio of over-education is explained by a quadric function of years since migration (YSM) with other explanatory variables. The observed variable $overeducation_{it}$ takes the value of 1 if worker i is over-educated and is defined as 0 otherwise. Z_{it} denotes a set of personal or job characteristics of individual i at time period t; ED_{it} denotes actual years of education obtained by individual *i* at time *t*. M_i is a dummy variable, and it takes the value of 1 if individual i is an immigrant, 0 otherwise. The coefficient of M_i, δ_2, measures the initial over-education gap of immigrants upon arrival relative to comparable natives. YSM_{it} denotes the number years of residence since migrating to the host country. The coefficient of YSM_{it}, δ_6, measures the way in which the over-education gap varies as immigrants spend time in the host country. The over-education rates of immigrants are expected to signify their levels

of assimilation. Therefore, the coefficient of YSM_{it} is predicted to be negative. δ_7, the coefficient of YSM_{it}^2 examines the rate of over-education in a linear or quadric style over time. A quadratic form was chosen to examine the non-liner relationship between the rate of over-education and years since migration. The rate of over-education is expected to be decreasing with increased years of residence because immigrants are more likely to find a better education-occupation match after gaining Australian experience or education. And the relationship may be flatter when years since migration reach a certain point. This non-liner relationship is examined by a quadratic form. However, the result shows that the coefficient on the quadratic term is insignificant and the coefficient on YSM is negatively significant, which justifies the use of a linear relationship between rate of over-education and YSM.

$\sum_{j=1}^{m}[\bar{X}_i \ \delta_j]$ represents the Mundlak adjustments (where is m is the number of explanatory variables).

The unobservable individual specific μ_i as a function of individual means, that is

$\mu_i = \sum_{j=1}^{m}[\bar{X}_i \ \delta_j] + \eta_i$, where $\eta_i \sim \mathrm{N}(0,\sigma_\eta^2)$.

It assumes zero correlation between the means of time varying explanatory variables and η_i. And $\varepsilon_{i,t}$ denotes the disturbance terms, which are assumed to be independent and identically distributed (*iid*).

To further examine the effects of age on arrival and year of arrival on the probability of being over-educated, I replace YSM_{it} and YSM_{it}^2 with age on arrival and year of arrival dummy variables, respectively, in order to avoid an over-specification problem.

Part 2: Impacts of over-education on earnings

Unobserved heterogeneity, such as unobserved ability, motivation or work efforts

influence earnings, and also are correlated with observed education and skills. If these unobserved individual effects, u_i, are correlated with explanatory variables, cross-sectional analysis would result in omitted unobservable biases. Longitudinal data captures the same individual over time. Thus, unobservable individual effects are eliminated by using a panel fixed effects model. Thus, estimation results from fixed effects models are consistent. However, this model cannot evaluate the time-invariant explanatory variables because they are removed by within-group transformation. In contrast, a random effects Generalised Least Squares (GLS) model assumes that u_i is uncorrelated with explanatory variables in which GLS uses the optimal combination of within-group and between-group variations. If individual effects do not matter, then the GLS estimator is equal to the ordinary least squares (OLS) estimator. A Hausman test is used to identify whether the random effects GLS estimator is biased.

Two specifications are employed to examine earnings effects. One specification is to examine the effect of over-education on earnings through years since migration (YSM). Thus, assimilation effects for immigrants are found by the significance of YSM. The other specification is to examine the impacts of over-education on earnings from both pre-migration and post-migration human capital perspectives. By doing so, the transferability of immigrants' human capital by their country of origin is evaluated. These two specifications are expressed by Models 2 and 3 respectively.

In this section, the analysis focuses on the link between over-education and earnings. The following questions are of interest in the empirical analysis. How does over-education impact, directly or indirectly, on earnings via years since migration and migration status? Is the impact of over-education on earnings affected by unobserved heterogeneity, such as, personal ability or variable quality or under-valuation of immigrant qualifications?

The standard Over-education, Required-education, Under-education (ORU) earnings model (as originally proposed by Duncan and Hoffman (1981)[13]) is widely used in 'over-education' empirical research. Based on the standard ORU earnings model, the extended

[13] This is referred to Section 2.6.1 in Essay one.

earnings' model is applied into this study for issues of interest.

The ORU earnings model decomposes actual years of education (S_a) into required years of education (S_r), years of over-education (S_o), and years of under-education (S_u). Thus $S_a = S_r + S_o - S_u$, where $S_o = S_a - S_r$ for the over-educated (i.e. if $S_a > S_r$), and 0 otherwise. Similarly, $S_u = S_r - S_a$ for the under-educated if (i.e. $S_r > S_a$), and 0 otherwise.

Then the log of earnings in the ORU model can be written as:

$$(3.7) \qquad lny = \alpha_1 + \beta_r S_r + \beta_o S_o + \beta_u S_u + \delta_1 X_1 + \varepsilon$$

lny is the natural logarithm of earnings, X_1 is a vector of a variety of other control variables that generally includes personal characteristics and job characteristics, S_r, S_o, S_u are, respectively, the years of required education, over-education, and under-education. α_1 is the intercept term, and ε is an error term.

Equation (3.7) estimates β_r, β_o, β_u continuously, and β_r, β_o, β_u are the rates of returns to required education, over-education and under-education respectively.

Prior literature on 'over-education' has consistently found that $\beta_r > \beta_o$ and $\beta_o > 0$, such that the return of over-education is lower than the return to required education; and the return to over-education is positive (Cohn, 1992; Groot, 1996; Rumberger, 1987; Sicherman, 1991[14]). In contrast, they also found that $\beta_u < \beta_r$ and $\beta_u < 0$, which means the return to under-education is lower than the return to required education; and that it is a negative return (Hartog, 2000).

In panel data settings the ORU model is expressed as follows:

[14] This is referred to Essay one.

$$(3.8) \qquad lny_{i,t} = \beta_r S_{i,t}^r + \beta_o\left(S_{i,t}^a - S_{i,t}^r\right) + \beta_u\left(S_{i,t}^r - S_{i,t}^a\right) + \delta X_{i,t} + \alpha_i + \varepsilon_{i,t}$$

$$i = 1, \dots, N;\ t = 1, \dots, T$$

Where $lny_{i,t}$ denotes the hourly wage from main job of individual i at year t; $X_{i,t}$ is personal characteristics and job characteristics of individual i at year t; α_i denotes the unobservable individual-specific effect and $\varepsilon_{i,t}$ denotes the remainder disturbance, assumed independent and identically distributed i.i.d (0, σ_ε^2). $S_{i,t}^a$ denotes the years of actual education for individual i at year t and $S_{i,t}^r$ is the years of required education for individual i at year t. Thus, ($S_{i,t}^a - S_{i,t}^r$) is the years of over-education when $S_{i,t}^a > S_{i,t}^r$; 0, otherwise. Likewise, $\left(S_{i,t}^r - S_{i,t}^a\right)$ is years of under-education when $S_{i,t}^r > S_{i,t}^a$; 0 $otherwise$. β_r is the rate of returns to required education, β_o is the rate of return to over-education and β_u is the rate of penalty to under-education.

The extended ORU earnings model is built by adding interaction terms to Equation (3.8) to examine the impacts of educational mismatch, years since migration and migrant status on the return to over-education, after controlling for the individual effects. By doing so, I can examine the earnings gap between immigrants and natives via educational mismatch. These results reveal an added and less-studied explanation for the existing earnings disadvantage for immigrants in the Australian labour market.

Model 2: The extended ORU earnings model (over-education earnings impact via years since migration and occupation)

$$(3.9)\quad lny_{i,t} = \beta_r S_{i,t}^r + \beta_o\left(S_{i,t}^a - S_{i,t}^r\right) + \beta_u\left(S_{i,t}^r - S_{i,t}^a\right) + \beta_{rM}(S_{i,t}^r \times \mathrm{M})$$
$$+ \beta_{oM}[\left(S_{i,t}^a - S_{i,t}^r\right) \times \mathrm{M}] + \beta_{uM}[\left(S_{i,t}^r - S_{i,t}^a\right) \times \mathrm{M}] + \theta_1 \mathrm{Z_{it}} + \theta_2 \mathrm{M_i}$$
$$+ \theta_3 YSM_{it} + \theta_4 YSM_{it}^2 + \sum_{k=1}^{2}[\theta_{kYSM}\left(TYP_{k,it} \times \mathrm{YSM}_{it}\right)$$
$$+ \theta_{kYSM2}\left(TYP_{k,i} \times YSM_{it}^2\right)] + \mu_i + \varepsilon_{\mathrm{it}}$$
$$i = 1, \dots, N;\ t = 1, \dots, T; k = 1,2$$

The error term is denoted by $\mu_i + \varepsilon_{i,t}$. The unobservable individual-specific effect μ_i is assumed not to change over time, and the random disturbance, ε_{it}, is assumed to be independent and identically distributed, i.i.d (0, σ_ε^2).

$\mathrm{Z_{it}}$ denotes a set of personal characteristics, such as years of experience. $lny_{i,t}$ is the natural log of hourly wage from main job in constant (2009) dollars for the *i* th individual in period t.

β_o , β_u, and β_r estimate the magnitude of earnings effect of a one unit change in the years of over-education, years of under-education, and the required years of education, respectively among natives.

The coefficient of the interaction terms, β_{oM} , β_{uM}, β_{rM} evaluate the difference of earnings effects between natives and migrants who have the same type of educational mismatch.

$TYP_{k,it}$ is a binary variable[15], which corresponds to the three types of educational mismatch. k takes the value of 1 if individual *i* is over-educated at time period t, and 0

[15] See Verdugo and Verdugo (1989) for the applications of these dummy variables specifications in cross-sectional data.

otherwise. k equals 2 if individual *i* at time t is under-educated, 0 otherwise. Educationally matched is the reference category.

The coefficient of M_i, θ_2 , denotes the initial earnings gap between immigrants and natives.

YSM_{it} denotes the number of years of residence since migrating to the host country for individual i at time t. The coefficient of YSM_{it}, θ_3 , denotes assimilation effects. Based on previous studies, θ_3 is expected to have a positive sign. The significance of coefficient YSM_{it}^2 reveals the linear or quadratic relationship between earnings and the number of years since migration. If immigrants work in jobs requiring qualifications that are below their educational attainment, this may lengthen their assimilation process with the consequence that they catch up with the natives' earnings more slowly over time, or not at all. Thus, the coefficient of interaction terms, $TYP_{1,it} \times YSM_{it}$, θ_{1ysm} , is negative if over-education slows immigrants' earnings assimilation in the host-country.

The second extended earnings model is modified based on the first earnings model. I replace ED_{it} and YSM_{it}^2 with four continuous variables ($ED_{1,it}$, $ED_{2,it}$, $EXP_{1,it}$ and $EXP_{2,it}$) and three interaction terms. Variables capturing pre-migration human capital are ED_{1it} and $EXP_{1,it}$. $ED_{1,it}$ denotes the years of education abroad and $EXP_{1,it}$ denotes the years of potential work experience abroad. Similarly, post-migration human capital is controlled by $ED_{2,it}$ and $EXP_{2,it}$. They denote the years of domestic education and the years of potential domestic work experience, respectively[16].

$ED_{2,it}$ and $EXP_{2,it}$ may absorb the effect of years since migration (YSM_{it}) on the rate of over-education for immigrants; therefore, in the following extended model, I exclude YSM_{it} and YSM_{it}^2.

By doing so, I can examine the impact of over-education on earnings from pre-migration

[16]Based on the data, $ED_{1,it}$ =0 and $EXP_{1,it}$ =0 for natives. Thus, the coefficient on $ED_{1,it}$, $EXP_{1,it}$ and $EXP_{1,it}^2$measure their effects for immigrants only.

human capital and post-migration human capital perspective.

This model is expressed as:

Model 3: The effect of over-education on earnings via pre-migration and post-migration human capital

$$(3.10)\quad \ln y_{i,t} = \alpha_0 + \alpha_1 Z_{it} + \alpha_2 M_i + \sum_{j=1}^{2}(\Upsilon_j ED_{j,it} + \beta_j EXP_{j,it} + \xi_j EXP_{j,it}^2) + \sum_{j=1}^{2}\sum_{k=1}^{3}[\Upsilon_{jk}(ED_{j,it} \times TYP_{k,it}) + \beta_{jk}(EXP_{j,it} \times TYP_{k,it}) + \xi_{jk}(EXP_{j,it}^2 \times TYP_{k,it})] + \Upsilon_{2M}(ED_{2,it} \times M_i) + \beta_{2M}(EXP_{2,it} \times M_i) + \xi_{2M}(EXP_{2,it}^2 \times M_i) + \sum_{k=1}^{3}[\Upsilon_{2kM}(ED_{2,it} \times TYP_{k,it} \times M_i) + \beta_{2kM}(EXP_{2,it} \times TYP_{k,it} \times M_i) + \xi_{2kM}(EXP_{2,it}^2 \times TYP_{k,it} \times M_i)] + u_i + \varepsilon_{i,t}, \quad \varepsilon \sim N(0, \sigma^2 I_n)$$

$$i = 1, \dots, N;\ t = 1, \dots, T; k = 1,2,3\ ; j = 1,2$$

Where Z_{it} denotes a set of personal characteristics; j is the indicator of abroad and domestic, with the value of 1 if education or experience obtained from abroad and the value of 2 if education or experience is acquired in Australia.

$TYP_{k,it}$ is defined the same as in Model 2.

β_1 and γ_1 measure the portability of immigrants' experience abroad and education abroad respectively. If foreign experience and foreign education are not recognised by employers,

and are less valued in the destination country compared with host-country experience and education, then β_1 and γ_1 are predicted to be positive and smaller than β_2 and γ_2 , respectively.

The coefficients of the interaction terms education or experience with M_i present the effects of education or experience on earnings between immigrants and natives. For example, the coefficient of $EXP_{2,it} \times M_i$, β_{2M} , estimates the earnings difference from each year of Australian experience between natives and immigrants.

In addition, coefficients of interaction terms between mismatch status and education abroad or experience abroad display the earnings differential from each year of education abroad or experience abroad between over-educated or under-educated immigrants and adequately educated immigrants. For example, the coefficient of$EXP_{1,it} \times TYP_{1,it}$, β_{11}, estimates the earnings difference between over-educated immigrants and adequately educated immigrants by holding other variables constant.

Furthermore, the mismatch effects are examined by the coefficients of the interaction terms between mismatch status, Australian experience or Australian education for natives and immigrants. These interaction terms evaluate the earnings difference due to experience or education between natives and immigrants with the same types of mismatch status. For example, the coefficient of $ED_{2,it} \times TYP_{1,it} \times M_i$, γ_{21M} , presents the earnings difference from each year of Australian education between over-educated natives and over-educated immigrants.

3.4 Data and variables

3.4.1 Data

The data used to examine the incidence of over-education and immigrants' assimilation in Australia is taken from the wave 1 to wave 9 (years 2001 to 2009) responding person

file of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Survey, Australia's first nationally representative household panel survey, began in 2001 and interviews are now conducted annually. This longitudinal survey overcomes the disadvantage of cross-sectional survey. It is designed to follow the same individuals over time, and it allows researchers to analyse the dynamics of change at the individual and household level.

The sample for the current study includes all full-time[17] male workers, who were aged from 23 to 64 in the initial survey year. In order to make fully use of the panel data features I use a balanced data set to select the observations who had taken part in each year of the survey. With pooled 2001-2009 data, the full sample size used in this study is composed of 18,250 observations with 2,732 individuals. Among the employed (17,644 observations, with 2,681 individuals), 90% is employed full-time.

Workers in part-time jobs may have chosen to do so for reasons of family or other personal commitments or preferences. Therefore, part-time workers may be more likely to accept mismatched jobs in terms of education and occupation match in exchange for other job characteristics, such as the flexibility of hours of work, or shorter distances to work. These supply side job mismatches are less likely to affect workers' work attitudes and behaviour. Thus, these mismatches are less likely to reduce workers' productivity and result in wage penalties. In addition, part-time jobs are also shown to have a different pay structure which adjusts for other job-related fringe benefits. Therefore, I consider full-time workers for a more comparable group of employees and earnings scales. In the initial stages of the study the potential impact of selection into both employment and also full-time employment was examined using a Heckman selection adjustment. The results showed that control for selection for either selection did not change the results.

Of this full-time sample, 79 per cent are native-born and 21 per cent are immigrants.

[17] At an early stage, I also examined the incidence of over-education and its effects on earnings for the entire employed sample; this was achieved by using the Heckman selection model to control for sample selection issue. Results are not sensitive to the sample selection. The Heckman adjustment did not alter the results. Results are available in Appendix 3A.

Among the immigrants surveyed, 13 per cent have English as their first language and 8 per cent did not learn English as their first language. Most ESB immigrants come from developed countries such as the United Kingdom (50 per cent), New Zealand (23 per cent), South Africa (3 per cent) and the United States of America (3 per cent). Unlike the ESB immigrants, NESB immigrants are diverse, coming from over 60 different countries, including Vietnam (13 per cent), China (including Rep, Hong Kong and Taiwan, 10 per cent), India (6 per cent), Philippines (5 per cent), and The Netherlands (4 per cent).

The mean characteristics of the full-time sample of natives, ESB immigrants and NESB immigrants are shown in Table 3.2. The full definition of variables is available in Appendix 3D. There is significant difference between these three groups across a number of personal characteristics. The average age of ESB immigrants is 44.70, about one year older than NESB immigrants (43.81) and four years older than natives (41.12). The mean of the year of arrival in Australia is 1978 at age 18 for ESB immigrants; and 1984 at age 23 for NESB immigrants. Thus, the mean of years since migration is 26.32 for ESB immigrants and 20.65 for NESB immigrants, which indicates that ESB immigrants have been in Australia six years longer than NESB immigrants. The hourly wages for the main job are found to be slightly higher for natives ($29.81) than for NESB immigrants ($29.50) but lower than for ESB immigrants ($32.49).

Table 3.2 presents further detailed information with respect to education and experience obtained abroad and domestically. After arriving in Australia both ESB and NESB Immigrants invest their human capital activity. Among the full-time sample, average years of domestic experience are higher than that obtained elsewhere. NESB immigrants have an average 2.14 years more experience abroad and 3.53 years less domestic experience than ESB immigrants. Conversely, years of education obtained overseas are slightly higher than those achieved in Australia.

On average, immigrants are better educated than natives. In Table 3.2, the educational attainment is highest among NESB immigrants (14.57) who have attended a further 4.23 years of formal education in Australia. Among ESB immigrants, the average number of years of education abroad is 8.38, with 5.69 years further education completed in

Australia giving a total of 14.08 years. Natives have 13.76 years of educational attainment which is lower that for immigrants.

It is worth noting that although the NESB group has a higher average years of education (14.57) than the ESB (14.08) group and natives (13.76), their average number of required years of education to perform a job is slightly lower for NESB (14.30) immigrants than it is for ESB (14.39) immigrants and higher than for natives (14.25). NESB workers earn less than ESB workers and natives. This evidence encourages the test of the hypothesis that NESB immigrants are more likely to undertake jobs in which they are over-educated in comparison with ESB immigrants and natives. In contrast, among both natives and ESB immigrants, the required years of education to perform a job exceed their actual years of education. This implies that they are more likely to have higher level jobs and earn more.

Two measures of qualifications are used based on credential type and the country in which they were obtained. The structures of credential type also show that immigrants are highly educated. 44 per cent of NESB immigrants and 30 per cent of ESB have qualifications above a Bachelor degree; in contrast, only 22 per cent of Australians have obtained these qualifications.

Most ESB immigrants come from advanced countries and their qualifications are valued in Australia. However, NESB immigrants may experience more difficulty in adapting to their new lives even if they work in skilled categories. Furthermore, NESB immigrants may work in occupations that require lower level of educational attainment in instances in which their overseas credentials are not recognised by Australian employers.

The motivation for getting a matched job drives NESB immigrants to study in Austria and obtain local degrees even though they may already have overseas qualifications. As a result, Australian qualifications may be more valued among NESB rather than ESB immigrants. This evidence is found in Table 3.2. Among NESB immigrants, the proportion of Australian qualifications is 43 per cent, compared to 41 per cent for ESB immigrants.

Table 3. 2: Summary Statistics by Country of Birth

	Full-time Sample					
	Native		ESB		NESB	
VARIABLES	mean	sd	mean	sd	mean	sd
Personal Characteristics						
Age	41.12	9.96	44.70	9.91	43.81	9.79
Disability/Impairment	0.13	0.33	0.14	0.34	0.11	0.31
Poor English	/	/	/	/	0.04	0.21
Year of Arrival	/	/	1978	13.03	1984	12.74
Arrived 1947-1979	/	/	0.50	0.50	0.30	0.46
Arrived 1980-1989	/	/	0.29	0.46	0.30	0.46
Arrived 1990-2001	/	/	0.21	0.41	0.39	0.49
Age on Arrival	/	/	18.38	12.08	23.16	11.56
Age 0-12	/	/	0.40	0.49	0.22	0.41
Age 13-22	/	/	0.17	0.37	0.24	0.42
Age 23-34	/	/	0.34	0.47	0.38	0.49
Age 35-60	/	/	0.10	0.29	0.16	0.37
Years since Migration-YSM	/	/	26.32	13.08	20.65	12.65
YSM2/100	/	/	8.64	7.36	5.86	6.94
Job Characteristics						
Unemployment Rate	0.03	0.17	0.03	0.18	0.06	0.23
Unemployment Rate (ABS)	0.05	0.01	0.05	0.01	0.05	0.01
Hourly wage	29.81	15.75	32.49	18.23	29.50	15.24
Log Hourly wage	3.28	0.50	3.34	0.54	3.27	0.49
Human Capital						
Years of experience (total)-EXP	21.36	10.30	24.63	10.38	23.25	10.44
$EXP^2/100$	5.62	4.74	7.14	5.22	6.49	4.98
Years of Domestic experience-EXP_2	21.36	10.30	19.90	10.28	16.37	10.60
$EXP_2^2/100$	5.62	4.74	5.02	4.46	3.80	4.42
Years of experience abroad-EXP_1	/	/	4.73	6.35	6.87	7.22
$EXP_1^2/100$	/	/	0.63	1.32	0.99	1.55
Years of actual education (total)-ED	13.76	2.40	14.08	2.55	14.57	2.52
Years of domestic education-ED_2	13.76	2.40	5.69	5.97	4.23	5.08
Years of education abroad-ED_1	/	/	8.38	6.13	10.34	5.37
With Qualification	0.66	0.46	0.69	0.45	0.72	0.44
Based on degree type						
Postgraduate	0.09	0.31	0.16	0.37	0.18	0.40
Bachelor	0.13	0.36	0.14	0.37	0.26	0.43
Advanced diploma	0.11	0.30	0.11	0.31	0.12	0.33
Certificate	0.33	0.47	0.29	0.45	0.16	0.37
Based on country achieved						
Australian qualification	0.69	0.46	0.41	0.49	0.43	0.49
Overseas qualification	/	/	0.30	0.46	0.31	0.46
Individuals	1987		317		1202	
Observations	12606		2025		198	

Source: HILDA-Release 9 (Wave 1-Wave 9)

Furthermore, based on year of arrival, age on arrival and duration of residence, there is an important source of change in immigrants' region of origin. The compositions of immigrants may reflect the changes of Australian immigration policy from the preference for specific countries towards a selection of immigrants according to their labour market performance. There is 30 per cent of NESB in contrast to 50 per cent of ESB came into Australia between 1947 and 1979. Since 1980, Australian immigration policy starts to emphasis on skilled immigrants. Thus, this leads to a large increase in the proportion of NESB immigrants. 69 per cent of NESB came to Australia between 1980 and 2001 which implies recent NESB immigrants contribute the big fraction of NESB immigrants. More than 60 per cent of NESB immigrants live less than 20 years in Australia, reversely, 65 per cent of ESB immigrants stay over 20 years. 40 per cent of ESB, which is about double of NESB immigrants, arrived under the age of 12 years old. Among NESB immigrants, 54 per cent migrated to Australia after 23.

Labour market conditions seem to have different impacts on immigrants. Overall, 6 per cent of NESB are unemployed, which is one per cent higher than the average unemployment rate based on Australian Bureau of Statistics (ABS). In contrast, both ESB immigrants (3%) and natives (3%) have relatively lower unemployment rate than NESB immigrants (6%). I use unemployment rate to control for the labour market condition.

3.4.2 Variables

HILDA does not provide direct information for variables of interest, thus they are derived from the relevant variables.

The earning variables used in this study are log hourly wage from main job. To derive the hourly wage for main jobs, the first step is to convert nominal earnings to real earnings. I use 2009 as a base year, reference ABS CateNo6345.0 labour price index, and generate real earnings for each year by using nominal earnings divided by the wage price index. To account for non-responding (in responding households) persons' wages which are presented as missing data, the variable I have chosen is imputed weekly gross wages and

salary for main jobs[18]. After converting the imputed nominal weekly gross wages and salary from main job to real imputed weekly gross wages and salary, the hourly wage from main job is derived by using imputed real weekly gross wages and salary from main jobs divided by combined hours per week usually worked in the main job. Then I convert the hourly wage into the natural logarithm of hourly wage, which is the dependent variable in the earnings model.

Years since migration (YSM) measures years of duration in Australia for immigrants[19].

Years of actual education are derived by four variables from HILDA. To evaluate the effects of qualification, I categorise qualifications into five categories: Postgraduate, Bachelor, Diploma, Certificate, and No qualification. Postgraduate includes Doctorate, Masters, Graduate Diploma, Graduate Certificate and Bachelor with Honours; this requires over 17 years of education. Bachelor covers a Bachelor degree without Honours and takes 16 years of education to achieve. Diploma includes Advanced diploma and Diploma, and requires 15 years of education. Certificate includes Certificate I, Certificate II, Certificate III or Certificate IV; these require over 13 years of education. 'No qualification' covers workers without qualifications, representing less than 13 years of education.

After examining education abroad and experience abroad for natives, I found that few Australians (0.4 per cent) have obtained overseas qualifications, and even a smaller percentage have had overseas work experience. The low percentage of population limits research on foreign education for Australian. In addition, Australian's overseas experience is not available from existing data and also is not derived by the other variables. Thus, I could not test how natives' human capital abroad affects their local working performance. I construct both ED_1 and EXP_1 as zero for native Australians by excluding

[18] Imputation methods are used to deal with missing cases. Since income is a sensitive issue for some people who do not report their income in interview, thus missing data occurs. Nearest Neighbour Regression imputation, and little and Su imputation are applied to the imputation of data for responding persons. A full description of the imputation process for the income variables is provided by Hayes and Watson (2009).

[19] It is defined as zero for natives, while for immigrants, its derivation is provided in the Appendix 3C.

these Australians[20].

Age at migration is assumed to have an effect on assimilation. Wilkins (2003) examined the impact of age at migration for Australian immigrants by using data from the Australian Bureau of Statistics Education and Training Survey (ETS) 1997. Empirical results show that younger arrivals have lower initial earnings but faster earnings growth compared to older arrivals. If the age on arrival is between 1 and 6, then this group of young immigrants is more likely to come to Australia with their adult parents who are the migration decision makers. This young arrival group is assumed to have no initial stock of human capital and to accumulate their human capital after migration, thus they become more likely to perform similarly to natives. If the age on arrival in Australian is over 6 years, immigrants are more likely to have received education overseas and have an initial stock of human capital, but their human capital obtained elsewhere may be less valued in Australia. They are more likely to face difficulties when entering into the labour market, such as; having unrecognised educational qualifications, poor knowledge of the domestic labour market, and a low level of English proficiency. Previous research has found that elementary school education is equally valued and is quite portable across national boundaries (Friedberg, 2000). Therefore, I define four cohorts based on their age at migration: 0-12, 13-22, 23-34, and 35-60. Notably, the distribution of poor English among NESB increases with age at migration, which suggests as expected that language proficiency is affected by age on arrival. After adding these variables, the coefficients of YSM are changed from significant to non-significant which implies that age on arrival takes effect on immigrants' assimilation.

The arrival cohorts' quality may have a subtle effect on immigrants' assimilation. Successive and high quality immigrants would have greater productivity in Australia which may accelerate their assimilations' rate compared to their counterparts. The heterogeneity of average productivity among different arrival cohorts would have an effect on the coefficient of years since migration (YSM). Thus, the estimated effects of

[20] 51 of 7807 Australians (0.7 per cent) have overseas school education or post school education. Among them, 32 (0.4 per cent) Australians have obtained overseas qualifications and 5 of them completed their both school and post school in overseas.

years since migration may reflect either immigrants' assimilation or changes in the 'quality' of the cohorts. Ignoring to consider arrival cohorts 'quality' would bias estimated effect of immigrants' assimilation (Borjas, 1985). Thus, to investigate whether there are unobserved differences in productivity across immigrants from different arrival periods, I define three cohorts based on their years of arrival in 1947-1979, 1980-1989 and 1990-2001. After adding these variables, the coefficients of YSM are changing from significant to non-significant which may imply that the cohorts' quality does take an effect on the immigrants' assimilation.

As English is the main language in Australia, NESB immigrants with difficulties in English are more likely to decrease their expectations while job searching, and to accept jobs which require education below their level of attainment. Therefore, proficiency in spoken English may have a significant effect on the rate of over-education and on immigrants' assimilation. I collapse four classifications into two: those who speak English well, and those who speak English poorly[21].

The unemployment rate represents the percentage of the labour force that is currently unemployed and actively looking for work. It is also a common indicator of a country's economic conditions. It is used as a control for labour market conditions. I have collected the annual unemployment rate[22] (years 2001 to 2009) from the Australian Bureau of Statistics (ABS) as a reference. Higher unemployment rates may force some workers to accept mismatched employment positions due to the limited availability of positions. Alternatively, when the unemployment rate is high, those who remain in employment may be those who are in better matched position, such that the incidence of mismatch

[21] Hgeab-how well speaks English among population who speaks other language at home. Answer 1-very well; 2-well; 3-Not well; 4-Not at all.

[22] According to HILDA User Manual, the highest percentage of individual interviews conducted in September which is one month later than the date of beginning interviews. Thus, I choose September as base month; collect September annually unemployment rate (years 2001 to 2009) from ABS Cat. No. 6202.0 as a reference. The unemployment rates decrease from 7.1 per cent in year 2001 to 3.8 per cent at year 2007, keep slightly increase to 4.1 per cent until September 2008, and then increase by 1.7 per cent to 5.8 per cent in September 2009. This big amount rise of unemployment rate may be explained by economic downturn in 2009, which might has significant effect on the labour force movement in Australia.

decreases with unemployment. This variable is an annual rate.

3.4.3 Extent of over-education

The over-education measure in my analysis is based on the Mode method and it is derived at the two digit occupational category level for greater accuracy. In the initial stages of this study I evaluated four alternative measures of over-education. The Mode method was adopted as the preferred method based on the literature that generally favours the Mode method. In particular, in panel analysis the cross-wave Mode is more appropriate for defining the required education when compared to the other three measures.

Alternative measures are based on: cross-wave Mode (Mode) as adopted here, mean plus one standard deviation (Range-one), mean plus half standard deviation (Range-half) and Job Analysis (JA). Job Analysis (JA) is not updated over time, and there is lack of consideration for the heterogeneity of jobs. Range-one (mean plus one standard deviation) and Range-half (mean plus half standard deviation) represent the symmetry between over-education and under-education; and the cut-off points of one standard and half standard deviation are arbitrary.

The Job Analysis (JA) measure is a systematic evaluation by professional job analysts who specify the level and type of education required based on grading the occupation. This measure is derived from information in regard to the respondents' occupations. For example, the *Dictionary of Occupational Titles* (DOT) (U.S. Department of Labour 1965) developed by the United States (U.S.) Employment Service, contains detailed descriptions of all occupations in the U.S. economy and information on a number of occupational characteristics, the Standard Occupational Classification System (SOCS) in the United Kingdom (UK), and the Australian and New Zealand Standard Classification of Occupation (ANZSCO). The ANZSCO is referred to for defining the required education in a number of studies (Chiswick and Miller, 2006; Kler, 2007; Green,Kler and Leeves 2007). JA fails to account for the educational variations in jobs within occupations because of job aggregation, which is where the job analyst considers the same job title

requiring the same educational requirement. The heterogeneity error is generated by aggregating error, where the heterogeneity within an occupation is ignored (Halaby, 1994). In addition, due to the large amount of expenditure required for updating new codes, existing codes may lack depth and be out of date, which will bias the criteria of the required qualification.

Self-Reported (SR) or Worker Self-Assessment (WA) is a subjective measure which evaluates over-education by asking the respondents the required educational level for their job. Because this method measures the required level of education based on the answers of workers, on the one hand, SR measure "has the advantage of drawing on all local, up-to-date information. The assessment deals, in principle, precisely with the respondent's job, not with any kind of aggregate". On the other hand, an SR measure could be biased due to classification error (Dieter Verhaest & Omey, 2006a), where workers might overstate job requirements or merely recite hiring practice standards (Joop Hartog, 2000; Kler, 2005).

Realised Match (RM) includes Mean measure and Modal Education (Mode) measure. It is referred to as the empirical or the statistical measure of over-education. It was first introduced by Verdugo and Verdugo (1989) who defined that a worker is over-educated if his education is higher than one standard deviation above the average for his or her occupation (in the 1980 census occupation code). Conversely, a worker is under-educated if his education is lower than one standard deviation below the average for his 1980 census occupation code. The advantage of this measure is that the mean is derived directly from the existing data, so it is always available. However, this measure also has its drawbacks. For example, RM only assesses frictional mismatches but fails to consider structural sources of over and under-education (Kiker et al., 1997; Dieter Verhaest & Omey, 2006b). Kiker, et al. (1997) noted concerns as this measure is more sensitive to technological change and changes in workplace organisation than others. It is likely to be misinformed by the development of insufficient schooling over time. "one-standard deviation away from the mean" implies the symmetry between over-education and under-education, which is not rational. And the cut-off point is arbitrary. Moreover, as is similar to JA, the mean method ignores job variations within occupations (Halaby, 1994).

The Modal method (Mode) is the other Realised Match (RM) measure. It was proposed by Kiker, et al.(1997). Mode measure estimates the level of required education by computing the amount of education that most commonly occurs within an occupational category (Stephen Rubb, 2003). Mode measure proves more accurately than the mean method by considering the asymmetry between over-education and under-education and by being less sensitive to outliers or technological change. Kiker, Santos and Oliveira (1997) proved that Mode criterion is preferred to Verdugo and Verdugo's Mean criterion by using a very simple example. They found Verdugo and Verdugo's Mean criterion to be changing gradually and that it could produce classification errors before correcting itself but that the Mode changes more freely reflecting each period's educational requirements of most workers at a given time.

In the initial stage of the study, the above measurements were evaluated, with the exception of Self-Reported (SR) and Worker Self-Assessment (WA) due to lack of related information in the HILDA data. The analyses provide support that the different methods are generally comparable, and that the mode is a reasonable measure to define the required years of education.

Based on this cross-wave Mode method, there is a very high incidence rate of over-education in Australia. Evidence can be found from Table 3.3 that migrants are more likely to be over-educated than natives. In addition, NESB migrants are more vulnerable to over-education than their ESB counterparts. Among full-time workers aged 23 to 64, Table 3.3 shows that NESB immigrants have the highest rate of over-education, 42 per cent compared to 31 per cent for ESB immigrants and 25 per cent for natives. It reveals that mismatch is very serious among NESB immigrants. Almost half (42 per cent) of full-time NESB migrants' workers are employed in positions that there are below their educational attainments.

Table 3. 3: The Extent of Over-education by Country of Origin

	Full-time Sample					
	Native		ESB		NESB	
VARIABLES	mean	sd	mean	sd	mean	sd
Educational mismatch						
Over-educated	0.25	0.43	0.31	0.46	0.42	0.49
Under-educated	0.36	0.48	0.33	0.47	0.28	0.45
Matched	0.39	0.49	0.36	0.48	0.30	0.46
Years of over-education	0.58	1.33	0.70	1.38	1.07	1.70
Years of under-education	1.07	1.70	1.02	1.71	0.80	1.51
Years of required education	14.25	1.87	14.39	1.98	14.30	2.04

Source: HILDA-Release 9 (Wave 1-Wave 9)

This evidence is consistent with Green, Kler and Leeves (2007) and Kler (2007). Both papers use the immigrant longitudinal data to Australia (LSIA). Green, Kler and Leeves (2007) applied Job Analysis (JA)[23] to measure the required education. They found that NESB Immigrants are more likely to be over-educated, with the incidence of over-education between 32% and 49%. Kler (2007) examined the effects of over-education among tertiary educated immigrants. The rate of over-education was found to be around 16% for immigrants from English Speaking Countries. Among Asian immigrants, approximately 50% are over-educated. Among other NESB immigrants, the rate of over-education is close to 40%.

Table 3.4 lists the sample mean information of characteristics for three mismatching groups between their actual education and required education to work in their occupations among full-time workers by country of birth. The ESB group earns most and the NESB group earns least. Over-educated groups have more educational attainments than comparable matched or under-educated groups, and they work in jobs which require less education than their actual educational attainment. Their occupational levels are lower but earn more than matched groups, which imply there is a positive return to years of

[23] Job Analysis (JA) is a systematic evaluation by professional job analysts who specify the required level (and type) of education based on grading the occupation and deriving from information on the respondents' occupations. It was originated to measure the required education by Eckhaus (1964).

over-education by accounting for required education to their jobs. The high incidence rates of over-education are found among works with Postgraduate or Advanced diploma or diploma qualifications. Works with Bachelor degree or Certificate have more chance to get matched jobs. Compared to Overseas qualification, Australian qualifications are seemly to help immigrants to get matched jobs.

In contrast, under-educated workers have more potential work experience, and less actual years of education than required years of education to do their jobs. Under-educated natives and ESB workers earn less even if they work in high occupational level jobs than the comparable matched or over-educated workers. However, with lower required years of education and actual years of education, under-educated NESB workers earn more than matched NESB workers. The information tell that controlling for the required years of education, there is a negative return to years of under-education for natives and ESB workers, but a positive return for NESB workers.

The left bottom of graph in Figures 3.1 and 3.2 also reflects the distribution of qualification based on Degree type across natives, ESB and NESB immigrants. Obviously, immigrants have higher educational attainment than Natives. Both ESB and NESB immigrants have higher rates of Postgraduate qualifications which are 16% and 18% respectively compared to natives (9%). There is the similar rate of Bachelor degrees among ESB immigrants (14%) and natives (13%), while NESB immigrants have the highest proportion of Bachelor degrees (26%) which is 12 per cent higher than ESB immigrants. The smallest proportion of education level for these three groups are Advanced diploma or diploma, which is 11 per cent among natives and ESB immigrants, and 12 per cent among NESB immigrants. 33 per cent of natives, 29 per cent of ESB and 16 per cent of NESB immigrants have Certificate qualifications. Among natives, 33 per cent have no qualifications, which are 2 per cent higher than ESB and 5 per cent higher than NESB immigrants.

Figures 3.1 and 3.2 further present the incidence of over-education and shares of qualification based on degree type and country of achieved by age at migration and year of arrival respectively.

Figure 3.1 shows insignificant effects on the incidence of over-education for ESB

immigrants who migrated as a child or as an adult. However, significant impacts are found among NESB immigrants. Younger NESB immigrants who migrated to Australia at less than 12 years of age are more likely to find a job which matches their level of education, with a 27 per cent incidence of over-education.

However, when they migrated at an older age, the incidence of over-education increases from 35 per cent (when migrating at age 13 to 22) to 44 per cent (when migrating at age 35 to 60). ESB immigrants who migrated at age 23 to 34 are a highly educated group relative to the other three age arrival cohorts, with 43 per cent of them achieved above Bachelor degree and only 17 per cent of them are without qualification. Thus, they are expected to have better labour market performance outcomes than the other three groups.

Figure 3.2 tells us earlier NESB immigrants are less likely to be over-educated compared to recent immigrants. Only 19 per cent of immigrants who arrived between 1947 and 1979 are over-educated. Then it increases to 40 per cent for immigrants who arrived between 1980 and 1989, to 50 per cent for immigrants who arrived between 1990 and 2001. This higher rate of over-education among recent NESB immigrants may come from their higher years of education attainment, rather than from education-occupation mismatches.

Let us take a look at the rest bar information in Figure 3.2. The distribution of qualification type for ESB who arrived before 1989 is quite similar as that of native, in which Post graduate or Bachelor degree takes around 23 to 24 per cent. Later arrivals have quite high educational attainment, such as, 53 per cent of ESB who arrived between 1990 and 2001 have at least Bachelor degree.

There is a big degree jump for NESB arrival cohorts. The earlier NESB arrival cohort has the least qualification compared to later arrivals, which is only 15 per cent of NESB who arrived before 1979 with Bachelor degree but it increases to 50 per cent for NESB who arrived after 1980.

Recent high educational attainment of immigrant may come from the favoured skilled immigrants' policy. However, the objective of policy is to allocate immigrant at matched job. Question is raised here, 50 per cent of NESB who arrived between 1990 and 2001 are found to do jobs under their educational attainment.

In addition, there is a fraction with overseas qualification based on countries where qualifications are obtained. Such as, 4 to 9 per cent of immigrants who arrived before 1979 have overseas qualification; around half of them have Australian qualification. Even though 70 per cent of immigrants who arrived between 1980 and 1989 have qualification, but in which only 25 per cent of ESB have Australian qualification contrary to 43 per cent of NESB. The similar evident is also found for immigrants who arrived between 1990 and 2001. This evidence may imply NESB immigrants are more likely to face difficulty. They have to do more educational investment than ESB immigrants to obtain a good matched job in Australia.

Table 3. 4: Statistics for Full-time Sample by Educational Mismatches and Country of Birth

	Over-educated			Matched			Under-educated		
VARIABLES	**Native** mean (sd)	**ESB** mean (sd)	**NESB** mean (sd)	**Native** mean (sd)	**ESB** mean (sd)	**NESB** mean (sd)	**Native** mean (sd)	**ESB** mean (sd)	**NESB** mean (sd)
Marriage Status	0.77	0.86	0.83	0.76	0.84	0.73	0.75	0.83	0.84
	(0.42)	(0.35)	(0.37)	(0.42)	(0.37)	(0.44)	(0.44)	(0.38)	(0.37)
Has Children aged 14 or less	0.45	0.42	0.45	0.48	0.42	0.48	0.41	0.38	0.42
	(0.50)	(0.49)	(0.50)	(0.50)	(0.49)	(0.50)	(0.49)	(0.49)	(0.49)
Disability or Impairment	0.12	0.14	0.10	0.12	0.15	0.12	0.14	0.12	0.11
	(0.33)	(0.35)	(0.29)	(0.33)	(0.36)	(0.32)	(0.34)	(0.32)	(0.31)
Poor English			0.03			0.04			0.08
			(0.16)			(0.19)			(0.27)
Job Scale	56.08	61.55	57.21	47.73	50.94	56.69	48.10	50.92	47.66
	(23.82)	(23.62)	(24.90)	(23.60)	(22.90)	(25.11)	(24.04)	(23.80)	(23.28)
Hourly wage	32.61	35.74	31.75	30.30	32.89	28.40	27.30	29.04	27.32
	(16.87)	(19.78)	(17.52)	(15.70)	(19.19)	(13.85)	(14.56)	(14.76)	(12.33)
Log Hourly wage	3.36	3.45	3.33	3.30	3.35	3.24	3.20	3.24	3.21
	(0.53)	(0.51)	(0.51)	(0.48)	(0.53)	(0.48)	(0.48)	(0.54)	(0.48)
Year of Arrival		1,979.74	1,988.21		1,978.54	1,984.14		1,976.00	1,977.11
		(12.86)	(9.78)		(12.83)	(13.92)		(13.14)	(12.44)
Arrived 1947-1979		0.45	0.15		0.47	0.30		0.58	0.53
		(0.50)	(0.36)		(0.50)	(0.46)		(0.49)	(0.50)
Arrived 1980-1989		0.27	0.35		0.32	0.28		0.28	0.26
		(0.44)	(0.48)		(0.47)	(0.45)		(0.45)	(0.44)
Arrived 1990-2001		0.28	0.50		0.21	0.42		0.14	0.21
		(0.45)	(0.50)		(0.41)	(0.49)		(0.35)	(0.40)

Table 3.4 *(Continued)*

	Over-educated			Matched			Under-educated		
VARIABLES	**Native** mean (sd)	**ESB** mean (sd)	**NESB** mean (sd)	**Native** mean (sd)	**ESB** mean (sd)	**NESB** mean (sd)	**Native** mean (sd)	**ESB** mean (sd)	**NESB** mean (sd)
Age on Arrival	/	19.81	26.78	/	18.69	21.39	/	16.72	19.64
	/	(12.10)	(10.87)	/	(12.01)	(11.52)	/	(11.94)	(11.09)
Age 0-12	/	0.35	0.14	/	0.39	0.26	/	0.45	0.30
	/	(0.48)	(0.35)	/	(0.49)	(0.44)	/	(0.50)	(0.46)
Age 13-22	/	0.14	0.17	/	0.14	0.25	/	0.22	0.31
	/	(0.34)	(0.38)	/	(0.35)	(0.43)	/	(0.42)	(0.47)
Age 23-34	/	0.43	0.46	/	0.37	0.34	/	0.22	0.31
	/	(0.50)	(0.50)	/	(0.48)	(0.47)	/	(0.41)	(0.46)
Age 35-60	/	0.08	0.23	/	0.10	0.15	/	0.11	0.08
	/	(0.27)	(0.42)	/	(0.30)	(0.36)	/	(0.31)	(0.27)
Years since Migration									
YSM	/	24.72	16.48	/	25.90	20.40	/	28.26	27.09
	/	(12.97)	(9.76)	/	(12.90)	(13.92)	/	(13.17)	(12.42)
Human Capital									
Years of experience (total)	20.12	22.57	21.13	19.94	24.06	20.95	23.79	27.15	28.80
	(9.99)	(9.88)	(9.06)	(9.82)	(9.75)	(10.62)	(10.57)	(10.96)	(10.14)
Years of experience abroad	/	4.90	8.53	/	4.54	5.69	/	4.76	5.67
	/	(6.27)	(7.19)	/	(5.99)	(7.00)	/	(6.78)	(7.05)
Years of domestic experience	20.12	17.68	12.61	19.94	19.51	15.26	23.79	22.39	23.13
	(9.99)	(9.43)	(8.10)	(9.82)	(9.84)	(10.73)	(10.57)	(10.97)	(10.53)
Years of education (total)	15.66	15.96	16.16	14.39	14.54	14.84	11.72	11.82	11.94
	(2.00)	(2.09)	(1.91)	(1.37)	(1.38)	(1.36)	(2.03)	(2.20)	(2.08)
Years of domestic education	15.66	6.31	4.19	14.39	5.79	4.93	11.72	5.02	3.56
	(2.00)	(6.39)	(4.85)	(1.37)	(6.23)	(5.54)	(2.03)	(5.16)	(4.82)
Years of education abroad	/	9.65	11.97	/	8.75	9.91	/	6.81	8.37
	/	(6.47)	(5.12)	/	(6.28)	(5.55)	/	(5.25)	(4.78)

Table 3.4 *(Continued)*

	Over-educated			Matched			Under-educated		
VARIABLES	**Native** mean (sd)	**ESB** mean (sd)	**NESB** mean (sd)	**Native** mean (sd)	**ESB** mean (sd)	**NESB** mean (sd)	**Native** mean (sd)	**ESB** mean (sd)	**NESB** mean (sd)
With Qualification	0.90	0.90	0.91	0.94	0.94	0.96	0.29	0.30	0.24
	(0.30)	(0.30)	(0.29)	(0.24)	(0.23)	(0.19)	(0.45)	(0.46)	(0.43)
Based on degree type									
Postgraduate	0.41	0.51	0.47	0.02	0.02	0.02	/	/	/
	(0.49)	(0.50)	(0.50)	(0.13)	(0.15)	(0.13)	/	/	/
Bachelor	0.15	0.13	0.25	0.27	0.32	0.44	0.01	0.02	0.02
	(0.36)	(0.34)	(0.43)	(0.44)	(0.47)	(0.50)	(0.12)	(0.14)	(0.14)
Advanced diploma	0.22	0.17	0.15	0.01	0.02	0.04	0.11	0.14	0.18
	(0.42)	(0.37)	(0.36)	(0.12)	(0.13)	(0.20)	(0.31)	(0.35)	(0.39)
Certificate	0.11	0.09	0.04	0.64	0.58	0.46	0.16	0.14	0.04
	(0.32)	(0.29)	(0.19)	(0.48)	(0.49)	(0.50)	(0.37)	(0.34)	(0.19)
Based on country achieved									
Australian qualification	0.90	0.55	0.49	0.94	0.51	0.57	0.29	0.19	0.18
	(0.30)	(0.50)	(0.50)	(0.24)	(0.50)	(0.50)	(0.45)	(0.40)	(0.38)
Overseas qualification		0.35	0.42		0.43	0.39		0.10	0.06
		(0.48)	(0.49)		(0.50)	(0.49)		(0.31)	(0.25)
Without Qualification	0.10	0.10	0.09	0.06	0.06	0.04	0.71	0.70	0.76
	(0.30)	(0.30)	(0.29)	(0.24)	(0.23)	(0.19)	(0.45)	(0.46)	(0.43)
Educational mismatch									
Years of over-education	2.31	2.26	2.55	/	/	/	/	/	/
	(1.74)	(1.61)	(1.76)	/	/	/	/	/	/
Years of under-education	/	/	/	/	/	/	2.99	3.05	2.83
	/	/	/	/	/	/	(1.53)	(1.61)	(1.53)
Years of required education	13.36	13.71	13.61	14.39	14.54	14.84	14.71	14.88	14.77
	(2.79)	(2.84)	(2.62)	(1.37)	(1.38)	(1.36)	(1.20)	(1.25)	(1.16)
Observations	3,166	653	504	4,935	751	358	4,505	701	340

Figure 3. 1: Incidence of Over-education and Shares of Qualification based on Degree Type and Country of Highest Qualification by Age on Arrival

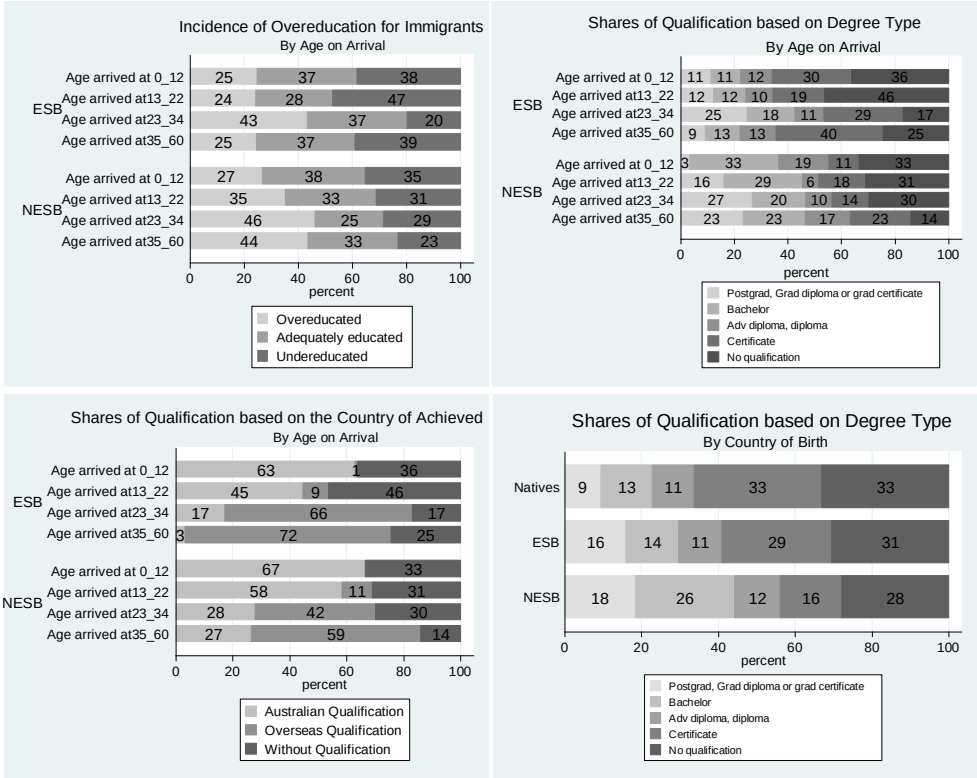
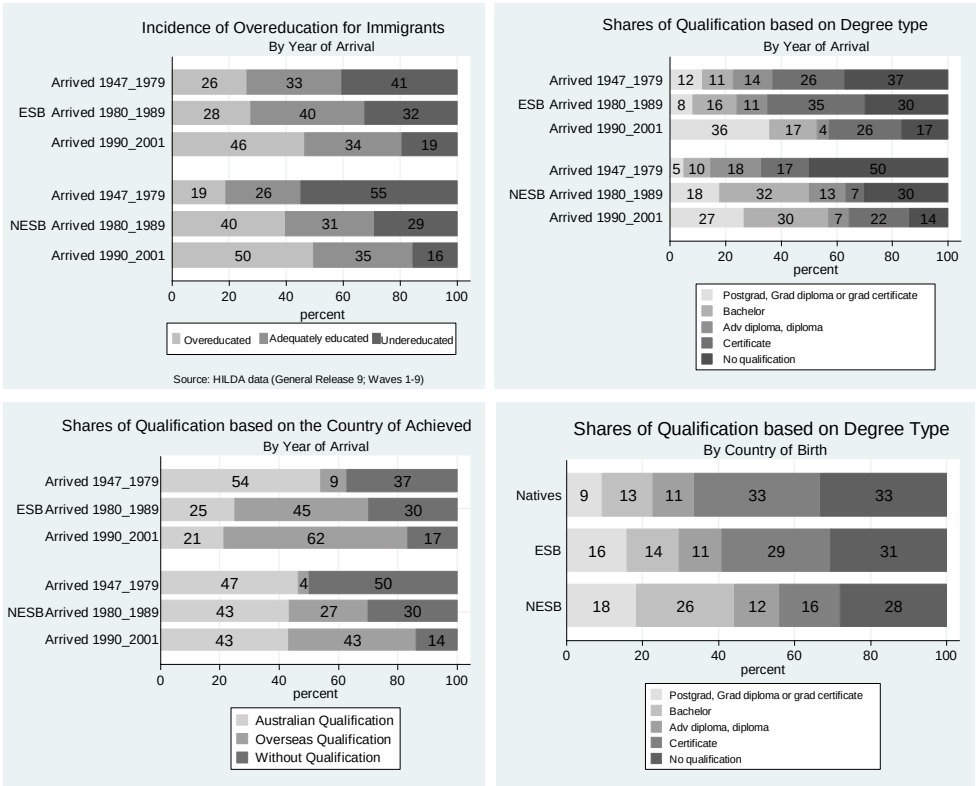


Figure 3. 2: Incidence of Over-education and Shares of Qualification based on Degree Type and Country of Highest Qualification by year of Arrival



3.5 Determinants of over-education results

As noted earlier, the endogeneity due to individual heterogeneity is addressed by a correlated random effects logit[24] model with Mundlak correction. In this section, a random effects (RE) logit model and a correlated random effects (CRE) logit model are employed to examine the determinants of over-education among natives and immigrants. I use the results from a random effects logit model as a benchmark to compare the results from a correlated random effects logit model. The differing results will reveal the endogeneity issue. I employ two samples separately for comparison purposes. The first sample contains ESB immigrants and the native-born, and the second consists of NESB immigrants and the native-born. Thus, I can determine specific effects for ESB and NESB immigrants respectively by comparing them with natives. The dependent variable for the outcome equation is the odds ratio of being over-educated.

Based on Model 1 in Equation (3.6), the results of the estimations for natives and ESB immigrants and for natives and NESB immigrants are reported in Tables 3.5 to 3.8.

Tables 3.5 and 3.6 report the results for random effects logit model and correlated random effects logit model among Native and ESB immigrants. Similarly, Tables 3.7 and 3.8 present the results among Native and NESB immigrants.

The comparison of results in Tables 3.5 and 3.6 reveal the endogeneity issue which is addressed by the correlated random effects (CRE) logit model with Mundlak (1978) correction. Likewise, the same principle is applied to Tables 3.7 and 3.8.

As discussed before, duration of residency, age on arrival and years of arrival may influence the rate of over-education. To examine these effects, based on Equation (3.6), four specifications are employed respectively. The first specification contains a quadratic

[24] I also employed a random effects probit model to examine the determinants of over-education. The results are consistent with the results obtained from the random effects logit model.

in years since migration (YSM)[25]. The second specification employs a linear variable for YSM and its results are given in Column (1). The third and the fourth specifications replace YSM quadratic forms with age cohorts, and years of arrival cohorts respectively to examine these age and cohorts effects. Results are presented in Columns (2) and (3). For each specification, I employ both random effects logit model and correlated random effects logit model. The first set of results reported for each specification is the base random effects logit model (Tables 3.5 and 3.7), and the second controls for Mundlak adjustment, as my preferred model (Tables 3.6 and 3.8).

Marginal effects are reported. Marginal effects are derived as the coefficient multiplied by the density function (the probability of a positive outcome), evaluated at sample mean values of explanatory variables. Tables 3.5 and 3.7 report marginal effects results from random effect logit model for Natives and ESB immigrant and for Natives and NESB immigrants, respectively. Likewise, Tables 3.6 and 3.8 report marginal effects results from correlated random effects logit model.[26]

Overall, immigrants are 28 to 56 per cent more likely to be over-educated than natives, in particular, a high incidence of over-education is found among NESB immigrants (56.1% in Column (1) of Table 3.7). However, once the endogeneity issue is controlled by Mundlak correction, results from Tables 3.6 and 3.8 present that the propensity of over-education for immigrations is 87 to 94 per cent higher than for natives. This reveals immigrants have a serious education-occupation mismatch in Australia.

Workers who hold Postgraduate qualifications or diploma qualifications are more likely to be over-educated than others. Individuals with a Bachelor degree or specific educational Certificate achieve better education-occupation matches than those with other types of qualifications. This result does not change after Mundlak correction. It is robust.

[25] The results from both random effects logit and correlated random effects logit estimations show that there is no significant effect of quadratic YSM on the probability of over-education, thus this result is not reported but is available upon request.

[26] I also applied a fixed effect logit for comparison. The fixed effects logit does not estimate the distribution of individual effects or the coefficients of time invariant variables. I have found very small coefficients from the fixed effects logit regression.

Immigrants with diplomas reduce the probability of being over-educated by 7 per cent and NESB immigrants with certificates reduce the probability of being over-educated by 6 to 7 per cent compared to natives with the same qualifications. However, these effects become insignificant with Mundlak correction.

Years since migration, representing the duration of residency in Australia does help an NESB immigrant to achieve a better education-occupation match; this is shown in the negative sign on YSM in Column (1) of Tables 3.7. Results show that there is a negative significant effect of linear YSM on the incidence of over-education, and this effect applies only to NESB immigrants. On the contrary, after accounting for the endogeneity due to the correlation between individual effects and error term, years since migration do not improve education-occupation mismatch for NESB immigrants. The coefficient of YSM is insignificant in Column (1*) of Table 3.8.

Among NESB immigrants, results from Column (2) Table 3.7 and Column (2*) in Table 3.8 show that migrating as a child helps migrants to reduce the probability of being over-educated in employment. Immigrants who migrated at less than 12 years of age have 10 per cent lower probability of over-education rate in comparison to others who migrate between 34 to 60 years of age. These effects do not apply to ESB immigrants.

Results from Column (3) in Tables 3.7 and Column (3*) in Table 3.8 reveal that earlier NESB immigrants, who arrived between 1947 and 1979, have 10 to 12 per cent of less likelihood to be over-educated than recent immigrants who arriving between 1990 and 2000. However, this evidence is not found among ESB immigrants.

The evidence from random effects logit estimations is consistent with previous study. Years since migration, younger entrants and earlier arrival have a significant effect on reducing the probability of over-education among NESB immigrants. However, once I account for the endogeneity issue, immigrants have extremely higher incidence of over-education than natives. And years since migration do not help them to improve their education-occupation mismatch situation.

Table 3. 5: Random Effects (RE) logit Estimations of the Determinants of Over-education among Natives and ESB Immigrants
(Model 1 Random Effects (RE) logit Estimations)

Dependent variable =1 if workers are observed to be over-educated
Sample: Natives (N) and ESB Immigrants

Explanatory Variables	(1) RE logit Marginal Effects	(2) RE logit Marginal Effects	(3) RE logit Marginal Effects	Pr(over-education|u_i=0) =11.8% Mean of X
Immigrant (M)	0.379**	0.277*	0.314**	0.143
Human Capital	(0.156)	(0.154)	(0.140)	
Years of education	0.078***	0.078***	0.078***	13.720
	(0.010)	(0.010)	(0.010)	
Postgraduate	0.477***	0.480***	0.477***	0.115
	(0.145)	(0.145)	(0.145)	
Bachelor	-0.120***	-0.120***	-0.120***	0.146
	(0.022)	(0.022)	(0.022)	
Diploma	0.133*	0.135*	0.133*	0.102
	(0.074)	(0.075)	(0.074)	
Certificate	-0.179***	-0.179***	-0.179***	0.320
	(0.024)	(0.024)	(0.024)	
Postgraduate × M	-0.039	-0.041	-0.040	0.024
	(0.039)	(0.039)	(0.039)	
Bachelor × M	-0.010	-0.011	-0.011	0.022
	(0.044)	(0.044)	(0.044)	
Diploma × M	-0.072***	-0.074***	-0.072***	0.016
	(0.023)	(0.022)	(0.023)	
Certificate × M	-0.012	-0.016	-0.014	0.040
	(0.040)	(0.039)	(0.039)	
EXP	-0.005***	-0.005***	-0.005***	22.264
	(0.002)	(0.002)	(0.002)	
EXP^2	0.012***	0.012***	0.012***	6.106
	(0.004)	(0.004)	(0.004)	
Disability or impairment	0.005	0.005	0.005	0.148
	(0.012)	(0.012)	(0.012)	
Years since Migration-YSM	-0.002	/	/	26.320
	(0.001)	/	/	
Age on Arrival				
Age 0-12	/	-0.010	/	0.399
	/	(0.050)	/	
Age 13-22	/	-0.036	/	0.166
	/	(0.045)	/	
Age 23-34	/	0.013	/	0.340
Year of Arrival	/	(0.059)	/	
Arrived 1947-1979	/	/	-0.041	0.500
	/	/	(0.031)	
Arrived 1980-1989	/	/	-0.016	0.293
	/	/	(0.040)	
Control for States	YES	YES	YES	
Control for unemployment	YES	YES	YES	
Control for time periods	YES	YES	YES	
Mundlak Correction	**NO**	**NO**	**NO**	
Observations	14,711	14711	14711	
Individuals	2,313	2,313	2,313	
Log likelihood	-4536	-4536	-4536	

Notes: Dependent variable is the probability of over-education in full-time job. Constant is included.
Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are Natives, no qualification, Age 35-60, Year 2009, Arrived 1990-2001; and QLD.

The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, ACT), Unemployment, Unemployment × M, time periods dummy variables. Full Results are available upon request.

Sample: Natives and English Speaking Background (ESB) immigrants.

Source: HILDA-Release 9 (Wave 1-Wave 9).

Table 3. 6: Correlated Random Effects (CRE) logit Estimations of the Determinants of Over-education among Natives and ESB Immigrants
(Model 1 Correlated Random Effects (CRE) logit Estimations)

Dependent variable =1 if workers are observed to be over-educated
Sample: Natives (N) and ESB Immigrants

Explanatory Variables	(1*) CRE logit Marginal Effects	(2*) CRE logit Marginal Effects	(3*) CRE logit Marginal Effects	Pr(over-education|u_i=0) =11.9% Mean of X
Immigrant (M)	0.924***	0.937***	0.914***	0.143
Human Capital	(0.079)	(0.059)	(0.098)	
Years of education	-0.029	-0.027	-0.027	13.720
	(0.584)	(0.597)	(0.583)	
Postgraduate	0.223	0.229	0.227	0.115
	(0.362)	(0.365)	(0.364)	
Bachelor	-0.116*	-0.115*	-0.115*	0.146
	(0.064)	(0.064)	(0.064)	
Diploma	-0.064	-0.063	-0.063	0.102
	(0.076)	(0.077)	(0.077)	
Certificate	-0.215***	-0.214***	-0.215***	0.320
	(0.069)	(0.069)	(0.069)	
Postgraduate × M	-0.025	-0.035	-0.034	0.024
	(0.147)	(0.132)	(0.134)	
Bachelor × M	0.090	0.076	0.076	0.022
	(0.275)	(0.259)	(0.260)	
Diploma × M	-0.081	-0.084*	-0.084*	0.016
	(0.050)	(0.047)	(0.046)	
Certificate × M	0.087	0.078	0.078	0.040
	(0.235)	(0.226)	(0.226)	
EXP	-0.149	-0.147	-0.147	22.264
	(0.585)	(0.599)	(0.584)	
EXP^2	0.010	0.010	0.010	6.106
	(0.007)	(0.007)	(0.007)	
Disability or impairment	-0.002	-0.002	-0.002	0.148
	(0.012)	(0.012)	(0.012)	
Years since Migration-YSM	-0.003	/	/	26.320
	(0.005)	/	/	
Age on Arrival				
Age 0-12	/	-0.032	/	0.399
	/	(0.043)	/	
Age 13-22	/	-0.052	/	0.166
	/	(0.038)	/	
Age 23-34	/	-0.001	/	0.340
Year of Arrival	/	(0.055)	/	
Arrived 1947-1979	/	/	-0.040	0.500
	/	/	(0.032)	
Arrived 1980-1989	/	/	-0.010	0.293
	/	/	(0.043)	
Control for States	YES	YES	YES	
Control for unemployment	YES	YES	YES	
Control for time periods	YES	YES	YES	
Mundlak Correction	**YES**	**YES**	**YES**	
Observations	14,711	14,711	14711	
Individuals	2,313	2,313	2,313	
Log likelihood	-4504	-4504	-4505	

Notes: Dependent variable is the probability of over-education in full-time job. Constant is included.
Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are Natives, no qualification, Age 35-60, Year 2009, Arrived 1990-2001; and QLD.

The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, ACT), Unemployment, Unemployment × M, time periods dummy variables. Full Results are available upon request.

Sample: Natives and English Speaking Background (ESB) immigrants.

Source: HILDA-Release 9 (Wave 1-Wave 9).

Table 3. 7: Random Effects (RE) logit Estimations of the Determinants of Over-education among Natives and NESB Immigrants

(Model 1 Random Effects (RE) logit Estimations)

Dependent variable =1 if workers are observed to be over-educated

Sample: Natives (N) and NESB Immigrants

	(1) RE logit	(2) RE logit	(3) RE logit	Pr(over-education|u_i=0) =11.9%
Explanatory Variables	Marginal Effects	Marginal Effects	Marginal Effects	Mean of X
Immigrant (M)	0.561***	0.283	0.253	0.093
Human Capital	(0.191)	(0.206)	(0.170)	
Years of education	0.082***	0.081***	0.082***	13.746
	(0.011)	(0.011)	(0.011)	
Postgraduate	0.467***	0.472***	0.463***	0.114
	(0.156)	(0.155)	(0.157)	
Bachelor	-0.127***	-0.127***	-0.128***	0.154
	(0.023)	(0.023)	(0.023)	
Diploma	0.129	0.131*	0.127	0.102
	(0.079)	(0.079)	(0.079)	
Certificate	-0.184***	-0.184***	-0.185***	0.312
	(0.026)	(0.026)	(0.026)	
Postgraduate × M	0.007	0.030	0.006	0.018
	(0.085)	(0.099)	(0.086)	
Bachelor × M	-0.009	0.042	-0.004	0.023
	(0.056)	(0.074)	(0.058)	
Diploma × M	-0.068**	-0.061	-0.058	0.012
	(0.033)	(0.037)	(0.039)	
Certificate × M	-0.070**	-0.062*	-0.062*	0.015
	(0.032)	(0.035)	(0.036)	
EXP	-0.005***	-0.006***	-0.005***	21.924
	(0.002)	(0.002)	(0.002)	
EXP^2	0.013***	0.012***	0.012***	5.955
	(0.004)	(0.004)	(0.004)	
Disability or impairment	0.006	0.006	0.006	0.143
	(0.013)	(0.013)	(0.013)	
Poor English	-0.049	-0.048	-0.046	0.04
	(0.055)	(0.057)	(0.057)	
Years since Migration-YSM	-0.007***	/	/	20.650
	(0.002)	/	/	
Age on Arrival				
Age 0-12	/	-0.097***	/	0.220
	/	(0.019)	/	
Age 13-22	/	-0.056	/	0.235
	/	(0.043)	/	
Age 23-34	/	-0.045	/	0.379
Year of Arrival	/	(0.046)	/	
Arrived 1947-1979	/	/	-0.102***	0.304
	/	/	(0.014)	
Arrived 1980-1989	/	/	-0.021	0.303
	/	/	(0.044)	
Control for States	YES	YES	YES	
Control for unemployment	YES	YES	YES	
Control for time periods	YES	YES	YES	
Mundlak Correction	**NO**	**NO**	**NO**	
Observations	13,808	13,808	13808	
Individuals	2,185	2,185	2,185	
Log likelihood	-4234	-4238	-4235	

Notes: Dependent variable in outcome equation is the probability of over-education in full-time job. Constant is included. Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are Natives, no qualification, Age 35-60, Year 2009, Arrived 1990-2001; and QLD.

The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, ACT), Unemployment, Unemployment × M, time periods dummy variables. Full Results are available upon request.

Sample: Natives and Non-English Speaking Background (NESB) immigrants. Source: HILDA-Release 9 (Wave 1-Wave 9).

Table 3. 8: Correlated Random Effects (CRE) logit Estimations of the Determinants of Over-education among Natives and NESB Immigrants
(Model 1 Correlated Random Effects (CRE) logit Estimations)

Dependent variable =1 if workers are observed to be over-educated
Sample: Natives (N) and NESB Immigrants

Explanatory Variables	(1*) CRE logit Marginal Effects	(2*) CRE logit Marginal Effects	(3*) CRE logit Marginal Effects	Pr(over-education|u_i=0) =11.9% Mean of X
Immigrant (M)	0.873***	0.937***	0.872***	0.093
Human Capital	(0.184)	(0.030)	(0.186)	
Years of education	0.117***	0.116***	0.117***	13.746
	(0.031)	(0.031)	(0.031)	
Postgraduate	0.257	0.260	0.259	0.114
	(0.395)	(0.396)	(0.396)	
Bachelor	-0.113	-0.113	-0.113	0.154
	(0.071)	(0.071)	(0.071)	
Diploma	-0.058	-0.058	-0.058	0.102
	(0.085)	(0.085)	(0.085)	
Certificate	-0.211***	-0.211***	-0.211***	0.312
	(0.070)	(0.070)	(0.070)	
Postgraduate × M	0.680	0.844**	0.727	0.018
	(1.180)	(0.345)	(0.959)	
Bachelor × M	0.263	0.646	0.331	0.023
	(1.641)	(1.378)	(1.701)	
Diploma × M	-0.076	-0.064	-0.078	0.012
	(0.179)	(0.242)	(0.174)	
Certificate × M	-0.001	-0.003	-0.004	0.015
	(0.143)	(0.141)	(0.142)	
EXP	-0.006**	-0.007**	-0.006**	21.924
	(0.003)	(0.003)	(0.003)	
EXP^2	0.016**	0.015**	0.016**	5.955
	(0.008)	(0.008)	(0.008)	
Disability or impairment	-0.002	-0.002	-0.002	0.143
	(0.013)	(0.013)	(0.013)	
Poor English	-0.045	-0.054	-0.046	0.04
	(0.078)	(0.070)	(0.076)	
Years since Migration-YSM	-0.000	/	/	20.650
	(0.006)	/	/	
Age on Arrival				
Age 0-12	/	-0.100***	/	0.220
	/	(0.018)	/	
Age 13-22	/	-0.069*	/	0.235
	/	(0.036)	/	
Age 23-34	/	-0.049	/	0.379
Year of Arrival	/	(0.044)	/	
Arrived 1947-1979	/	/	-0.097***	0.304
	/	/	(0.017)	
Arrived 1980-1989	/	/	-0.017	0.303
	/	/	(0.046)	
Control for States	YES	YES	YES	
Control for unemployment	YES	YES	YES	
Control for time periods	YES	YES	YES	
Mundlak Correction	**YES**	**YES**	**YES**	
Observations	13,808	13,808	13808	
Individuals	2,185	2,185	2,185	
Log likelihood	-4208	-4210	-4209	

Notes: Dependent variable is the probability of over-education in full-time job. Constant is included. Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are Natives, no qualification, Age 35-60, Year 2009, Arrived 1990-2001; and QLD. The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, ACT), Unemployment, Unemployment × M, time periods dummy variables. Full Results are available upon request.

Sample: Natives and Non-English Speaking Background (NESB) immigrants.

Source: HILDA-Release 9 (Wave 1-Wave 9).

3.6 Impact of over-education on earnings results

The earnings model, in turn, examines over-education effects on earnings via years since migration or via pre-migration human capital and post-migration human capital. This model examines potential earnings penalties associated with over-education and it demonstrates the effects of over-education on immigrants' assimilation.

Pooled OLS analysis is based on the assumption of homogenous individuals and the random assignment of workers to jobs. Therefore, its result may be biased due to the unobserved heterogeneity of individuals and jobs. In contrast, longitudinal analysis allows the evaluation of unobserved heterogeneity on the earnings. In this section, I apply fixed effects models to address individual heterogeneity. I also report pooled OLS estimation as a benchmark to examine unobserved heterogeneity effects. Pooled OLS estimation results are reported in Appendix 3B.

As discussed previously, each case includes two specifications based on Models 2 and 3. One specification is over-education effects on earnings via years since migration based on Model 2, which demonstrates immigrants' assimilation effects. The other specification studies over-education effects on earnings via pre-migration and post-migration human capital based on Model 3, which implies transferability of immigrants' human capital.

Due to heterogeneity across different cohorts, thus, I decompose samples for further issues of interest. Thus, the specific impacts of over-education on earnings are examined by age on arrival, year of arrival and country of qualification, respectively.

Age at migration is assumed to have an effect on assimilation. When immigrants migrate younger than the age of 12, they are more likely to obtain local education and achieve local qualification. Thus, their labour market performance is similar to native. When immigrants enter Australia between 13 and 22 years old, most of them have obtained certain years of foreign elementary schooling which are equally valued as domestic schooling (Friedberg, 2000), they will continue their education in Australia. This cohort has mixed years of

education from both overseas and domestic. Thus, their labour market outcome is expected to be different from natives. Cohort enter between aged 23 and 34 years old might have achieved overseas qualifications and they are more likely to face initial earnings disadvantage and obtain earnings growth through assimilation process. Older arrival cohort might use overseas experience to offset their earnings disadvantage in host country. However, each age cohort may have a different extent of over-education and have certain earning consequence from that. Therefore, I define four cohorts based on their age at migration: 0-12, 13-22, 23-34, and 35-60.

Similarly, I decompose immigrants into ESB immigrants and NESB immigrants. Then I divide ESB or NESB immigrants sample into three groups based on year of arrival (1947-1979, 1980-1989, and 1990-2001) in Australia. I combine each of them with the entire natives into three subsamples. Estimations are analysed separately between ESB immigrants and NESB immigrants. The comparison is executed among natives and different immigrant cohort based on year of arrival. The purpose of this section is to compare the labour market performance among recent immigrants' arrivals or earlier immigrants' arrivals with natives via years since migration and pre-migration and post-migration human capital. Both assimilation effect and transferability of human capital are examined based on year of arrival.

According to countries where achieved qualification, I decompose ESB or NESB immigrants sample into three subsamples (holding Australian qualification, or overseas qualification, or without qualification), then combine each subsample with the entire natives sample to study qualification impact via over-education.

With panel fixed effects estimations to control for the unobserved heterogeneity, a number of significant empirical findings for overall earnings effect and specific earnings effect are emerged as follows.

Overall earnings effect

- Panel fixed effects show that unobserved heterogeneity plays a very important role in earnings.

- On the whole, there is a stronger assimilation effect found for ESB, rather than NESB immigrants. Furthermore, Over-education slows the NESB immigrants' assimilation process.
- The big earning disadvantage for NESB immigrants is not only because significant returns to pre-migration human capital do not exist, but also returns to domestic education are discounted and valued less than natives.

Age at migration earnings effect

- ESB immigrants who migrated at age 23 to 34 have stronger assimilation effects than those who migrated at less than 12 years of age. And over-education boost their earnings via post-migration experience. This evidence gives some implication for immigration policy. This age arrival group is highly educated with overseas education, even has high incidence of over-education. But this over-education status has not lead to earnings disadvantage.
- Assimilation effects are found only for NESB immigrants who migrated at less than 12 years of age. There is a significant earnings penalty from education-occupation mismatch for NESB immigration who migrated at age 13 to 22 and at age 35 to 60 relative to natives.

Year of arrival earnings effect

- Assimilation effects are found for ESB who migrated between 1990 and 2001.
- Immigrants who migrated after 1990 have a higher 'quality' (highly educated-see Figure 3.2) than earlier entries, which is shown they have better labour market performance than the group who migrated between 1980 and 1989. However, if they are over-educated, then they have lower earnings than natives.

Country of qualification earnings effect

- Stronger assimilation effects are found for ESB with overseas qualification.

- Overseas qualification is transferable and valued in Australia only for ESB immigrants, not for NESB immigrants.
- Assimilation effects are found only for NESB immigrants with Australian qualification.
- Over-education status reduces earnings for NESB immigrants with overseas qualification.

The detailed analyses on earnings effect are provided in the following sections. Section 3.6.1 provides estimation results when examining the impact of over-education on earnings via years since migration based on Model 2 and its sub-sections further report results by overall effect, age on arrival, year of arrival and country of qualification. Similarly, Section 3.6.2 presents earnings results from pre-migration and post-migration human capital aspect, and both results from overall effects and sub-group specific earnings effects are given in sub-sections.

3.6.1 Impacts of over-education on earnings via years since migration

In this section, overall earnings effect via years since migration is examined in Section 3.6.1.1 and specific earnings effects via years since migration based on age on arrival, year of arrival and country of qualification are discussed in Section 3.6.1.2.

More specifically, Tables 3.9 gives overall effects. Table 3.10 to Table 3.15 evaluate earnings for specific sub-groups to study the age on arrival effect, year of arrival cohort 'quality' effect and country of qualification effect based on Model 2 in Equation (3.9).

3.6.1.1 Overall earnings effect via years since migration

Overall effects are examined in this section. Overall effects are considered based on subsamples of natives and ESB immigrants, and natives and NESB immigrants.

Following Model 2 in Equation (3.9), estimation results are given in Table 3.9. The first column reports fixed effects estimations for full-time ESB immigrants and natives. The

second column presents results for full-time NESB immigrants and natives. The Hausman test rejects the null hypothesis that individual specific error is uncorrelated with the explanatory variables of the wage equation. Therefore, fixed effects estimates are preferred to random effects, and full results are shown in Appendix 3B.

After accounting for individual effect, fixed effects estimations reveal that years since migration (YSM) have a stronger effect on earnings for ESB immigrants than for NESB immigrants. That is, an ESB immigrant improves his earnings by 2.4 per cent for each year of staying in Australia, which is 1 per cent higher than for NESB immigrant (1.4 per cent). Longitudinal estimations suggest a much stronger effect of assimilation for ESB immigrants than for NESB immigrants.

Compared to over-educated natives with the same characteristics, over-educated ESB immigrants seemingly have similar returns to year of over-education. This effect is shown by the insignificant effects on interaction terms between years of over-education and immigrant status. In contrast, according to the panel fixed effects estimation in column (2), NESB immigrants suffer a 9 per cent lower return for the additional year of over-education than comparable natives. This suggests that educational mismatch is a serious problem among NESB immigrants, and that it can explain the earnings penalty from education-occupation mismatch. Similar effects are also found in the return to years of required education, which is shown in Column (2), for each year of required education, as NESB immigrants have a 9 per cent lower return than natives. This indicates that NESB suffer earnings penalties not only from the education-occupation mismatch but also when they possess adequate years of education.

Table 3. 9: The Effect of Over-education on Earnings via Years since Migration for Natives and Immigrants (Model 2 Overall effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars

	(1)	(2)
	Natives and ESB Immigrants	**Natives and NESB Immigrants**
Explanatory Variables	Panel-FE	Panel-FE
Human capital		
Years of over-education	0.049***	0.047***
	[0.016]	[0.015]
Years of under-education	-0.036**	-0.035**
	[0.015]	[0.015]
Years of required education	0.045***	0.044***
	[0.015]	[0.015]
Years of over-education × M	-0.020	-0.090**
	[0.035]	[0.040]
Years of under-education × M	-0.009	0.072
	[0.037]	[0.045]
Years of required education × M	-0.004	-0.088**
	[0.035]	[0.041]
Years since migration-YSM		
YSM	0.024***	0.014*
	[0.007]	[0.008]
$YSM^2/100$	-0.035***	-0.009
	[0.011]	[0.015]
Over-educated ×YSM	0.004	0.004
	[0.004]	[0.004]
Over-educated ×$YSM^2/100$	-0.010	-0.015
	[0.009]	[0.011]
Under-educated ×YSM	0.004	-0.000
	[0.004]	[0.005]
Under-educated ×$YSM^2/100$	-0.008	-0.001
	[0.008]	[0.013]
EXP	0.040***	0.038***
	[0.003]	[0.003]
$EXP^2/100$	-0.052***	-0.050***
	[0.005]	[0.005]
Constant	1.997***	2.149***
	[0.165]	[0.167]
Control for States	YES	YES
Control for unemployment	YES	YES
Control for time periods	YES	YES
Control for additional variables˘	YES	YES
Individuals	2313	2185
Observations	14711	13808

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Based categories are natives, no qualification, being matched YSM, being matched $YSM^2/100$, QLD, Year 2009.

˘The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables. The full set of results is reported in Table 3B.1.

Source: HILDA-Release 9.

3.6.1.2 Specific earnings effect via years since migration

Specific earnings effects are considered in 3 sections based on the specific subsamples structured by age on arrival, year of arrival and country of qualification. I analyse each specific effect, separately between ESB immigrants and NESB immigrants.

Age on arrival effect

The results when immigrants are split into four cohorts according to age at migration are reported in Tables 3.10 and 3.11.

1) Age on arrival effect among ESB immigrants

In Table 3.10, Panel fixed effects results show that ESB immigrants who migrated at age 23 to 34 have fastest assimilation rate compared to the other age arrival cohorts, with an extra year since migration raising earnings by 3 per cent in a quadric form. This positive significant effect is also found among ESB immigrants who migrated at less than 12 years of age.

The significance of over-education effect on years since migration found among the cohort who migrated at age 23 to 34 and an additional year of over-education increase their earnings by 1 per cent. Previous evidence in Figure 3.1 tells us this cohort is structured by highly educated people, among them, 83 per cent with qualification, only 17 per cent without qualification. As discussed before, ESB immigrants who migrated at age 23 to 34 are more likely to have received overseas qualifications and they are more likely to be over-educated. The incidence rate of over-education is 43 per cent among this cohort. Even though, this cohort is more likely to work in jobs required education less than their obtained education, but the extra years of education raise their earnings. The evidence implies that overseas qualification for ESB immigrants play an important role and are recognised by Australian employers. There is no significant effect of over-education on years since migration among the other three cohorts.

2) Age on arrival effect among NESB immigrants

Assimilation effects for NESB immigrants are found only among younger arrivals who migrated at younger than 12 years of age, which can be seen in Columns (1) of Table 3.11. For the youngest arrival cohort, they suffer initial earning disadvantages but have a 7 per cent earnings growth to each additional year in Australia. There is no significant assimilation effect found among the left three age arrival cohorts.

Over-education has a large earnings penalty for NESB immigrants who migrated at older than 12 years of age. They reduce their earnings by 18 per cent to 70 per cent for each additional year of over-education compared to natives. In addition, they also have a lower return by 20 per cent to 70 per cent for each year of required education than natives.

For the cohort who migrated at age 35 to 60, there are two potential reasons to explain an earnings loss. They are revealed in Figure 3.1, those are, the distribution of higher education and unrecognised foreign qualification. Among this cohort, 59 per cent of them have overseas qualification and 27 per cent of them have Australian qualification. 44 per cent of them are over-educated. Earnings penalty from both year of over-education and year of required education implies that the earnings gap between NESB immigrants and natives is not only from education-occupation mismatches but also from earning inequality in nature even after considering the unobserved heterogeneity. Even though 58 per cent of NESB cohort migrated at age 13 to 22 have Australian qualification, they seemly have not improve their earnings status, in fact, they are the group who suffers the largest earnings penalty.

In summary, positive assimilation process is found among all ESB age arrival cohorts but only among NESB immigrants who migrated at less than 12 years of age. Over-education is a barrier and it slows assimilation process for NESB immigrants who migrated at age 13 to 22 and at age 35 to 60. In contrast, over-education boosts earnings growth for both NESB and ESB who migrated at age 23 to 34. This evidence can give some implication about immigration policy. There are significant assimilation effects among younger arrivals. Immigrants who entered at age 23 to 34 have overseas qualification, and are more likely to be over-educated, however, their over-education seemly boost rather than reducing their earnings.

Table 3. 10: The Effect of Over-education on Earnings via Years since Migration for Natives and ESB Immigrants (Model 2 Age on Arrival Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars

	Sample: Natives and ESB Immigrants			
	(1) Native & ESB migrated at age 0-12	(2) Native & ESB migrated at age 13-22	(3) Native & ESB migrated at age 23-34	(4) Native & ESB migrated at age 35-60
Explanatory Variables	Panel-FE	Panel-FE	Panel-FE	Panel-FE
Human capital				
Years of over-education × M	-0.032	0.016	-0.054	0.016
	[0.064]	[0.068]	[0.055]	[0.095]
Years of under-education × M	0.001	-0.118	0.068	0.007
	[0.066]	[0.075]	[0.062]	[0.105]
Years of required education × M	-0.024	0.076	-0.047	0.030
	[0.063]	[0.071]	[0.057]	[0.097]
Years since migration-YSM				
YSM	0.030*	0.011	0.033***	0.032
	[0.017]	[0.021]	[0.011]	[0.022]
$YSM^2/100$	-0.041*	-0.074**	-0.039	0.008
	[0.022]	[0.036]	[0.027]	[0.080]
Over-educated ×YSM	0.004	-0.007	0.013*	0.022
	[0.005]	[0.013]	[0.007]	[0.021]
Over-educated ×$YSM^2/100$	-0.010	0.031	-0.054**	-0.090
	[0.012]	[0.034]	[0.024]	[0.102]
Under-educated ×YSM	0.007	-0.008	-0.013	0.030
	[0.005]	[0.011]	[0.010]	[0.023]
Under-educated ×$YSM^2/100$	-0.013	0.033	0.037	-0.139
	[0.011]	[0.027]	[0.032]	[0.106]
EXP	0.039***	0.038***	0.039***	0.039***
	[0.003]	[0.003]	[0.003]	[0.003]
$EXP^2/100$	-0.052***	-0.050***	-0.049***	-0.051***
	[0.005]	[0.005]	[0.005]	[0.005]
Control for States	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES
Control for additional variables˘	YES	YES	YES	YES
Constant	2.023***	2.048***	2.061***	2.036***
	[0.172]	[0.174]	[0.173]	[0.174]
Individuals	2118	2045	2093	2018
Observations	13446	12956	13321	12806

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, Year 2009.

˘ The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables. The full set of results is reported in Table 3B.2.

Source: HILDA-Release 9.

Table 3. 11: The Effect of Over-education on Earnings via Years since Migration for Natives and NESB Immigrants (Model 2 Age on Arrival Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars

	Sample: Natives and NESB Immigrants			
	(1)	(2)	(3)	(4)
	Native & NESB migrated at age 0-12	Native & NESB migrated at age 13-22	Native & NESB migrated at age 23-34	Native & NESB migrated at age 35-60
Explanatory Variables	Panel-FE	Panel-FE	Panel-FE	Panel-FE
Human capital				
Years of over-education × M	0.611	-0.701**	-0.065	-0.177**
	[0.397]	[0.329]	[0.048]	[0.075]
Years of under-education × M	-0.616	0.695**	0.001	0.284**
	[0.408]	[0.323]	[0.063]	[0.128]
Years of required education × M	0.610	-0.695**	-0.062	-0.195**
	[0.396]	[0.328]	[0.049]	[0.078]
Years since migration-YSM				
YSM	0.068***	-0.016	0.000	-0.016
	[0.026]	[0.021]	[0.015]	[0.030]
$YSM^2/100$	-0.096***	0.018	0.077*	0.140
	[0.035]	[0.048]	[0.046]	[0.131]
Over-educated ×YSM	-0.006	0.001	0.008	-0.017
	[0.011]	[0.012]	[0.009]	[0.024]
Over-educated ×$YSM^2/100$	0.015	-0.007	-0.039	0.128
	[0.028]	[0.042]	[0.038]	[0.138]
Under-educated ×YSM	-0.000	-0.014	0.014	-0.023
	[0.010]	[0.013]	[0.016]	[0.046]
Under-educated ×$YSM^2/100$	-0.000	0.042	-0.043	-0.031
	[0.023]	[0.040]	[0.056]	[0.220]
EXP	0.038***	0.039***	0.038***	0.039***
	[0.003]	[0.003]	[0.003]	[0.003]
$EXP^2/100$	-0.050***	-0.050***	-0.050***	-0.050***
	[0.005]	[0.005]	[0.005]	[0.005]
Control for States	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES
Control for additional variables˘	YES	YES	YES	YES
Constant	1.878***	2.262***	2.089***	2.096***
	[0.198]	[0.196]	[0.171]	[0.174]
Individuals	2036	2035	2058	2017
Observations	12871	12889	13062	12804

Notes:
The Hausman test rejects random effects results and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, Year 2009.

˘ The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables, disability or impairment, and poor English. The full set of results is reported in Table 3B.3.

Source: HILDA-Release 9.

Year of arrival effect

The results when immigrants are decomposed three cohorts according to year of arrival are reported in Tables 3.12 and 3.13.

1) Year of arrival effect among <u>ESB immigrants</u>

Estimation results are reported in Table 3.12. Results from Panel fixed effects reveal that year since migration (YSM) has a positive significant effect on earnings for ESB immigrants who arrived between 1990 and 2001 (7.6%). This strong assimilation process is found for matched ESB workers who arrived after 1990, that is because this cohort is associated with higher quality (more educated workers) or recognised overseas qualifications (see Figure 3.2).

Educational mismatches seemly play a same role among ESB immigrants since there is no significant effect found on the coefficients of interaction terms between education mismatches and migrant status. For ESB immigrants who arrived between 1980 and 1989, positive sign on interaction item of being over-educated and YSM indicate that over-educated ESB worker enjoy an earning premium for each year of staying in Australia.

The evidence shows that ESB immigrants who migrated after 1990 have a better labour market outcome if they get matched jobs. Otherwise, they suffer an earnings loss from education-occupation mismatches. It also implies this cohort has better quality than the other two arrival cohorts.

2) Year of arrival effect among <u>NESB immigrants</u>

For NESB immigrants, estimation results from year of arrival effect are differing from those for ESB immigrants. Earlier NESB immigrants who migrated between 1947 and 1979, is the only group, which is found to have a positive, but insignificant assimilation effect when their residencies lengthen. In Column (1) of Table 3.13, accounting for the

unobserved heterogeneity with fixed effects estimation, they have a significant earnings growth by 2 per cent per year following migration in a quadric form. In particular, these earlier arrivals take the earnings advantage from over-education, but the rest two other NESB arrival groups who migrated after 1980 suffer earnings penalty from both over-education and required education. NESB immigrants earn 8 per cent to 16 per cent less than natives for each year of required education, which imply the natural earnings inequality between NESB immigrants and natives. And the additional year of over-education worsen NESB earnings by 8 to 16 per cent relative to natives. On average, NESB immigrants arrived after 1990 earn more than natives. This reveals NESB immigrants 'quality' is increasing, with 57 per cent of them holding above Bachelor degree (see Figure 3.2). However, if they are over-educated, then they earn 8 per cent less than comparable over-educated natives for each year of over-education.

Table 3. 12: The Effect of Over-education on Earnings via Years since Migration for Natives and ESB Immigrants (Model 2 Year of Arrival Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars

	Sample: Natives and ESB Immigrants		
	(1)	(2)	(3)
	Native & ESB migrated at between 1947 and 1979	Native & ESB migrated at between 1980 and 1989	Native & ESB migrated at between 1990 and 2001
Explanatory Variables	Panel-FE	Panel-FE	Panel-FE
Human capital			
Years of over-education × M	-0.069	0.059	-0.004
	[0.058]	[0.071]	[0.050]
Years of under-education × M	-0.002	-0.053	0.064
	[0.061]	[0.075]	[0.060]
Years of required education × M	-0.049	0.086	-0.005
	[0.058]	[0.071]	[0.052]
Years since migration-YSM			
YSM	0.023	-0.010	0.076***
	[0.020]	[0.030]	[0.018]
$YSM^2/100$	-0.035	0.053	-0.278***
	[0.025]	[0.074]	[0.094]
Over-educated ×YSM	-0.002	0.022**	0.000
	[0.006]	[0.011]	[0.017]
Over-educated ×$YSM^2/100$	0.005	-0.088*	0.022
	[0.013]	[0.046]	[0.106]
Under-educated ×YSM	0.011**	-0.003	-0.018
	[0.005]	[0.013]	[0.021]
Under-educated ×$YSM^2/100$	-0.019*	-0.015	0.056
	[0.011]	[0.049]	[0.139]
EXP	0.040***	0.038***	0.039***
	[0.003]	[0.003]	[0.003]
$EXP^2/100$	-0.052***	-0.049***	-0.050***
	[0.005]	[0.005]	[0.005]
Control for States	YES	YES	YES
Control for unemployment	YES	YES	YES
Control for time periods	YES	YES	YES
Control for additional variables˘	YES	YES	YES
Constant	2.057***	2.014***	2.039***
	[0.174]	[0.176]	[0.171]
	2161	2083	2043
Individuals	13658	13222	13043
Observations	0.0438	0.0428	0.0508

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, Year 2009.

˘ The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables. The full set of results is reported in Table 3B.4.

Source: HILDA-Release 9.

Table 3. 13: The Effect of Over-education on Earnings via Years since Migration for Natives and NESB Immigrants (Model 2 Year of Arrival Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars

	Sample: Natives and NESB Immigrants		
	(1)	(2)	(3)
Explanatory Variables	Native & NESB migrated at between 1947 and 1979 Panel-FE	Native & NESB migrated at between 1980 and 1989 Panel-FE	Native & NESB migrated at between 1990 and 2001 Panel-FE
Human capital			
Years of over-education × M	0.789**	-0.161*	-0.079*
	[0.386]	[0.093]	[0.045]
Years of under-education × M	-0.786**	0.136	-0.008
	[0.392]	[0.102]	[0.077]
Years of required education × M	0.762**	-0.154	-0.078*
	[0.385]	[0.093]	[0.046]
Years since migration-YSM			
YSM	0.020	-0.016	-0.040*
	[0.026]	[0.043]	[0.023]
$YSM^2/100$	-0.040	0.157	0.218*
	[0.036]	[0.120]	[0.122]
Over-educated ×YSM	-0.010	0.017	0.003
	[0.010]	[0.015]	[0.017]
Over-educated ×$YSM^2/100$	0.024	-0.078	-0.004
	[0.026]	[0.073]	[0.116]
Under-educated ×YSM	-0.005	0.036*	0.047
	[0.008]	[0.019]	[0.029]
Under-educated ×$YSM^2/100$	0.017	-0.188**	-0.230
	[0.019]	[0.081]	[0.154]
EXP	0.039***	0.038***	0.039***
	[0.003]	[0.003]	[0.003]
$EXP^2/100$	-0.050***	-0.049***	-0.050***
	[0.005]	[0.005]	[0.005]
Control for States	YES	YES	YES
Control for unemployment	YES	YES	YES
Control for time periods	YES	YES	YES
Control for additional variables˘	YES	YES	YES
Constant	1.799***	2.116***	2.110***
	[0.210]	[0.175]	[0.170]
Individuals	2052	2045	2062
Observations	12971	12970	13079

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, Year 2009.

˘ The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables. The full set of results is reported in Table 3B.5.

Source: HILDA-Release 9.

Country of qualification effect

The results when immigrants are categorised three cohorts according to country where they achieved highest qualification are reported in Tables 3.13 and 3.14.

1) Country of qualification effect among ESB immigrants

In Table 3.14, I found that years since migration have a significant and positive effect on earnings only among ESB immigrants who hold overseas qualifications. They experience a faster growth rate by 5 per cent from each year since migration than an ESB worker who holds Australian qualification (in Column (2) of Table 3.14). This implies overseas qualification is more valued than Australian qualification for ESB immigrants by local employers.

ESB immigrants who do not have any qualification experience an 8 per cent higher return to each year of over-education and required education, but an 8 per cent lower return to each year of under-education than comparable natives.

In summary, ESB immigrants with overseas qualifications experience a faster earnings growth from year since migration than ESB immigrants with Australian qualifications or without qualifications. This evidence further reveals that overseas qualification is valuable and transferable to the Australian labour market for ESB immigrants.

2) Country of qualification effect among NESB immigrants

Based on Model 2, the result is reported in Table 3.15. In contrast to the results from Table 3.14 for ESB immigrants, years since migration have significant effects on earnings for NESB immigrants who hold Australian qualification, rather than NESB immigrants who hold overseas qualification. That is, each year since migration increases earnings by 2 per cent for NESB immigrants who hold Australian qualification.

Relatively, earnings penalty from over-education is very serious for NESB workers who hold overseas qualification. In Column (2) of Table 3.15, NESB workers have 12 per cent lower return to each year of over-education, and 12 per cent lower return to each year of required education than natives. This clearly shows that overseas qualification for NESB immigrants is not recognised by Australian employer.

In summary, overseas qualification is valued in Australia for ESB immigrants but not for NESB immigrants. Australian qualification improves earnings for NESB immigrants.

Table 3. 14: The Effect of Over-education on Earnings via Years since Migration for Natives and ESB Immigrants (Model 2 Country of Qualification Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars

	Sample: Natives and ESB Immigrants		
	(1)	(2)	(3)
Explanatory Variables	Native & ESB with Australian Qualification Panel-FE	Native & ESB with Overseas Qualification Panel-FE	Native & ESB without qualification Panel-FE
Human capital			
Years of over-education × M	-0.036	-0.023	0.800**
	[0.046]	[0.056]	[0.366]
Years of under-education × M	0.076	0.182*	-0.842**
	[0.076]	[0.101]	[0.365]
Years of required education × M	-0.012	-0.025	0.821**
	[0.047]	[0.057]	[0.365]
Years since migration-YSM			
YSM	0.008	0.046***	0.003
	[0.012]	[0.012]	[0.014]
$YSM^2/100$	-0.025	-0.061**	0.002
	[0.018]	[0.028]	[0.023]
Over-educated ×YSM	0.002	0.003	0.010
	[0.005]	[0.008]	[0.009]
Over-educated ×$YSM^2/100$	-0.003	-0.026	-0.024
	[0.012]	[0.028]	[0.021]
Under-educated ×YSM	-0.000	-0.010	0.008
	[0.007]	[0.024]	[0.007]
Under-educated ×$YSM^2/100$	-0.003	-0.002	-0.017
	[0.014]	[0.082]	[0.015]
EXP	0.040***	0.039***	0.039***
	[0.003]	[0.003]	[0.003]
$EXP^2/100$	-0.052***	-0.050***	-0.051***
	[0.005]	[0.005]	[0.005]
Control for States	YES	YES	YES
Control for unemployment	YES	YES	YES
Control for time periods	YES	YES	YES
Control for additional variables˘	YES	YES	YES
Constant	2.070***	-2.629	1.640***
	[0.170]	[6.607]	[0.244]
Individuals	2129	2083	2090
Observations	13486	13231	13206

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.
Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, Year 2009.

˘ The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables. The full set of results is reported in Table 3B.6.

Source: HILDA-Release 9.

Table 3. 15: The Effect of Over-education on Earnings via Years since Migration for Natives and NESB Immigrants (Model 2 Country of Qualification Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars

	Sample: Natives and NESB Immigrants		
	(1)	(2)	(3)
Explanatory Variables	Native & NESB with Australian Qualification Panel-FE	Native & NESB with Overseas Qualification Panel-FE	Native & NESB without qualification Panel-FE
Human capital			
Years of over-education × M	-0.036	-0.122**	0.010
	[0.065]	[0.052]	[0.040]
Years of under-education × M	0.005	0.092	/
	[0.116]	[0.156]	/
Years of required education × M	-0.028	-0.116**	-0.004
	[0.065]	[0.053]	[0.026]
Years since migration-YSM			
YSM	0.024**	-0.022	0.025
	[0.012]	[0.016]	[0.020]
$YSM^2/100$	-0.041*	0.171***	-0.040
	[0.022]	[0.053]	[0.035]
Over-educated ×YSM	0.007	0.018*	-0.016
	[0.006]	[0.010]	[0.011]
Over-educated ×$YSM^2/100$	-0.020	-0.085**	0.035
	[0.015]	[0.040]	[0.027]
Under-educated ×YSM	0.000	0.013	-0.013
	[0.015]	[0.033]	[0.010]
Under-educated ×$YSM^2/100$	0.000	-0.028	0.028
	[0.036]	[0.112]	[0.021]
EXP	0.039***	0.038***	0.038***
	[0.003]	[0.003]	[0.003]
$EXP^2/100$	-0.051***	-0.050***	-0.050***
	[0.005]	[0.005]	[0.005]
Control for States	YES	YES	YES
Control for unemployment	YES	YES	YES
Control for time periods	YES	YES	YES
Control for additional variables˘	YES	YES	YES
Constant	2.061***	2.105***	2.054***
	[0.172]	[0.172]	[0.176]
Individuals	2072	2047	2048
Observations	13118	12979	12923

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, Year 2009.

˘ The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables. The full set of results is reported in Table 3B.7.

Source: HILDA-Release 9.

3.6.2 Impacts of over-education on earnings via pre-migration and post-migration human capital

Years since migration have improved ESB immigrants' earnings and shown that there is a positive assimilation among ESB immigrants. Does overseas education and experience accumulate domestic education and experience to raise immigrants' earnings? In this section, I will analyse the impact of over-education on earnings via pre-migration education and experience and post-migration education and experience based on Model 3 in Equation (3.10). Two sub-sections provide results for overall earnings effects (Table 3.16), and specific sub-groups earnings effects (Table 3.17 to 3.22).

In Model 3, double interaction and triple interaction terms result in small cell cases, consequently, most coefficients on these terms are estimated with less precision and become insignificant. Therefore, caution is needed when it comes to interpreting results for those coefficients.

3.6.2.1 Overall earnings effect via pre-migration human capital and post-migration human capital

Table 3.16 reports estimation results from pre-migration and post-migration human capital, based on Model 3 in Equation (3.10).

Pooled OLS results from Columns (1) and (4) in Table 3B.8 show that pre-migration education is significantly less valued than post-migration education for both ESB and NESB immigrants in the Australian labour market. For ESB immigrants, the return to years of education abroad and years of experience abroad is 9 per cent and 1.6 per cent respectively. These returns are both lower than that of the return to domestic years of education (9.3 per cent) and experience (1.8 per cent). For NESB immigrants, the return to education abroad is 2.6 per cent lower than to domestic education, while experience obtained overseas has moderately higher return than domestic experience. This is partly consistent with Friedberg's (2000) finding that the returns to domestic schooling and experience are 8.8 per cent and 1.4 per cent, and both are higher than the return to foreign

education (7.6 per cent) and experience (0.3 per cent). ESB immigrants have 3.8 lower returns to each additional year of domestic experience in quadric form than comparable natives. However, being over-educated boosts the return to domestic experience even though it has negative effects on the return to education abroad. Over-educated NESB immigrants enjoy a 1.8 per cent higher return to years of Australian education but suffer a 2.5 per cent lower return to years of Australian experience than over-educated natives.

In contrast to results drawn from pooled OLS estimation, results in Columns (1) and (2) of Table 3.16 from panel fixed effects estimations show that pre-migration education and experience have no significant effects on NESB immigrants' earnings in Australia. However, notably, on average, ESB immigrants improve their Australian earnings by 6 per cent for each foreign year of education. Compared to matched ESB and NESB immigrants with similar characteristics, under-educated ESB and NESB immigrants have, respectively, 1.5 per cent and 1.8 per cent higher return to each year of education abroad.

Coefficients of the interaction terms in the second panel of Table 3.16 reveal a native-immigrant earnings gap from a domestic education and experience perspective. This is marked by bold font. Education matched ESB immigrants earn 2.8 per cent more than comparable education matched natives from each year of domestic experience in a quantic form. Education matched NESB immigrants earn 4.8 per cent less than comparable education matched natives from each year of domestic education. Overall education mismatch effects on earnings are not found in panel fix effects estimations.

In summary, panel fixed effects show that unobserved heterogeneity plays a very important role in earnings. In longitudinal estimation, the big earning disadvantage for NESB immigrants is not only because significant returns to pre-migration human capital do not exist, but also returns to domestic education are discounted and valued less than natives. On the whole, there is a stronger assimilation effect found for ESB, rather than NESB immigrants. Furthermore, over-education slows the NESB immigrants' assimilation process.

Table 3. 16: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and Immigrants (Model 3 Overall Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars		
	(1)	(2)
	Natives and ESB Immigrants	**Natives and NESB Immigrants**
Explanatory Variables	Panel-FE	Panel-FE
Pre-migration human capital		
Education abroad	0.061***	-0.019
	[0.019]	[0.031]
Experience abroad	0.043	0.048
	[0.047]	[0.060]
Experience abroad SQR/100	0.065	0.013
	[0.169]	[0.149]
Over-educated × Education abroad	0.001	0.002
	[0.006]	[0.007]
Under-educated × Education abroad	0.015*	0.018*
	[0.008]	[0.010]
Over-educated × Experience abroad	0.004	-0.014
	[0.013]	[0.015]
Over-educated × Experience abroad SQR/100	0.028	0.069
	[0.056]	[0.058]
Post-migration human capital		
Education in Australia (AU)	0.034***	0.033***
	[0.006]	[0.006]
Education in Australia × M	-0.002	-0.047
	[0.016]	[0.030]
Experience in Australia	0.040***	0.040***
	[0.003]	[0.003]
Experience in Australia SQR/100	-0.056***	-0.056***
	[0.007]	[0.007]
Experience in Australia× M	0.027***	-0.002
	[0.008]	[0.010]
Experience in Australia SQR/100 × M	-0.060***	0.015
	[0.018]	[0.025]
Over-educated × Education in AU	-0.001	-0.001
	[0.002]	[0.002]
Over-educated × Education in AU×M	0.002	-0.012
	[0.006]	[0.008]
Over-educated × Experience in AU	-0.001	-0.001
	[0.003]	[0.003]
Over-educated × Experience in AU SQR/100	0.007	0.007
	[0.008]	[0.008]
Over-educated × Experience in AU×M	-0.001	0.014
	[0.008]	[0.010]
Over-educated × Experience in AU SQR/100×M	-0.010	-0.047
	[0.021]	[0.029]
Control for States	YES	YES
Control for unemployment	YES	YES
Control for time periods	YES	YES
Control for additional variables˘	YES	YES
Constant	2.101***	2.246***
	[0.100]	[0.103]
Individuals	2313	2185
Observations	14711	13808

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.
Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are natives, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad SQR/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU SQR/100.
˘The model includes additional variables. The full set of results is reported in Table 3B.8. Source: HILDA-Release 9.

3.6.2.2 Specific earnings effect via pre-migration human capital and post-migration human capital

Specific earnings effects are considered in 3 sections based on the specific subsamples structured by age on arrival, years of arrival and country of qualification. I analyse each specific effect, separately between ESB immigrants and NESB immigrants.

Following Model 3 in Equation (3.10), estimation results are given in Tables 3.17 to 3.22.

Age on arrival effect

The results when immigrants are split into four cohorts according to age at migration are reported in Tables 3.17 and 3.18.

1) Age on arrival effect among <u>ESB immigrants</u>

Estimation results are reported in Table 3.17. Foreign education for ESB immigrants who migrated at less than 12 years of age has significant effects on their earnings. The payoff is 7 per cent to education abroad for this ESB group. They arrive without any overseas experience. The payoff to each year of experience obtained in Australia for ESB immigrants is 2 per cent more than that of natives in a quadric form, but it is statistically insignificant.

For ESB immigrants who migrated at age 13 to 22, their overseas experience has a positive significant effect on their earnings in Australia.

For ESB immigrants who migrated at age 23 to 34, there is no significant effect on earnings from per-human capital; however, their post-migration experience and over-education improve their earnings. This result is consistent with that in column (3) of Table 3.10. This cohort is more likely to have overseas qualification and is more likely to be over-educated. However, their qualifications are recognised by Australian employers and

over-education boosts their earnings in Australia.

For ESB who migrated at age 35 to 60, pre-migration education and experience have a positive significant effect on earnings, which show that pre-migration human capital are transferable and accumulate their earnings in Australia. Post-migration education and experience also improve their earnings by 38 per cent and 7 per cent more than those of natives respectively, which can be seen from Column (4) in Table 3.17. However, if they are over-educated, their over-education effect on post-migration experience reduces their earnings by 6 per cent compare to natives.

To summarise, both education and experience abroad have a positive effect on earnings, which reveals the portability of pre-migration human capital for ESB immigrants. Education-occupation mismatch does not have a significant effect on earnings in Australia from pre-migration human capital. Post-migration experience acquired in Australia accumulates more earnings for ESB immigrants than for natives except for ESB immigrants who arrived at age 13 to 22, which partially explains assimilation effect is from domestic experience accumulation. Older arrival ESB cohorts have large payoffs to both their pre-migration and post-migration human capital, but once they are over-educated, their payoffs are discounted by over-education status. ESB immigrants who migrated at age 35 to 60 raise their earnings by 7 per cent more for each year of Australian experience, but reduce earnings by 6 per cent more for each year of Australian experience via over-education than natives.

2) Age on arrival effect among <u>NESB immigrants</u>

On the contrary to results from ESB immigrants, the results indicate no transferability of pre-migration human capital for NESB immigrants. In Table 3.14, both education and experience abroad do not have a positive significant effect on earnings in Australia. Moreover, cohort who migrated at less than 12 years of age is the only group who has greater earnings from each years of experience in Australia than natives. They earn 4.3 per cent more than natives to each year of their Australian experience, but this effect is observed only for younger NESB arrival cohort who migrated at less than 12 years of age,

not for the other age cohorts. For the other three cohorts, not only their foreign education and experience do not help to increase their earnings but also, their domestic education and experience are discounted on earnings compared to natives with same characteristics. The reason for assimilation effects among younger NESB arrivals in Column (1) of Table 3.13 is explained by their Australian experience improving their earnings in a quadric form.

I found negative earnings effects of post-migration education and experience among NESB immigrants who migrated at age 13 to 22 relative to natives, even though not significant, but maybe explain the largest penalty in Column (2) of Table 3.13.

Over-educated NESB immigrants who migrated at age 23 to 34 raise their earnings by 3.3 per cent more than over-educated natives to each year of Australian experience. This information is associated with Column (3) in Table 3.13; this cohort who migrated at age 23 to 34 does not have earning disadvantage from over-education.

In summary, panel fixed effects estimation shows that pre-migration human capital for NESB immigrants is non-transferable and not valued in the host country. In contrast, it appears to be portable and highly valued in Australia for ESB immigrants.

In summary, positive assimilation process is found among all ESB age arrival cohorts but only among NESB immigrants who migrated at less than 12 years of age. Over-education is a barrier and it slows assimilation process for NESB immigrants who migrated at age 13 to 22 and at age 35 to 60. And further evidence shows that this assimilation process is from years of Australian experience.

Table 3. 17: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and ESB Immigrants (Model 3 Age on Arrival Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars				
	Sample: Natives and ESB Immigrants			
	(1)	(2)	(3)	(4)
Explanatory Variables	Native & ESB migrated at age 0-12 Panel-FE	Native & ESB migrated at age 13-22 Panel-FE	Native & ESB migrated at age 23-34 Panel-FE	Native & ESB migrated at age 35-60 Panel-FE
Pre-migration human capital				
Education abroad	0.072*	/	0.024	0.402***
	[0.041]	/	[0.039]	[0.152]
Over-educated × Education abroad	-0.017	-0.020	0.002	-0.080
	[0.018]	[0.020]	[0.012]	[0.080]
Under-educated × Education abroad	0.004	-0.021	0.060**	-0.086
	[0.019]	[0.022]	[0.024]	[0.088]
Experience abroad	/	1.228*	0.005	2.443***
	/	[0.691]	[0.075]	[0.503]
Experience abroad SQR/100	/	-15.228**	0.365	-4.708***
	/	[6.410]	[0.445]	[0.998]
Over-educated × Experience abroad	/	-0.044	-0.008	0.150
	/	[0.123]	[0.045]	[0.124]
Over-educated × Experience abroad SQR/100		0.228	0.085	-0.321
		[2.452]	[0.304]	[0.311]
Post-migration human capital				
Education in Australia × M	0.002	0.070	-0.049	0.378**
	[0.020]	[0.070]	[0.038]	[0.152]
Over-educated × Education in AU×M	-0.002	-0.019	0.007	-0.102
	[0.010]	[0.023]	[0.022]	[0.095]
Experience in Australia× M	0.023	-0.008	0.031**	0.066**
	[0.014]	[0.021]	[0.013]	[0.028]
Experience in Australia SQR/100 × M	-0.051*	-0.046	-0.048	-0.183*
	[0.029]	[0.039]	[0.033]	[0.097]
Over-educated × Experience in AU×M	0.008	0.001	0.014	-0.061*
	[0.015]	[0.022]	[0.014]	[0.035]
Over-educated × Experience in AU SQR/100×M	-0.027	0.029	-0.066*	0.196
	[0.035]	[0.054]	[0.037]	[0.138]
Control for States	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES
Control for additional variables˘	YES	YES	YES	YES
Constant	2.181***	2.212***	2.167***	1.679***
	[0.092]	[0.096]	[0.104]	[0.149]
Individuals	2118	2045	2093	2018
Observations	13446	12956	13321	12806

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad SQR/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU SQR/100.

˘The model includes additional variables. The full set of results is reported in Table 3B.9.

Source: HILDA-Release 9.

Table 3. 18: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and NESB Immigrants (Model 3 Age on Arrival Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars				
	Sample: Natives and NESB Immigrants			
	(1)	(2)	(3)	(4)
	Native & NESB migrated at age 0-12	Native & NESB migrated at age 13-22	Native & NESB migrated at age 23-34	Native & NESB migrated at age 35-60
Explanatory Variables	Panel-FE	Panel-FE	Panel-FE	Panel-FE
Pre-migration human capital				
Education abroad	/	/	-0.003	/
	/	/	[0.053]	/
Over-educated × Education abroad	0.033	-0.010	-0.001	0.020
	[0.036]	[0.021]	[0.023]	[0.062]
Under-educated × Education abroad	0.049	-0.004	0.039	-0.023
	[0.036]	[0.030]	[0.026]	[0.067]
Experience abroad	/	/	0.059	0.208
	/	/	[0.145]	[0.185]
Experience abroad SQR/100	/	/	0.072	-0.240
	/	/	[0.668]	[0.330]
Over-educated × Experience abroad	/	0.046	-0.001	-0.038
	/	[0.362]	[0.087]	[0.102]
Over-educated × Experience abroad SQR/100	/	1.443	-0.093	0.219
	/	[9.091]	[0.483]	[0.270]
Post-migration human capital				
Education in Australia × M	0.052	-0.080	-0.030	-0.007
	[0.072]	[0.061]	[0.054]	[0.125]
Over-educated × Education in AU×M	-0.019	-0.006	-0.013	-0.128
	[0.015]	[0.023]	[0.027]	[0.086]
Experience in Australia× M	0.043*	-0.015	-0.023	-0.004
	[0.022]	[0.022]	[0.018]	[0.039]
Experience in Australia SQR/100 × M	-0.090**	0.022	0.145**	0.027
	[0.045]	[0.058]	[0.057]	[0.160]
Over-educated × Experience in AU×M	0.013	0.024	0.034*	-0.041
	[0.022]	[0.031]	[0.019]	[0.045]
Over-educated × Experience in AU SQR/100×M	-0.039	-0.089	-0.133**	0.213
	[0.053]	[0.088]	[0.061]	[0.195]
Control for States	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES
Control for additional variables˘	YES	YES	YES	YES
Constant	2.190***	2.222***	2.212***	2.166***
	[0.095]	[0.093]	[0.102]	[0.101]
Individuals	2036	2035	2058	2017
Observations	12871	12889	13062	12804

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad SQR/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU SQR/100.

˘The model includes additional variables. The full set of results is reported in Table 3B.10.

Source: HILDA-Release 9.

Year of arrival effect

The purpose of this section is to compare the labour market performance among recent and earlier immigrants' arrivals with natives, via pre-migration and post-migration human capital. The transferability of human capital is examined based on year of arrival.

The results when immigrants are split into three cohorts based on year of arrival are reported in Tables 3.19 and 3.20.

1) Year of arrival effect among ESB immigrants

As can be seen from Table 3.19, once YSM is replaced with post-migration human capital, for ESB immigrants who arrived before 1980, their per-migration education has a positive significant effect on their earnings in Australia, that is, 9 per cent to each additional year of overseas education accumulation on their hourly wage. However, for the other two cohorts, not significant but positive effects are found. A negative significant return to years of experience abroad is found for matched ESB immigrants who arrived between 1980 and 1989.

Post-migration education has the same return for ESB immigrants as that for natives. This is can be seen from the insignificant effects on the interaction terms between Australian education and migrant status. Post-migration experience has a positive impact on earnings for ESB immigrants relative to natives, but it is significant only for recent arrival ESB immigrants (arrived after 1990). That is, each year of Australian experience increases matched ESB immigrants' earnings by 8 per cent relative to matched natives. In addition, a substitute relationship is found both between over-education and domestic education, and between over-education and domestic experience for recent ESB entries (arrived after 1990). This result implies that recent ESB entries suffer more earnings loss from over-education than natives.

In summary, pre-migration education is portable for ESB immigrants who migrated before 1980. Post-migration experience enhances the earnings for recent arrival ESB

immigrants who arrived between 1990 and 2001. However, if they are over-educated, then their earnings are reduced due to education-occupation mismatch relative to over-educated natives.

2) Year of arrival effect among NESB immigrants

Results are presented in Table 3.20. Pre-migration human capital has no significant impacts on domestic earnings for NESB immigrants.

For NESB immigrants who arrived between 1980 and 1990, their further experience in Australia has significantly less return than that of natives. Over-educated NESB immigrants earn 6 per cent lower return to each year of education abroad than adequately educated NESB immigrants. Post-migration education has the same return as that of native. But, over-educated NESB workers lower their return to each year of Australian education by 6 per cent than over-educated natives. Furthermore, post-migration experience for NESB immigrants has 9 per cent lower return than that of comparable natives in a quartic form. However, over-educated NESB workers increase their return to each year of Australian experience by 18 per cent than over-educated natives in a quartic form. This result indicates that over-educated NESB immigrants who migrated between 1980 and 1990 improve their earnings through Australian work experience by staying over time in Australia.

For the other two NESB arrival cohorts (migrated before 1980 and migrated after 1990), there are no significant effects found from pre-migration education and experience on their earnings in Australia. And also post-migration education and experience have similar effects on earnings relative to natives.

As seen from Figure 3.2, over 50 per cent of NESB immigrants who migrated after 1980 have above Bachelor degrees, and over 40 per cent of them are over-educated. They suffer an earnings loss from education-occupation mismatch.

Table 3. 19: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and ESB Immigrants (Model 3 Year of Arrival Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars			
	Sample: Natives and ESB Immigrants		
	(1)	(2)	(3)
Explanatory Variables	ESB migrated between 1947 and 1979 Panel-FE	ESB migrated between 1980 and 1989 Panel-FE	ESB migrated between 1990 and 2001 Panel-FE
Pre-migration human capital			
Education abroad	0.088***	0.035	0.039
	[0.034]	[0.030]	[0.076]
Over-educated × Education abroad	-0.025	-0.000	0.010
	[0.017]	[0.016]	[0.010]
Under-educated × Education abroad	0.005	0.013	0.032**
	[0.016]	[0.019]	[0.015]
Experience abroad	0.093	-0.203**	/
	[0.110]	[0.100]	/
Experience abroad SQR/100	/	2.480***	0.097
	/	[0.866]	[0.223]
Over-educated × Experience abroad	0.048	-0.005	0.023
	[0.078]	[0.021]	[0.023]
Over-educated × Experience abroad SQR/100	-0.483	0.048	-0.044
	[1.060]	[0.095]	[0.093]
Post-migration human capital			
Education in Australia × M	0.013	-0.012	0.060
	[0.030]	[0.024]	[0.039]
Over-educated × Education in AU×M	-0.012	-0.001	-0.045*
	[0.013]	[0.012]	[0.027]
Experience in Australia× M	0.027	0.013	0.080***
	[0.017]	[0.021]	[0.021]
Experience in Australia SQR/100 × M	-0.056*	-0.015	-0.342***
	[0.032]	[0.059]	[0.109]
Over-educated × Experience in AU×M	0.015	0.020	-0.051**
	[0.017]	[0.025]	[0.026]
Over-educated × Experience in AU SQR/100×M	-0.033	-0.106	0.264*
	[0.037]	[0.074]	[0.142]
Control for States	YES	YES	YES
Control for unemployment	YES	YES	YES
Control for time periods	YES	YES	YES
Control for additional variables˘	YES	YES	YES
Constant	2.141***	2.153***	2.189***
	[0.098]	[0.103]	[0.102]
Individuals	2161	2083	2043
Observations	13658	13222	13043

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.
Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad SQR/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU SQR/100.

˘The model includes additional variables. The full set of results is reported in Table 3B.11.

Source: HILDA-Release 9.

Table 3. 20: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and NESB Immigrants (Model 3 Year of Arrival Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars			
	Sample: Natives and NESB Immigrants		
	(1)	(2)	(3)
Explanatory Variables	Native & NESB migrated between 1947 and 1979 Panel-FE	Native & NESB migrated between 1980 and 1989 Panel-FE	Native & NESB migrated between 1990 and 2001 Panel-FE
Pre-migration human capital			
Education abroad	/	0.124	-0.047
	/	[0.082]	[0.046]
Over-educated × Education abroad	-0.023	-0.063***	0.007
	[0.035]	[0.018]	[0.013]
Under-educated × Education abroad	-0.016	-0.001	-0.000
	[0.030]	[0.023]	[0.024]
Experience abroad	/	0.037	0.074
	/	[0.300]	[0.076]
Experience abroad SQR/100	/	/	-0.077
	/	/	[0.177]
Over-educated × Experience abroad	0.117	0.017	-0.020
	[0.083]	[0.036]	[0.027]
Over-educated × Experience abroad SQR/100	-0.956	-0.083	0.091
	[0.622]	[0.220]	[0.094]
Under-educated × Experience abroad	0.237**	0.086*	-0.008
	[0.105]	[0.046]	[0.051]
Under-educated × Experience abroad SQR/100	-1.863**	-0.655**	0.015
	[0.870]	[0.263]	[0.177]
Post-migration human capital			
Education in Australia × M	-0.036	0.104	-0.074
	[0.057]	[0.079]	[0.046]
Over-educated × Education in AU×M	-0.025	-0.058***	-0.017
	[0.031]	[0.015]	[0.021]
Experience in Australia× M	0.016	-0.082***	-0.037
	[0.032]	[0.030]	[0.027]
Experience in Australia SQR/100 × M	-0.031	0.444***	0.177
	[0.058]	[0.109]	[0.146]
Over-educated × Experience in AU×M	0.030	0.176***	0.010
	[0.036]	[0.035]	[0.030]
Over-educated × Experience in AU SQR/100×M	-0.074	-0.667***	-0.061
	[0.070]	[0.129]	[0.168]
Under-educated × Experience in AU×M	0.003	0.088**	0.045
	[0.033]	[0.039]	[0.052]
Under-educated × Experience in AU SQR/100×M	-0.005	-0.451***	-0.227
	[0.063]	[0.135]	[0.245]
Control for States	YES	YES	YES
Control for unemployment	YES	YES	YES
Control for time periods	YES	YES	YES
Control for additional variables˘	YES	YES	YES
Constant	2.209***	2.166***	2.243***
	[0.094]	[0.119]	[0.099]
Individuals	2052	2045	2062
Observations	12971	12970	13079

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.
Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad SQR/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU SQR/100. ˘The model includes additional variables. The full set of results is reported in Table 3B.12. Source: HILDA-Release 9.

Country of qualification effect

Further information from country of qualification is found from human capital perspective.

This section aims to examine the role of country of study where qualification is obtained on the impact of over-education on earnings via pre-migration and post-migration education and experience. The evidence will reveal the transferability of human capital based on country of qualification.

Following Model 3 in Equation (3.10), estimation results when immigrants are categorised into three cohorts according to country where they achieved their highest qualifications are reported in Tables 3.21 and 3.22.

1) Country of qualification effect among <u>ESB immigrants</u>

When considering country of qualification effects among natives and ESB immigrants, results are reported in Table 3.21.

I found pre-migration education has a positive significant impact on earnings for ESB immigrants without qualification. Pre-migration education and experience have positive, but no significant impact on earnings for ESB immigrants who hold qualification. In addition, post-migration experience improves earnings of ESB immigrants holding overseas qualification by 5 per cent more than that of natives.

In summary, ESB immigrants with overseas qualifications experience a faster earnings growth from year since migration than ESB immigrants with Australian qualifications or without qualifications. And their earnings growth partially comes from the high return to their each year of domestic experience. This evidence further reveals that overseas qualification is valuable and transferable to the Australian labour market for ESB immigrants.

2) Country of qualification effect among NESB immigrants

Table 3.22 presents estimation results among native and NESB immigrants from country of qualification aspect.

I found that for NESB immigrants, the reason for low earnings is not only from negative return to over-education via pre-migration human capital but also from less return to domestic experience.

In Table 3.22, pre-migration education and experience have no significant effects on earnings among all types of NESB immigrant.

For NESB immigrants who hold Australian qualification, pre-migration education and experience have no significant effect on earnings via over-education. An over-educated NESB worker has a 3 per cent lower return to each year of post-migration education, but a 5 per cent higher return to each year of domestic experience than an over-educated native. Over-education helps a NESB worker who holds Australian qualifications via his domestic experience following migration after accounting for individual heterogeneity. This result implies work experience obtained in Australia play an important role to improve NESB immigrants' earnings.

Among NESB immigrants who hold overseas qualifications, an over-educated NESB worker has a 2 per cent more return to each year of education abroad, but a 6 per cent less return to each year of experience abroad than an adequately educated NESB worker.

Table 3. 21: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and ESB Immigrants (Model 3 Country of Qualification Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars			
	Sample: Natives and ESB Immigrants		
	(1)	(2)	(3)
Explanatory Variables	Native & ESB with Australian Qualification Panel-FE	Native & ESB with Overseas Qualification Panel-FE	Native & ESB without qualification Panel-FE
Pre-migration human capital			
Education abroad	0.126	0.118	0.849**
	[0.116]	[0.142]	[0.366]
Over-educated × Education abroad	-0.013	0.007	-0.003
	[0.011]	[0.008]	[0.027]
Under-educated × Education abroad	-0.011	0.037*	0.011
	[0.013]	[0.021]	[0.020]
Experience abroad	/	0.217	/
	/	[0.180]	/
Experience abroad SQR/100	0.756	-0.245	/
	[1.111]	[0.294]	/
Over-educated × Experience abroad	0.089*	-0.013	0.003
	[0.051]	[0.026]	[0.031]
Over-educated × Experience abroad SQR/100	-0.671	0.053	0.040
	[0.477]	[0.114]	[0.103]
Under-educated × Experience abroad	0.077	-0.124**	-0.016
	[0.053]	[0.051]	[0.024]
Under-educated × Experience abroad SQR/100	-0.695	0.549***	0.100
Post-migration human capital	[0.474]	[0.197]	[0.087]
Education in Australia × M	-0.015	0.056	/
	[0.038]	[0.143]	/
Over-educated × Education in AU×M	0.004	0.004	0.006
	[0.009]	[0.021]	[0.022]
Experience in Australia× M	0.016	0.047***	0.008
	[0.012]	[0.013]	[0.020]
Experience in Australia SQR/100 × M	-0.060**	-0.085***	-0.013
	[0.027]	[0.032]	[0.040]
Over-educated × Experience in AU×M	-0.005	0.010	0.006
	[0.013]	[0.014]	[0.023]
Over-educated × Experience in AU SQR/100×M	0.011	-0.060	-0.031
	[0.031]	[0.039]	[0.053]
Control for States	YES	YES	YES
Control for unemployment	YES	YES	YES
Control for time periods	YES	YES	YES
Control for additional variables˘	YES	YES	YES
Constant	2.187***	2.049***	1.967***
	[0.109]	[0.189]	[0.138]
Individuals	2129	2083	2090
Observations	13486	13231	13206

Notes:
The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.
Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad SQR/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU SQR/100.

˘The model includes additional variables. The full set of results is reported in Table 3B.13.

Source: HILDA-Release 9.

Table 3. 22: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and NESB Immigrants (Model 3 Country of Qualification Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars			
	Sample: Natives and NESB Immigrants		
	(1)	(2)	(3)
Explanatory Variables	Native & NESB with Australian Qualification Panel-FE	Native & NESB with Overseas Qualification Panel-FE	Native & NESB without qualification Panel-FE
Pre-migration human capital			
Education abroad	0.135	0.026	/
	[0.104]	[0.026]	/
Over-educated × Education abroad	-0.017	0.022	0.034
	[0.012]	[0.014]	[0.044]
Under-educated × Education abroad	0.008	0.084**	0.057
	[0.021]	[0.034]	[0.042]
Experience abroad	/	-0.027	/
	/	[0.147]	/
Experience abroad SQR/100	0.271	0.875	/
	[0.214]	[0.617]	/
Over-educated × Experience abroad	-0.012	-0.060*	-0.032
	[0.021]	[0.036]	[0.069]
Over-educated × Experience abroad SQR/100	0.050	0.299**	0.342
	[0.078]	[0.144]	[0.349]
Post-migration human capital			
Education in Australia × M	0.044	/	/
	[0.057]	/	/
Over-educated × Education in AU×M	-0.028***	0.032	0.055
	[0.011]	[0.025]	[0.043]
Under-educated × Education in AU×M	0.021	0.070*	0.080*
	[0.021]	[0.042]	[0.047]
Experience in Australia× M	-0.003	-0.027	0.053
	[0.014]	[0.019]	[0.040]
Experience in Australia SQR/100 × M	-0.013	0.174***	-0.089
	[0.034]	[0.064]	[0.076]
Over-educated × Experience in AU×M	0.050***	0.003	-0.047
	[0.016]	[0.021]	[0.037]
Over-educated × Experience in AU SQR/100×M	-0.140***	-0.062	0.086
	[0.045]	[0.061]	[0.081]
Under-educated × Experience in AU×M	-0.027	-0.036	-0.066*
	[0.026]	[0.046]	[0.037]
Under-educated × Experience in AU SQR/100×M	0.059	0.037	0.115
	[0.061]	[0.153]	[0.071]
Control for States	YES	YES	YES
Control for unemployment	YES	YES	YES
Control for time periods	YES	YES	YES
Control for additional variables˘	YES	YES	YES
Constant	2.164***	2.181***	2.200***
	[0.103]	[0.102]	[0.094]
Individuals	2072	2047	2048
Observations	13118	12979	12923

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad SQR/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU SQR/100.

˘The model includes additional variables. The full set of results is reported in Table 3B.14.

Source: HILDA-Release 9.

3.7 Summary

Based on recent Australian immigration policy, flows of skilled immigrants to Australia are increasing, such that endorsed skills would help immigrants to become more employable and thereby increase Australian productive capacity. However, if skilled immigrants disproportionately work at jobs that under-utilise their educational attainment, do they still contribute to the host country economy's development, or do they become a burden to the local economy?

This essay has provided evidence on the above question. Based on nine years of HILDA and longitudinal analyses, results show that NESB immigrants have a significantly higher incidence of over-education and they receive a large earnings penalty from over-education. Using over-education as an indicator in explaining immigrant assimilation, our results are summarised as below:

Firstly, 42 per cent of NESB immigrants have been found to work in jobs which require a lower educational standard than the one they possess. The determinants of over-education are examined by a correlated random effects logit model with Mundlak correction. After accounting for endogeneity, immigrants demonstrate extremely high rates of over-education than the native-born due to imperfect transferability of human capital in the host country. As time passes, the education-occupation mismatch situation for immigrants does not change with increased years since migration. Among NESB immigrants, younger entrants (who have migrated at younger than the age of 12) or earlier arrivals (who have arrived before 1979) are more likely to reduce the probability of over-education than are older entrants and later arrivals.

Secondly, the impact of education-occupation mismatch on earnings is examined by both pooled OLS analysis and longitudinal analysis. Earnings' effects, from the perspective of years since migration and that of transferability of human capital are examined. Overall effects and specific cohorts' effects are also examined. The results reveal that, in general,

ESB immigrants earn more, and NESB immigrants earn less than natives. After controlling for unobserved heterogeneity (such as motivation, ability etc.), year since migration is shown to have a significant impact on earnings for both ESB and NESB immigrants. ESB immigrants have a faster earnings growth than natives. Pre-migration education is highly valued and transferable for ESB immigrants; however, it has no significant impact on earnings for NESB immigrants. ESB immigrants have significantly larger returns to years of domestic experience than natives. In contrast, NESB immigrants have less return to both years of education and years of domestic experience than natives.

However, educational mismatches worsen the NESB earnings outcomes. With panel fixed effects estimation, NESB immigrants are shown to suffer a 9 per cent lower return to each additional year of over-education and a 9 per cent lower return to each year of required education than natives. This evidence suggests that the earning penalty among NESB immigrants is due, not only to skill under-utilisation, but perhaps also to an earnings disadvantage that cannot be accounted for by the extensive human capital variables included in my models.

There is a persistent earning gap between natives and NESB immigrants even when NESB immigrants achieve all their years of education in Australia, or when they migrated beyond age 12. For NESB immigrants with foreign or mixed qualification, it is very important to obtain employment with a good match; otherwise, a significant earnings loss will result from education-occupation mismatches.

These findings have implications for Australian immigration assimilation policies, which focus, not only on attracting skilled immigrants, but also on the likelihood and facilitation of employment into matched positions.

Appendix 3A: Sample Selection Estimations on the Incidence of Over-education

I accounted for self-selection of individuals since individuals observed in this sample are non-randomly selected into employment, and over-educated status occurs only under being employed. In both selection equation and outcome equation, dependent variables are dichotomous. Therefore, I adopt 'bivariate probit with sample selection' models to estimate the incidence of over-education.

Human capital among natives and immigrants has different effects on the rates of over-education. In this model, the sample includes both natives and immigrants for comparison purpose.

The selection equation estimates the probability of employment in full-time position for individual I is

$$(3A.1) \qquad P_r(FT_i^*) = \beta_0 + \beta_1 X_i + \nu_i\,, \quad \nu \sim N(0, \sigma^2 I_n)$$

Where Pr (FT_i^*) measure the probability of being employed in a full-time job, and FT_i^* is not observable, but I observe a dummy variable (FT_i) defined as: FT_i =1 if $FT_i^* > 0$; FTi = 0 otherwise.

X_i denotes a set of personal characteristics including immigrants' status, married status and education; Decisions to take a full-time or part-time role are quite different after having young child. The responsibility may push workers to do a full-time rather than a part-time job, thus X_i also includes a Dummy variable to represent having child aged 14 or less. Random error ν_i is assumed with zero mean and constant variance σ^2, I_n represents the n-dimensional identity matrix.Similarly, the outcome equation estimates the probability of being over-educated for individual i is

$$(3.A2) \qquad P_r(O_i^*) = \delta_0 + \delta_1 Z_i + \delta_2 M_i + \delta_3 ED_i + \delta_4 DQUA_i + \delta_5 (DQUA_i * M_i) + \delta_6 YSM_i + \delta_7 YSM_i^2 + \varepsilon_i \ , \quad \varepsilon \sim N(0, \sigma^2 I_n)$$

Where Pr (O_i^*) denotes the probability of being over-educated. O_i^* is unobservable, but I observe a dummy variable (O_i) defined as: $O_i = 1$ if $O_i^* > 0$; $O_i = 0$ otherwise. Z_i denotes a set of personal or job characteristics; ED_i denotes actual years of education. M_i is an immigrant dummy variable; YSM_i denotes the number years of residence since migrating to host country. The coefficient of M_i, δ_2, measures the initial over-education gap of immigrants upon arrival relative to comparable natives; while the coefficient of YSM_i, δ_6, measures how this gap varies as immigrants spend time in the host country. δ_7, the coefficient of YSM_i^2 examines rate of over-education in a linear or quadric style over time. The over-education rates of immigrants are expected to signify immigrants' assimilation. Therefore, the coefficient of YSM is predicted to be negative.

To examine the probability of being over-educated for full-time workers, the selection process is that employed in full-time workers have the probability to be over-educated, therefore, the probability of being over-educated under the condition where they are employed in full-time position, the equation is

$$(3A.3) \qquad P_r(O_i | FT_i = 1) = P_r(\varepsilon_i > -\delta_1 Z_i - \delta_2 M_i - \delta_3 ED_i - \delta_4 DQUA_i - \delta_5 (DQUA_i \times M_i) - \delta_6 YSM_i - \delta_7 YSM_i^2 | \ \nu \ i > -\beta_1 X_i)$$

This model requires the disturbance terms ν_i and ε_i are independent of both set of explanatory variables and they are normality of the distribution. The selection bias problem arises if the disturbance terms ν_i in the selection equation and ε_i in the outcome equation is correlated which is estimated by the correlation coefficient ρ. This implies that ε_i in the outcome equation will not have zero mean and is correlated with the explanatory variables, which leads to inconsistent estimates. Selection bias is equivalent to an omitted variable bias (Heckman, 1979). Heckman model requires there is at least

one variable in the selection equation that does not appear in the outcome equation.

To examine effects of age on arrival and year of arrival on the probability of being educated, I replace YSM_i and YSM_i^2 with age on arrival and year of arrival dummy variables respectively for avoiding multicollinearity problem.

When running above regressions, we should not ignore workers' self-selectivity into employment (Heckman, 1979). Only employed workers have the probability to work for a full-time job and to be over-educated, therefore, I call this first step sample selection. Firstly, I use the following selection probit model to obtain selection hazard variables (inverse Mills' ratio).

$$E_i^* = \beta_2 X_i + \beta_3 C_i + u_i \tag{3A.4}$$

$$Prob[E_i^* | E_i = 1] = \Phi(E_i \gamma) \tag{3A.5}$$

Where E_i is the vector of variables explaining the selection to work and γ is a vector of selection probit parameters. In this case, explanatory vector X_i contains immigrants, years of education, disability and impairment variable, marriage status and child aged 14 or less. C_i is the labor market conditions. In this study, I use unemployment rate from ABS to control labour market conditions. From Equation (3A.5), we obtain the inverse Mill's ratio:

$$\lambda_i = \frac{\Phi(E_i \gamma)}{\Psi(E_i \gamma)} \tag{3A.6}$$

Taking all the relevant decision combination into consideration, I substitute inverse Mill's ratio into Equations (3A.1) and (3A.2), then apply Heckman selection model to generate consistent estimations.

Earning comparison between natives and immigrants are examined in two samples. One

sample is natives and ESB immigrants, and the other sample consists of natives and NESB immigrants.

Also both outcome equations and selection equations are adjusted by selection into employment which is presented by variables invmillnE and invmillnN[27].

Based on pooled data, Tables 3A.2 and 3A.3 presents the probability of being over-educated from the Heckman probit model estimation after considering sample selection issue. The marginal effects results are reported.

As discussed before, duration of residency, age on arrival and years of arrival may have influence on the rate of incidence. To test these effects, based on Equation (3A.3), four specifications are employed respectively. The first Model contains a quadratic in years since migration (YSM), the second Model employs only a linear variable for YSM, the third Model and the fourth Model replace YSM quadratic forms with age cohorts and years of arrival cohorts respectively. For each Model, I test two samples separately for comparison purpose. The first sample contains native and ESB immigrant and the second sample covers native and NESB immigrant. Thus, by doing so, I can obtain specific effects for ESB and NESB immigrant respectively by comparing with native. Moreover, since people have different job preference when they enter the labour market, they may choose a part-time position rather than a full-time job. To be consistent with earnings study, I focus on analyses among full-time workers. Selecting or being selected into a full-time job is conditioned on employment. Thus, two steps selections are examined in each model, which is the probability of being over-education for full-time workers are evaluated after controlling being selected into employment. In selection equation, explanatory variables contain immigrant status, years of education, English proficiency, disability, unemployment and marriage and having children aged 14 or less. The dependent variable for outcome equation is the probability of being over-educated.

[27] These variables are shown in Tables 3A.2 and Tables 3A.3. invmillnE and invmillnN present the first step selection variable for the natives and ESB immigrants sample, and the natives and NESB immigrants sample respectively.

Marginal effects are reported.

The sample selection adjustment estimation results show a significant positive selection relationship between the probability of being over-educated and the probability of being full-time employed. It implies that educational attainment leads to better full-time employment opportunity, however at the cost of being over-educated. The positive coefficient on inverse miller ratio of first step selection for employment shows that there is a selection effect between the probability of being over-educated and the probability of being employed, which means that workers have to secure employment status by sacrificing education-occupation match. Moreover, coefficients on second selection variables [28] are positively significant among both the sample natives and NESB immigrants (2.4805) and the sample natives and ESB immigrants (2.3360). Here, rho indicates the correlation coefficient between selection equation and outcome equation. Results of the Wald test indicate the correlation is positively significant. This suggests that selection into full-time position enhance the probability of being over-educated for both samples.

Overall, immigrants are 18 to 37 per cent more likely to be over-educated than natives, in particular, the high incidence of over-education is found among NESB immigrants. In Model N2, NESB immigrants have 37 per cent higher rate of over-education than natives. Even though ESB immigrants have slight better education-occupation matches, still have 20 per cent of more likelihood to be over-educated than natives. Workers with Bachelor or Certificate perform better education-occupation matches than workers with other types of qualifications. NESB immigrants with Diploma have 8 per cent lower probability of being over-educated compared to natives with same qualification. Labour market condition, here, the unemployment rate does have a negative effect on over-education for natives after considering full-time selection. In particular, a larger negative effect is found among immigrants than natives, which implies that immigrant may sacrifice more

Then, generate the cumulative density function: capphi=normal (p1) and capphi is equivalent to$\Psi(E_i\,\gamma)$. This calculates inverse Mill's ratio lambda $\lambda_i = \frac{\Phi(E_i\,\gamma)}{\Psi(E_i\,\gamma)}$ in Equation (3A.6).

[28]It is represented by /athrho. The relation between /athrho and rho is: /athrho=$\frac{1}{2}$ln ($\frac{1+rho}{1-rho}$).

education-occupation match to secure their employment position. Disability or impairment seems to reduce chance of being over-educated. This may due to work place protection policy from potential discrimination. However, not as our expected, poor English seems no significant impact on increasing the probability of being over-educated. The reason is that people who speak poor English may have less chance to be employed. In the first step selection model, poor English has significant negative effect on the probability of being employed[29].

As expected, duration of residency in Australia does help NESB immigrants to achieve a better education-occupation match. This effect is shown by the negative sign on YSM in Model N1 and Model N2. The difference between Models N1 and N2 is that there is no significant effect of quadratic YSM in Model N1 but has a negative significant effect of linear YSM in Model N2, and also this effect only for NESB immigrants.

In addition, among NESB immigrants, Model N3 shows that migrating as a child helps migrants to reduce the probability of being over-educated after being selected into employment. Model N4 reveals that earlier immigrants, like the cohort arrived between 1947 and 1979, has 9 per cent of less likelihood to be over-educated compared to the recent cohort arriving between 1990 and 2000. However, this evidence is not found for ESB immigrants.

Based on pooled data by controlling for the sample selection issue, the evidence I found is consistent with previous study. Years since migration, younger entries and earlier arrival have a significant effect to reduce the probability of over-education for NESB immigrants.

[29] The first step selection for employment results is referring to Appendix 3A.1.

Table 3A. 1: Probit Estimations of the Probability of being employed

	Dependent Variable: The probability of being employed	
	(1) Sample Native-born & ESB immigrants	(2) Sample Native-born & NESB immigrants
VARIABLES	Employed Marginal Effects	Employed Marginal Effects
Immigrant (M)	-0.0174	0.00543
	(0.0237)	(0.0153)
Years of education	0.00367***	0.00348***
	(0.000417)	(0.000448)
Married	0.0318***	0.0287***
	(0.00388)	(0.00391)
Has children aged 14 or less	0.00460*	0.00482*
	(0.00252)	(0.00268)
Poor English	/	-0.0571**
	/	(0.0284)
Disability or impairment	-0.0361***	-0.0415***
	(0.00458)	(0.00512)
Year2001	-0.0157**	-0.0165**
	(0.00619)	(0.00646)
Year2002	-0.00910*	-0.00826
	(0.00550)	(0.00561)
Year2003	-0.000561	0.000294
	(0.00461)	(0.00476)
Year2004	0.00303	0.00716*
	(0.00424)	(0.00404)
Year2005	0.00338	0.00602
	(0.00420)	(0.00418)
Year2006	0.000499	0.000754
	(0.00451)	(0.00475)
Year2007	0.00730*	0.00740*
	(0.00383)	(0.00409)
Year2008	0.00354	0.00384
	(0.00422)	(0.00446)
NSW	-0.00327	-0.00205
	(0.00307)	(0.00329)
VIC	0.00189	-0.00109
	(0.00298)	(0.00336)
SA	0.00245	0.00293
	(0.00373)	(0.00402)
WA	0.0136***	0.0117***
	(0.00270)	(0.00339)
TAS	0.00294	0.00720
	(0.00570)	(0.00561)
NT	0.00961	0.0198***
	(0.00778)	(0.00473)
ACT	0.0141***	0.0192***
	(0.00525)	(0.00389)
Unemployment ×M	0.139	-0.481
	(0.291)	(0.323)
Observations	16,775	15,850

Notes: Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Source: HILDA-Release 9 (Wave 1-Wave 9).

Table 3A. 2: Probability of being Over-educated among Full-time Natives and ESB Immigrants

	Model E1		Model E2		Model E3		Model E4	
	Sample N&ESB		Sample N&ESB		Sample N&ESB		Sample N&ESB	
	(1)	(2)	(5)	(6)	(9)	(10)	(13)	(14)
VARIABLES	over-educated	FT	over-educated	FT	over-educated	FT	over-educated	FT
	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects
Immigrant (M)	0.1652	-0.3679	0.2049**	-0.3658	0.1410	-0.3830	0.1808**	-0.3630
	[1.498]	[-1.547]	[2.132]	[-1.538]	[1.533]	[-1.601]	[1.977]	[-1.528]
Years of education	0.0715***	0.0308**	0.0714***	0.0309**	0.0713***	0.0308**	0.0713***	0.0309**
	[9.153]	[2.070]	[9.143]	[2.072]	[9.175]	[2.070]	[9.140]	[2.073]
EXP	-0.0044**	/	-0.0043**	/	-0.0043**	/	-0.0042**	/
	[-2.102]	/	[-2.070]	/	[-2.075]	/	[-2.047]	/
$EXP^2/100$	0.0100**	/	0.0098**	/	0.0096**	/	0.0098**	/
	[2.182]	/	[2.149]	/	[2.097]	/	[2.133]	/
Postgraduate	0.3623***	/	0.3632***	/	0.3667***	/	0.3639***	/
	[5.154]	/	[5.169]	/	[5.236]	/	[5.187]	/
Bachelor	-0.1259***	/	-0.1255***	/	-0.1250***	/	-0.1252***	/
	[-4.512]	/	[-4.493]	/	[-4.483]	/	[-4.477]	/
Diploma	0.1408***	/	0.1413***	/	0.1427***	/	0.1417***	/
	[2.952]	/	[2.962]	/	[2.996]	/	[2.973]	/
Certificate	-0.1763***	/	-0.1762***	/	-0.1756***	/	-0.1759***	/
	[-8.303]	/	[-8.294]	/	[-8.298]	/	[-8.289]	/
Postgraduate × M	-0.0060	/	-0.0072	/	-0.0159	/	-0.0067	/
	[-0.176]	/	[-0.214]	/	[-0.477]	/	[-0.194]	/
Bachelor × M	-0.0341	/	-0.0347	/	-0.0425	/	-0.0361	/
	[-0.765]	/	[-0.783]	/	[-1.011]	/	[-0.826]	/
Diploma × M	-0.0599	/	-0.0594	/	-0.0619	/	-0.0591	/
	[-1.492]	/	[-1.471]	/	[-1.585]	/	[-1.458]	/
Certificate × M	-0.0104	/	-0.0097	/	-0.0166	/	-0.0120	/
	[-0.278]	/	[-0.258]	/	[-0.456]	/	[-0.326]	/
Years since migration-YSM	0.0017	/	-0.0012	/	/	/	/	/
	[0.455]	/	[-1.098]	/	/	/	/	/
YSM SQR/100	-0.0055	/	/	/	/	/	/	/
	[-0.795]	/	/	/	/	/	/	/
Disability or impairment	-0.0345**	-0.4975***	-0.0346**	-0.4978***	-0.0357**	-0.4982***	-0.0344**	-0.4979***
	[-2.256]	[-5.421]	[-2.265]	[-5.427]	[-2.343]	[-5.421]	[-2.253]	[-5.429]
married	/	0.1950**	/	0.1952**	/	0.1937**	/	0.1950**
	/	[2.272]	/	[2.275]	/	[2.252]	/	[2.274]
child_age14orless	/	0.2867***	/	0.2867***	/	0.2877***	/	0.2872***
Age on Arrival	/	[5.263]	/	[5.266]	/	[5.271]	/	[5.278]
Age 0-12	/	/	/	/	0.0113	/	/	/
	/	/	/	/	[0.232]	/	/	/
Age 13-22	/	/	/	/	-0.0239	/	/	/
	/	/	/	/	[-0.477]	/	/	/
Age 23-34	/	/	/	/	0.0701	/	/	/
Year of Arrival	/	/	/	/	[1.183]	/	/	/
Arrived 1947-1979	/	/	/	/	/	/	-0.0410	/
	/	/	/	/	/	/	[-1.301]	/
Arrived 1980-1989	/	/	/	/	/	/	-0.0077	/
	/	/	/	/	/	/	[-0.191]	/
Control for States	YES	YES	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES	YES	YES
Selection Control Employed								
invmillnE[†]	0.2856**	0.7362	0.2866**	0.7402	0.2999**	0.7321	0.2855**	0.7415
	[2.009]	[0.787]	[2.016]	[0.791]	[2.111]	[0.783]	[2.007]	[0.793]
/ athrho	2.3360***		2.3444***		2.2962***		2.3520***	
	[5.937]		[5.904]		[5.764]		[5.910]	
Log likelihood	-10118		-10119		-10114		-10118	
Chi-SQR	3205		3206		3164		3222	
rho	0.981		0.982		0.980		0.982	
Censored observations	1544		1544		1544		1544	
Observations	16255		16255		16255		16255	

Notes:

Dependent variable in outcome equation is the probability of over-education and in selection equation is the probability of working in full-time job; Constant is included; Robust z-statistics are in brackets. ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Wald test of independent equations is rejected in all Models which indicate the positive correlation is significant. Hence Heckman's technique should be used to adjust selection bias.

All models include two steps selection: First step selection control variables (inverse Mills' ratio) are obtained from probit estimation based on Equation (3A.5) and Equation (3A.6); Heckman Probit models are used to control for second step selection.

Base-categories are Native, no Certificate, Age 35-60, Arrived 1990-2001, Year 2009, and QLD.

All above notes are also applied to Table 3A.3. Sample is natives and ESB immigrants.

[†] invmillnE is the first step selection variable which is generated by Sample selection for natives and ESB immigrants full sample.

Source: HILDA-Release 9 (Wave 1-Wave 9).

Table 3A. 3: The Probability of being Over-educated among Full-time Natives and NESB Immigrants

	Model N1		Model N2		Model N3		Model N4	
	Sample N&NESB		Sample N&NESB		Sample N&NESB		Sample N&NESB	
VARIABLES	over-educated	FT	over-educated	FT	over-educated	FT	over-educated	FT
	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects
Immigrant (M)	0.2989*	0.2610	0.3696***	0.2565	0.2902**	0.2804	0.2231**	0.2626
	[1.927]	[0.987]	[3.094]	[0.969]	[2.308]	[1.061]	[2.087]	[0.991]
Years of education	0.0718***	0.0390***	0.0719***	0.0389***	0.0716***	0.0390***	0.0720***	0.0387***
	[8.717]	[2.709]	[8.713]	[2.704]	[8.734]	[2.703]	[8.772]	[2.698]
EXP	-0.0032	/	-0.0032	/	-0.0032	/	-0.0030	/
	[-1.460]	/	[-1.424]	/	[-1.420]	/	[-1.365]	/
$EXP^2/100$	0.0074	/	0.0072	/	0.0064	/	0.0067	/
	[1.492]	/	[1.450]	/	[1.296]	/	[1.360]	/
Postgraduate	0.3669***	/	0.3662***	/	0.3669***	/	0.3653***	/
	[5.049]	/	[5.044]	/	[5.079]	/	[5.038]	/
Bachelor	-0.1276***	/	-0.1279***	/	-0.1282***	/	-0.1284***	/
	[-4.314]	/	[-4.323]	/	[-4.360]	/	[-4.359]	/
Diploma	0.1421***	/	0.1419***	/	0.1427***	/	0.1412***	/
	[2.876]	/	[2.871]	/	[2.903]	/	[2.868]	/
Certificate	-0.1771***	/	-0.1774***	/	-0.1772***	/	-0.1777***	/
	[-8.116]	/	[-8.113]	/	[-8.149]	/	[-8.152]	/
Postgraduate × M	-0.0627	/	-0.0658*	/	-0.0520	/	-0.0603	/
	[-1.506]	/	[-1.654]	/	[-1.248]	/	[-1.470]	/
Bachelor × M	0.0278	/	0.0239	/	0.0561	/	0.0351	/
	[0.444]	/	[0.391]	/	[0.854]	/	[0.557]	/
Diploma × M	-0.0844*	/	-0.0850*	/	-0.0833*	/	-0.0748	/
	[-1.845]	/	[-1.866]	/	[-1.760]	/	[-1.517]	/
Certificate × M	-0.0563	/	-0.0622	/	-0.0531	/	-0.0482	/
	[-1.063]	/	[-1.246]	/	[-1.021]	/	[-0.873]	/
Years since migration-YSM	-0.0008	/	-0.0046***	/	/	/	/	/
	[-0.146]	/	[-3.090]	/	/	/	/	/
YSM SQR/100	-0.0077	/		/	/	/	/	/
	[-0.749]	/		/	/	/	/	/
Disability or impairment	-0.0316*	-0.4770***	-0.0315*	-0.4764***	-0.0319*	-0.4795***	-0.0319*	-0.4756***
	[-1.864]	[-5.147]	[-1.862]	[-5.140]	[-1.887]	[-5.176]	[-1.884]	[-5.136]
Poor English	-0.0391	-0.0596	-0.0374	-0.0579	-0.0371	-0.0571	-0.0352	-0.0619
	[-0.471]	[-0.180]	[-0.444]	[-0.175]	[-0.427]	[-0.173]	[-0.430]	[-0.187]
married	/	0.1962**	/	0.1959**	/	0.1975**	/	0.1954**
	/	[2.460]	/	[2.456]	/	[2.478]	/	[2.450]
child_age14orless	/	0.2811***	/	0.2813***	/	0.2788***	/	0.2795***
Age on Arrival	/	[5.121]	/	[5.125]	/	[5.078]	/	[5.097]
Age 0-12	/	/	/	/	-0.1013***	/	/	/
	/	/	/	/	[-2.675]	/	/	/
Age 13-22	/	/	/	/	-0.0594	/	/	/
	/	/	/	/	[-1.113]	/	/	/
Age 23-34	/	/	/	/	-0.0548	/	/	/
Year of Arrival	/	/	/	/	[-1.199]	/	/	/
Arrived 1947-1979	/	/	/	/	/	/	-0.0917***	/
	/	/	/	/	/	/	[-2.795]	/
Arrived 1980-1989	/	/	/	/	/	/	-0.0016	/
	/	/	/	/	/	/	[-0.035]	/
Control for States	YES	YES	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES	YES	YES
Selection Control								
Employed								
invmillnN[†]	0.2720*	0.9721	0.2740*	0.9694	0.2802*	0.9896	0.2805*	0.9586
	[1.786]	[1.111]	[1.800]	[1.107]	[1.832]	[1.130]	[1.847]	[1.098]
/athrho	2.4805***		2.4914***		2.5471***		2.4947***	
	[4.492]		[4.334]		[4.388]		[4.733]	
Log likelihood	-9710		-9710		-9715		-9712	
Chi-SQR	2889		2885		2939		2939	
rho	0.986		0.986		0.988		0.986	
Censored observations	1518		1518		1518		1518	
Observations	15326		15326		15326		15326	

Notes:

Sample is natives and NESB immigrants.

[†] invmillnN is the first step selection variable which is generated by Sample selection for natives and NESB immigrants

.Source: HILDA-Release 9 (Wave 1-Wave 9).

Appendix 3B: Earnings Effects

Table 3B. 1: The Effect of Over-education on Earnings via Years since Migration for Natives and Immigrants (Model 2 Overall Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars						
	Native (N) and ESB Immigrant			**Native (N) and NESB Immigrant**		
	(1)	(2)	(3)	(4)	(5)	(6)
	N&ESB	N&ESB	N&ESB	N&NESB	N&NESB	N&NESB
Explanatory Variables	Pooled OLS	Panel-FE	Panel-RE	Pooled OLS	Panel-FE	Panel-RE
Immigrant (M)	0.876***	/	0.378	0.070	/	0.361
	[0.208]	/	[0.289]	[0.296]	/	[0.349]
Years of over-education	0.090***	0.049***	0.068***	0.087***	0.047***	0.065***
	[0.007]	[0.016]	[0.011]	[0.007]	[0.015]	[0.011]
Years of under-education	-0.062***	-0.036**	-0.053***	-0.059***	-0.035**	-0.049***
	[0.006]	[0.015]	[0.010]	[0.006]	[0.015]	[0.010]
Years of required education	0.116***	0.045***	0.067***	0.113***	0.044***	0.064***
	[0.006]	[0.015]	[0.011]	[0.006]	[0.015]	[0.010]
Years of over-education × M	-0.080***	-0.020	-0.058**	-0.029	-0.090**	-0.069**
	[0.019]	[0.035]	[0.025]	[0.025]	[0.040]	[0.029]
Years of under-education × M	0.104***	-0.009	0.036	0.036*	0.072	0.048
	[0.016]	[0.037]	[0.025]	[0.021]	[0.045]	[0.030]
Years of required education × M	-0.075***	-0.004	-0.043*	-0.032	-0.088**	-0.066**
Years since migration-YSM	[0.016]	[0.035]	[0.024]	[0.023]	[0.041]	[0.028]
YSM	0.003	0.024***	0.014***	0.022***	0.014*	0.016***
	[0.004]	[0.007]	[0.005]	[0.005]	[0.008]	[0.006]
$YSM^2/100$	-0.009	-0.035***	-0.025***	-0.030***	-0.009	-0.012
	[0.008]	[0.011]	[0.009]	[0.010]	[0.015]	[0.012]
Over-educated ×YSM	0.003	0.004	0.004	-0.010**	0.004	0.003
	[0.004]	[0.004]	[0.003]	[0.005]	[0.004]	[0.004]
Over-educated ×$YSM^2/100$	-0.011	-0.010	-0.009	0.026**	-0.015	-0.012
	[0.010]	[0.009]	[0.008]	[0.012]	[0.011]	[0.011]
Under-educated × YSM	-0.007*	0.004	0.002	-0.007	-0.000	0.000
	[0.004]	[0.004]	[0.003]	[0.006]	[0.005]	[0.005]
Under-educated × $YSM^2/100$	0.006	-0.008	-0.003	0.011	-0.001	-0.002
	[0.008]	[0.008]	[0.008]	[0.012]	[0.013]	[0.012]
EXP	0.023***	0.040***	0.026***	0.024***	0.038***	0.024***
	[0.001]	[0.003]	[0.002]	[0.002]	[0.003]	[0.002]
$EXP^2/100$	-0.043***	-0.052***	-0.051***	-0.046***	-0.050***	-0.050***
	[0.003]	[0.005]	[0.004]	[0.003]	[0.005]	[0.004]
Postgraduate	-0.106**	-0.084	-0.028	-0.092**	-0.079	-0.011
	[0.042]	[0.104]	[0.072]	[0.042]	[0.104]	[0.071]
Bachelor	-0.047	-0.074	0.020	-0.037	-0.068	0.031
	[0.033]	[0.087]	[0.058]	[0.033]	[0.087]	[0.058]
Diploma	-0.152***	0.005	-0.080	-0.143***	0.009	-0.069
	[0.029]	[0.075]	[0.051]	[0.029]	[0.075]	[0.051]
Certificate	-0.138***	-0.012	-0.095**	-0.132***	-0.009	-0.087**
	[0.021]	[0.055]	[0.038]	[0.021]	[0.055]	[0.037]
Postgraduate × M	0.477***	0.036	0.265	0.233		0.406**
	[0.107]	[0.238]	[0.168]	[0.146]		[0.202]
Bachelor × M	0.409***	0.165	0.308**	-0.013	-0.026	0.299*
	[0.085]	[0.203]	[0.140]	[0.112]	[0.100]	[0.164]
Diploma × M	0.448***	-0.035	0.201*	0.038	0.311	0.153
	[0.073]	[0.166]	[0.119]	[0.092]	[0.337]	[0.153]
Certificate ×M	0.182***	-0.053	0.043	-0.025	-0.017	0.025
	[0.057]	[0.155]	[0.096]	[0.080]	[0.153]	[0.111]
Disability or impairment	-0.076***	-0.008	-0.015*	-0.072***	-0.006	-0.013
	[0.011]	[0.008]	[0.008]	[0.012]	[0.009]	[0.009]
Poor English	/	/	/	-0.188***	0.051	-0.001
	/	/	/	[0.065]	[0.078]	[0.072]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.504***	1.997***	2.070***	1.531***	2.149***	2.130***
	[0.080]	[0.165]	[0.124]	[0.079]	[0.167]	[0.123]
F-test	77.93	18.47	/	70.68	14.31	/
R^2	0.175	0.0290	0.154	0.174	0.00803	0.151
Individuals	2313	2313	2313	2185	2185	2185
Observations	14711	14711	14711	13808	13808	13808
R^2_within	/	0.0456	0.0419	/	0.0448	0.0406
rho	/	0.805	0.732	/	0.833	0.729
Hausman fe re test: Chi^2	/	124.4		/	227.0	
Prob>chi^2=	/	0		/	0	

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent. Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively. Based categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, and Year 2009. The models include qualifications dummy variables, States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables. Source: HILDA-Release 9.

Table 3B. 2: The Effect of Over-education on Earnings via Years since Migration for Natives and ESB Immigrants (Model 2 Age on Arrival Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars							
	Sample: Natives and ESB Immigrants							
	Native & ESB migrated at age 0-12		Native & ESB migrated at age 13-22		Native & ESB migrated at age 23-34		Native & ESB migrated at age 35-60	
Explanatory Variables	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE
Immigrant (M)	1.906***	/	-0.577	/	1.351***	/	-1.179	/
	[0.360]	/	[0.451]	/	[0.438]	/	[0.932]	/
Years of over-education	0.089***	0.049***	0.089***	0.048***	0.089***	0.048***	0.089***	0.048***
	[0.007]	[0.015]	[0.007]	[0.015]	[0.007]	[0.015]	[0.007]	[0.015]
Years of under-education	-0.061***	-0.036**	-0.061***	-0.035**	-0.061***	-0.036**	-0.060***	-0.035**
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of required education	0.115***	0.045***	0.115***	0.045***	0.115***	0.045***	0.115***	0.045***
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of over-education × M	-0.135***	-0.032	0.018	0.016	-0.099**	-0.054	0.079	0.016
	[0.031]	[0.064]	[0.039]	[0.068]	[0.039]	[0.055]	[0.082]	[0.095]
Years of under-education × M	0.142***	0.001	-0.013	-0.118	0.138***	0.068	-0.001	0.007
	[0.021]	[0.066]	[0.030]	[0.075]	[0.042]	[0.062]	[0.100]	[0.105]
Years of required education × M	-0.131***	-0.024	0.039	0.076	-0.111***	-0.047	0.104	0.030
Years since migration-YSM	[0.023]	[0.063]	[0.032]	[0.071]	[0.036]	[0.057]	[0.080]	[0.097]
YSM	-0.015	0.030*	0.023	0.011	-0.026***	0.033***	-0.000	0.032
	[0.011]	[0.017]	[0.015]	[0.021]	[0.009]	[0.011]	[0.027]	[0.022]
$YSM^2/100$	0.011	-0.041*	-0.041	-0.074**	0.075***	-0.039	0.042	0.008
	[0.016]	[0.022]	[0.032]	[0.036]	[0.023]	[0.027]	[0.118]	[0.080]
Over-educated ×YSM	-0.002	0.004	0.001	-0.007	0.021**	0.013*	0.025	0.022
	[0.006]	[0.005]	[0.017]	[0.013]	[0.009]	[0.007]	[0.030]	[0.021]
Over-educated $\times YSM^2/100$	0.001	-0.010	-0.001	0.031	-0.087***	-0.054**	-0.177	-0.090
	[0.014]	[0.012]	[0.043]	[0.034]	[0.027]	[0.024]	[0.134]	[0.102]
Under-educated × YSM	-0.010*	0.007	-0.022*	-0.008	-0.001	-0.013	0.024	0.030
	[0.006]	[0.005]	[0.012]	[0.011]	[0.011]	[0.010]	[0.030]	[0.023]
Under-educated $\times YSM^2/100$	0.012	-0.013	0.052*	0.033	-0.013	0.037	-0.160	-0.139
	[0.012]	[0.011]	[0.031]	[0.027]	[0.034]	[0.032]	[0.136]	[0.106]
EXP	0.024***	0.039***	0.024***	0.038***	0.024***	0.039***	0.025***	0.039***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]
$EXP^2/100$	-0.047***	-0.052***	-0.046***	-0.050***	-0.046***	-0.049***	-0.047***	-0.051***
	[0.003]	[0.005]	[0.003]	[0.005]	[0.003]	[0.005]	[0.003]	[0.005]
Postgraduate	-0.101**	-0.082	-0.102**	-0.082	-0.101**	-0.080	-0.099**	-0.081
	[0.042]	[0.104]	[0.042]	[0.104]	[0.042]	[0.103]	[0.042]	[0.103]
Bachelor	-0.042	-0.071	-0.042	-0.071	-0.041	-0.070	-0.040	-0.070
	[0.033]	[0.087]	[0.033]	[0.086]	[0.033]	[0.086]	[0.033]	[0.086]
Diploma	-0.149***	0.008	-0.149***	0.007	-0.148***	0.007	-0.147***	0.008
	[0.029]	[0.075]	[0.029]	[0.075]	[0.029]	[0.074]	[0.029]	[0.074]
Certificate	-0.135***	-0.011	-0.136***	-0.010	-0.135***	-0.011	-0.135***	-0.010
	[0.021]	[0.055]	[0.021]	[0.055]	[0.021]	[0.055]	[0.021]	[0.055]
Postgraduate × M	0.847***	0.063	-0.383	0.096	0.729***	0.029	-0.261	-0.497***
	[0.160]	[0.393]	[0.240]	[0.248]	[0.226]	[0.103]	[0.555]	[0.178]
Bachelor × M	0.679***	0.282	-0.637***	/	0.715***	/	-0.017	/
	[0.127]	[0.322]	[0.182]	/	[0.175]	/	[0.402]	/
Diploma × M	0.569***	-0.043	-0.117	0.179	0.839***	/	-0.086	0.038
	[0.107]	[0.269]	[0.146]	[0.287]	[0.155]	/	[0.325]	[0.408]
Certificate ×M	0.297***	0.323	-0.244*	/	0.343***	-0.046	0.086	/
	[0.087]	[0.270]	[0.127]	/	[0.112]	[0.217]	[0.251]	/
Disability or impairment	-0.073***	-0.006	-0.076***	-0.009	-0.077***	-0.007	-0.079***	-0.008
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Control for States	YES	YES	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES	YES	YES
Constant	1.500***	2.023***	1.496***	2.048***	1.506***	2.061***	1.503***	2.036***
	[0.080]	[0.172]	[0.079]	[0.174]	[0.079]	[0.173]	[0.079]	[0.174]
F-test	68.55	14.12	67.82	13.90	72.13	14.85	68.64	14.57
R^2	0.170	0.0222	0.174	0.0309	0.178	0.00376	0.177	0.0294
Individuals	2118	2118	2045	2045	2093	2093	2018	2018
Observations	13446	13446	12956	12956	13321	13321	12806	12806
R^2_within	/	0.0454	/	0.0440	/	0.0468	/	0.0465
rho	/	0.804	/	0.803	/	0.987	/	0.810
Hausman fe re test: Chi^2	/	210.4	/	86.28	/	109.2	/	87.15
Prob>chi^2=	/	0	/	7.07e-07	/	0	/	8.96e-07

Notes:

The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, and Year 2009.

The models include States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables.

Source: HILDA-Release 9.

Table 3B. 3: The Effect of Over-education on Earnings via Years since Migration for Natives and NESB Immigrants (Model 2 Age on Arrival Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars							
	Sample: Natives and NESB Immigrants							
	Native & NESB migrated at age 0-12		Native & NESB migrated at age 13-22		Native & NESB migrated at age 23-34		Native & NESB migrated at age 35-60	
Explanatory Variables	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE
Immigrant (M)	-0.497	/	-0.321	/	0.495	/	3.751***	/
	[0.690]	/	[0.604]	/	[0.509]	/	[0.890]	/
Years of over-education	0.089***	0.048***	0.089***	0.048***	0.089***	0.048***	0.089***	0.048***
	[0.007]	[0.015]	[0.007]	[0.015]	[0.007]	[0.015]	[0.007]	[0.015]
Years of under-education	-0.061***	-0.035**	-0.060***	-0.035**	-0.060***	-0.035**	-0.060***	-0.035**
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of required education	0.115***	0.045***	0.115***	0.044***	0.115***	0.044***	0.114***	0.045***
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of over-education × M	0.072	0.611	0.037	-0.701**	-0.014	-0.065	-0.323***	-0.177**
	[0.064]	[0.397]	[0.050]	[0.329]	[0.040]	[0.048]	[0.068]	[0.075]
Years of under-education × M	-0.044	-0.616	0.009	0.695**	0.003	0.001	0.423***	0.284**
	[0.042]	[0.408]	[0.043]	[0.323]	[0.037]	[0.063]	[0.116]	[0.128]
Years of required education × M	0.028	0.610	0.050	-0.695**	-0.029	-0.062	-0.352***	-0.195**
Years since migration-YSM	[0.050]	[0.396]	[0.045]	[0.328]	[0.040]	[0.049]	[0.072]	[0.078]
YSM	0.040***	0.068***	-0.037*	-0.016	-0.017	0.000	-0.010	-0.016
	[0.016]	[0.026]	[0.019]	[0.021]	[0.013]	[0.015]	[0.037]	[0.030]
$YSM^2/100$	-0.060***	-0.096***	0.099**	0.018	0.053	0.077*	0.065	0.140
	[0.022]	[0.035]	[0.046]	[0.048]	[0.035]	[0.046]	[0.180]	[0.131]
Over-educated ×YSM	-0.019*	-0.006	0.009	0.001	-0.014	0.008	-0.046	-0.017
	[0.010]	[0.011]	[0.016]	[0.012]	[0.012]	[0.009]	[0.033]	[0.024]
Over-educated $\times YSM^2/100$	0.035*	0.015	-0.018	-0.007	0.051	-0.039	0.232	0.128
	[0.021]	[0.028]	[0.053]	[0.042]	[0.043]	[0.038]	[0.193]	[0.138]
Under-educated × YSM	-0.017	-0.000	-0.011	-0.014	0.004	0.014	-0.012	-0.023
	[0.010]	[0.010]	[0.015]	[0.013]	[0.015]	[0.016]	[0.062]	[0.046]
Under-educated × $YSM^2/100$	0.030	-0.000	0.007	0.042	-0.001	-0.043	-0.028	-0.031
	[0.019]	[0.023]	[0.042]	[0.040]	[0.044]	[0.056]	[0.324]	[0.220]
EXP	0.024***	0.038***	0.025***	0.039***	0.025***	0.038***	0.025***	0.039***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]
$EXP^2/100$	-0.046***	-0.050***	-0.048***	-0.050***	-0.048***	-0.050***	-0.048***	-0.050***
	[0.003]	[0.005]	[0.003]	[0.005]	[0.003]	[0.005]	[0.003]	[0.005]
Postgraduate	-0.101**	-0.080	-0.100**	-0.080	-0.100**	-0.079	-0.098**	-0.080
	[0.042]	[0.103]	[0.042]	[0.103]	[0.042]	[0.103]	[0.042]	[0.103]
Bachelor	-0.042	-0.070	-0.040	-0.070	-0.040	-0.068	-0.039	-0.070
	[0.033]	[0.086]	[0.033]	[0.086]	[0.033]	[0.086]	[0.033]	[0.086]
Diploma	-0.149***	0.008	-0.148***	0.009	-0.148***	0.009	-0.147***	0.009
	[0.029]	[0.074]	[0.029]	[0.074]	[0.029]	[0.074]	[0.029]	[0.074]
Certificate	-0.136***	-0.010	-0.135***	-0.010	-0.135***	-0.009	-0.135***	-0.010
	[0.021]	[0.055]	[0.021]	[0.054]	[0.021]	[0.055]	[0.021]	[0.055]
Postgraduate × M	-0.045	-1.208	-0.627**	0.670*	0.307	0.026	2.382***	/
	[0.320]	[0.750]	[0.308]	[0.396]	[0.256]	[0.142]	[0.483]	/
Bachelor × M	-0.175	/	-0.473**	/	-0.135	/	1.647***	-0.235
	[0.259]	/	[0.232]	/	[0.195]	/	[0.374]	[0.224]
Diploma × M	-0.024	-1.831	-0.081	/	-0.103	/	0.993***	/
	[0.189]	[1.722]	[0.196]	/	[0.159]	/	[0.326]	/
Certificate ×M	-0.176	-1.452	-0.479***	1.729*	-0.159	-0.324	1.371***	/
	[0.194]	[1.290]	[0.160]	[0.894]	[0.145]	[0.211]	[0.271]	/
Disability or impairment	-0.076***	-0.007	-0.077***	-0.007	-0.074***	-0.009	-0.077***	-0.007
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Poor English	/	/	-0.100	-0.082	-0.175*	0.171	-0.297**	-0.061
	/	/	[0.243]	[0.147]	[0.095]	[0.123]	[0.139]	[0.142]
Control for States	YES	YES	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES	YES	YES
Constant	1.502***	1.878***	1.497***	2.262***	1.500***	2.089***	1.505***	2.096***
	[0.079]	[0.198]	[0.079]	[0.196]	[0.079]	[0.171]	[0.079]	[0.174]
F-test	67.47	13.94	65.62	13.39	68.37	14.27	66.30	13.98
R^2	0.174	0.00221	0.173	0.000968	0.177	0.0208	0.176	0.0124
Individuals	2036	2036	2035	2035	2058	2058	2017	2017
Observations	12871	12871	12889	12889	13062	13062	12804	12804
R^2_within	/	0.0456	/	0.0438	/	0.0459	/	0.0447
rho	/	0.969	/	0.972	/	0.806	/	0.847
Hausman fe re test: Chi^2	/	98.68	/	117.8	/	204.6	/	188.0
Prob>chi^2=	/	1.01e-08	/	0	/	0	/	0

Notes:

The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, and Year 2009.

The models include States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables.

Source: HILDA-Release 9.

Table 3B. 4: The Effect of Over-education on Earnings via Years since Migration for Natives and ESB Immigrants (Model 2 Year of Arrival Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars					
	Sample: Natives and ESB Immigrants					
	Native & ESB migrated between 1947 and 1979		Native & ESB migrated between 1980 and 1989		Native & ESB migrated between 1990 and 2001	
Explanatory Variables	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE
Immigrant (M)	2.230***	/	0.782	/	-0.196	/
	[0.446]	/	[0.634]	/	[0.515]	/
Years of over-education	0.089***	0.048***	0.089***	0.048***	0.089***	0.048***
	[0.007]	[0.016]	[0.007]	[0.015]	[0.007]	[0.015]
Years of under-education	-0.061***	-0.035**	-0.061***	-0.036**	-0.060***	-0.035**
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of required education	0.115***	0.045***	0.115***	0.045***	0.115***	0.045***
	[0.007]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of over-education × M	-0.122***	-0.069	-0.056	0.059	0.076*	-0.004
	[0.027]	[0.058]	[0.040]	[0.071]	[0.044]	[0.050]
Years of under-education × M	0.111***	-0.002	0.118***	-0.053	-0.060	0.064
	[0.019]	[0.061]	[0.038]	[0.075]	[0.055]	[0.060]
Years of required education × M	-0.108***	-0.049	-0.052	0.086	0.059	-0.005
Years since migration-YSM	[0.021]	[0.058]	[0.033]	[0.071]	[0.042]	[0.052]
YSM	-0.040**	0.023	-0.047	-0.010	0.037	0.076***
	[0.017]	[0.020]	[0.042]	[0.030]	[0.024]	[0.018]
$YSM^2/100$	0.039*	-0.035	0.177*	0.053	-0.374***	-0.278***
	[0.022]	[0.025]	[0.106]	[0.074]	[0.140]	[0.094]
Over-educated ×YSM	0.002	-0.002	0.045***	0.022**	-0.050**	0.000
	[0.006]	[0.006]	[0.015]	[0.011]	[0.025]	[0.017]
Over-educated × $YSM^2/100$	-0.009	0.005	-0.217***	-0.088*	0.347**	0.022
	[0.014]	[0.013]	[0.062]	[0.046]	[0.157]	[0.106]
Under-educated × YSM	-0.009*	0.011**	0.033**	-0.003	-0.066**	-0.018
	[0.005]	[0.005]	[0.016]	[0.013]	[0.031]	[0.021]
Under-educated × $YSM^2/100$	0.012	-0.019*	-0.203***	-0.015	0.539***	0.056
	[0.012]	[0.011]	[0.065]	[0.049]	[0.195]	[0.139]
EXP	0.023***	0.040***	0.025***	0.038***	0.025***	0.039***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]
$EXP^2/100$	-0.044***	-0.052***	-0.046***	-0.049***	-0.048***	-0.050***
	[0.003]	[0.005]	[0.003]	[0.005]	[0.003]	[0.005]
Postgraduate	-0.101**	-0.082	-0.103**	-0.081	-0.101**	-0.081
	[0.042]	[0.104]	[0.042]	[0.103]	[0.042]	[0.103]
Bachelor	-0.043	-0.071	-0.042	-0.071	-0.040	-0.070
	[0.033]	[0.087]	[0.033]	[0.086]	[0.033]	[0.086]
Diploma	-0.149***	0.008	-0.150***	0.006	-0.148***	0.008
	[0.029]	[0.075]	[0.029]	[0.074]	[0.029]	[0.074]
Certificate	-0.136***	-0.011	-0.137***	-0.011	-0.135***	-0.010
	[0.021]	[0.055]	[0.021]	[0.055]	[0.021]	[0.054]
Postgraduate × M	0.629***	0.487	0.435*	-0.687	-0.316	0.235
	[0.140]	[0.393]	[0.227]	[0.458]	[0.268]	[0.433]
Bachelor × M	0.427***	0.505	0.484***	-0.466	-0.226	0.285
	[0.113]	[0.311]	[0.174]	[0.404]	[0.206]	[0.403]
Diploma × M	0.417***	-0.003	0.575***	-0.249	0.079	0.210
	[0.094]	[0.269]	[0.147]	[0.312]	[0.190]	[0.298]
Certificate ×M	0.215***	/	0.167	-0.203	-0.130	-0.171
	[0.075]	/	[0.114]	[0.242]	[0.135]	[0.240]
Disability or impairment	-0.074***	-0.007	-0.081***	-0.009	-0.075***	-0.006
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.513***	2.057***	1.494***	2.014***	1.503***	2.039***
	[0.080]	[0.174]	[0.079]	[0.176]	[0.079]	[0.171]
F-test	68.50	14.20	72.02	15.51	70.09	15.45
R^2	0.168	0.0319	0.179	0.0209	0.177	0.0355
Individuals	2161	2161	2083	2083	2043	2043
Observations	13658	13658	13222	13222	13043	13043
R^2_within	/	0.0438	/	0.0428	/	0.0508
rho	/	0.796	/	0.828	/	0.801
Hausman fe re test: Chi^2	/	198.5	/	114.5	/	209.4
Prob>chi^2=	/	0	/	0	/	0

Notes:

The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, and Year 2009.

The models include States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables.

Source: HILDA-Release 9.

Table 3B. 5: The Effect of Over-education on Earnings via Years since Migration for Natives and NESB Immigrants (Model 2 Year of Arrival Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars					
	Sample: Natives and NESB Immigrants					
	Native & NESB migrated between 1947 and 1979		Native & NESB migrated between 1980 and 1989		Native & NESB migrated between 1990 and 2001	
Explanatory Variables	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE
Immigrant (M)	-0.638	/	-2.135**	/	1.815***	/
	[0.731]	/	[0.924]	/	[0.541]	/
Years of over-education	0.089***	0.048***	0.089***	0.048***	0.088***	0.048***
	[0.007]	[0.015]	[0.007]	[0.015]	[0.007]	[0.015]
Years of under-education	-0.061***	-0.035**	-0.060***	-0.035**	-0.059***	-0.035**
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of required education	0.115***	0.045***	0.114***	0.044***	0.114***	0.044***
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of over-education × M	0.055	0.789**	0.083	-0.161*	-0.139***	-0.079*
	[0.050]	[0.386]	[0.052]	[0.093]	[0.044]	[0.045]
Years of under-education × M	0.016	-0.786**	-0.103*	0.136	0.169**	-0.008
	[0.027]	[0.392]	[0.054]	[0.102]	[0.070]	[0.077]
Years of required education × M	0.008	0.762**	0.089*	-0.154	-0.148***	-0.078*
	[0.036]	[0.385]	[0.051]	[0.093]	[0.044]	[0.046]
Years since migration-YSM						
YSM	0.039	0.020	0.095	-0.016	-0.048*	-0.040*
	[0.025]	[0.026]	[0.064]	[0.043]	[0.029]	[0.023]
$YSM^2/100$	-0.048	-0.040	-0.191	0.157	0.216	0.218*
	[0.032]	[0.036]	[0.186]	[0.120]	[0.165]	[0.122]
Over-educated ×YSM	-0.014	-0.010	-0.005	0.017	-0.015	0.003
	[0.009]	[0.010]	[0.020]	[0.015]	[0.023]	[0.017]
Over-educated × $YSM^2/100$	0.014	0.024	-0.011	-0.078	0.126	-0.004
	[0.019]	[0.026]	[0.097]	[0.073]	[0.159]	[0.116]
Under-educated × YSM	-0.008	-0.005	-0.036	0.036*	0.025	0.047
	[0.008]	[0.008]	[0.025]	[0.019]	[0.035]	[0.029]
Under-educated × $YSM^2/100$	0.003	0.017	0.098	-0.188**	-0.065	-0.230
	[0.017]	[0.019]	[0.110]	[0.081]	[0.202]	[0.154]
EXP	0.024***	0.039***	0.024***	0.038***	0.024***	0.039***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]
$EXP^2/100$	-0.046***	-0.050***	-0.047***	-0.049***	-0.047***	-0.050***
	[0.003]	[0.005]	[0.003]	[0.005]	[0.003]	[0.005]
Postgraduate	-0.102**	-0.081	-0.098**	-0.079	-0.094**	-0.080
	[0.042]	[0.103]	[0.042]	[0.103]	[0.042]	[0.103]
Bachelor	-0.042	-0.071	-0.040	-0.068	-0.037	-0.069
	[0.033]	[0.086]	[0.033]	[0.086]	[0.033]	[0.086]
Diploma	-0.149***	0.007	-0.147***	0.009	-0.144***	0.009
	[0.029]	[0.074]	[0.029]	[0.074]	[0.029]	[0.074]
Certificate	-0.136***	-0.010	-0.134***	-0.010	-0.132***	-0.009
	[0.021]	[0.055]	[0.021]	[0.055]	[0.021]	[0.055]
Postgraduate × M	0.273	-1.481**	-0.481	-0.007	1.005***	/
	[0.238]	[0.725]	[0.320]	[0.187]	[0.301]	/
Bachelor × M	-0.344*	/	-0.605**	/	0.582**	-0.123
	[0.197]	/	[0.251]	/	[0.230]	[0.133]
Diploma × M	0.039	-3.059*	-0.480**	/	0.198	/
	[0.136]	[1.604]	[0.199]	/	[0.205]	/
Certificate ×M	-0.332**	-2.542**	-0.530***	0.653**	0.473***	-0.229
	[0.135]	[1.187]	[0.178]	[0.331]	[0.173]	[0.208]
Disability or impairment	-0.077***	-0.008	-0.073***	-0.006	-0.075***	-0.007
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Poor English	-0.262	-0.006	-0.303***	-0.068	-0.119	0.066
	[0.194]	[0.212]	[0.112]	[0.168]	[0.102]	[0.098]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.500***	1.799***	1.510***	2.116***	1.521***	2.110***
	[0.079]	[0.210]	[0.079]	[0.175]	[0.079]	[0.170]
F-test	66.39	13.09	67.89	14.39	66.14	14.07
R^2	0.174	0.00245	0.177	0.00910	0.172	0.0115
Individuals	2052	2052	2045	2045	2062	2062
Observations	12971	12971	12970	12970	13079	13079
R^2_within	/	0.0437	/	0.0466	/	0.0453
rho	/	0.977	/	0.839	/	0.835
Hausman fe re test: Chi^2	/	95.72	/	214.6	/	180.1
Prob>chi^2=	/	2.86e-08	/	0	/	0

Notes:

The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, Year 2009.

The models include States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables.

Source: HILDA-Release 9.

Table 3B. 6: The Effect of Over-education on Earnings via Years since Migration for Natives and ESB Immigrants (Model 2 Country of Qualification Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars					
	Sample: Natives and ESB Immigrants					
	Native & ESB with Australian Qualification		Native & ESB with Overseas Qualification		Native & ESB without qualification	
Explanatory Variables	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE
Immigrant (M)	0.841	/	-1.343	/	0.953***	/
	[0.812]	/	[0.990]	/	[0.286]	/
Years of over-education	0.089***	0.048***	0.089***	0.049***	0.089***	0.048***
	[0.007]	[0.015]	[0.007]	[0.015]	[0.007]	[0.015]
Years of under-education	-0.060***	-0.036**	-0.061***	-0.036**	-0.061***	-0.035**
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of required education	0.114***	0.045***	0.115***	0.045***	0.115***	0.045***
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of over-education × M	-0.055	-0.036	0.082	-0.023	-0.131***	0.800**
	[0.044]	[0.046]	[0.058]	[0.056]	[0.042]	[0.366]
Years of under-education × M	0.208**	0.076	0.039	0.182*	0.113***	-0.842**
	[0.089]	[0.076]	[0.116]	[0.101]	[0.018]	[0.365]
Years of required education × M	-0.050	-0.012	0.087	-0.025	-0.083***	0.821**
Years since migration-YSM	[0.046]	[0.047]	[0.056]	[0.057]	[0.019]	[0.365]
YSM	0.009	0.008	-0.013	0.046***	-0.005	0.003
	[0.007]	[0.012]	[0.008]	[0.012]	[0.011]	[0.014]
$YSM^2/100$	-0.021*	-0.025	0.052**	-0.061**	0.028	0.002
	[0.012]	[0.018]	[0.021]	[0.028]	[0.023]	[0.023]
Over-educated ×YSM	-0.002	0.002	0.014	0.003	0.028**	0.010
	[0.006]	[0.005]	[0.009]	[0.008]	[0.014]	[0.009]
Over-educated × $YSM^2/100$	0.001	-0.003	-0.066***	-0.026	-0.078**	-0.024
	[0.012]	[0.012]	[0.025]	[0.028]	[0.035]	[0.021]
Under-educated × YSM	-0.019**	-0.000	0.010	-0.010	0.001	0.008
	[0.008]	[0.007]	[0.025]	[0.024]	[0.010]	[0.007]
Under-educated × $YSM^2/100$	0.026*	-0.003	-0.074	-0.002	-0.030	-0.017
	[0.015]	[0.014]	[0.080]	[0.082]	[0.023]	[0.015]
EXP	0.025***	0.040***	0.024***	0.039***	0.024***	0.039***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]
$EXP^2/100$	-0.048***	-0.052***	-0.046***	-0.050***	-0.045***	-0.051***
	[0.003]	[0.005]	[0.003]	[0.005]	[0.003]	[0.005]
Postgraduate	-0.098**	-0.083	-0.103**	-0.081	-0.102**	-0.082
	[0.042]	[0.104]	[0.042]	[0.104]	[0.042]	[0.103]
Bachelor	-0.039	-0.072	-0.043	-0.070	-0.043	-0.072
	[0.033]	[0.087]	[0.033]	[0.086]	[0.033]	[0.086]
Diploma	-0.147***	0.007	-0.149***	0.008	-0.149***	0.007
	[0.029]	[0.075]	[0.029]	[0.075]	[0.029]	[0.074]
Certificate	-0.135***	-0.011	-0.136***	-0.011	-0.136***	-0.010
	[0.021]	[0.055]	[0.021]	[0.055]	[0.021]	[0.055]
Bachelor × M	-0.117	0.106	0.281**	0.055	/	/
	[0.093]	[0.105]	[0.111]	[0.106]	/	/
Diploma × M	0.015	-0.193	0.342**	/	/	/
	[0.124]	[0.171]	[0.171]	/	/	/
Certificate ×M	-0.285	/	0.300	/	/	/
	[0.176]	/	[0.214]	/	/	/
Disability or impairment	-0.079***	-0.007	-0.078***	-0.006	-0.072***	-0.010
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.498***	2.070***	1.505***	2.035***	1.510***	1.640***
	[0.079]	[0.170]	[0.080]	[0.173]	[0.080]	[0.244]
F-test	73.89	14.24	73.20	19.06	73.16	15.03
R^2	0.176	0.0256	0.178	0.0322	0.167	0.00136
Individuals	2129	2129	2083	2083	2090	2090
Observations	13486	13486	13231	13231	13206	13206
R^2_within	/	0.0433	/	0.0474	/	0.0441
rho	/	0.800	/	0.806	/	0.984
Hausman fe re test: Chi^2	/	188.2	/	110.8	/	197.4
Prob>chi^2=	/	0	/	0	/	0

Notes:

The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, and Year 2009.

The models include States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables.

Source: HILDA-Release 9.

Table 3B. 7: The Effect of Over-education on Earnings via Years since Migration for Natives and NESB Immigrants (Model 2 Country of Qualification Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars					
	Sample: Natives and NESB Immigrants					
	Native & NESB with Australian Qualification		Native & NESB with Overseas Qualification		Native & NESB without qualification	
Explanatory Variables	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE
Immigrant (M)	/	/	/	/	-0.452	/
	/	/	/	/	[0.467]	/
Years of over-education	0.088***	0.048***	0.089***	0.048***	0.089***	0.048***
	[0.007]	[0.015]	[0.007]	[0.015]	[0.007]	[0.015]
Years of under-education	-0.060***	-0.035**	-0.060***	-0.035**	-0.061***	-0.035**
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of required education	0.114***	0.044***	0.114***	0.044***	0.115***	0.044***
	[0.006]	[0.015]	[0.006]	[0.015]	[0.006]	[0.015]
Years of over-education × M	0.024	-0.036	-0.193***	-0.122**	0.045	0.010
	[0.059]	[0.065]	[0.062]	[0.052]	[0.054]	[0.040]
Years of under-education × M	-0.227*	0.005	-0.053	0.092	0.055**	/
	[0.130]	[0.116]	[0.240]	[0.156]	[0.024]	/
Years of required education × M	0.033	-0.028	-0.209***	-0.116**	0.018	-0.004
Years since migration-YSM	[0.061]	[0.065]	[0.063]	[0.053]	[0.031]	[0.026]
YSM	0.036***	0.024**	-0.006	-0.022	0.037**	0.025
	[0.007]	[0.012]	[0.013]	[0.016]	[0.017]	[0.020]
$YSM^2/100$	-0.050***	-0.041*	0.020	0.171***	-0.048	-0.040
	[0.013]	[0.022]	[0.038]	[0.053]	[0.034]	[0.035]
Over-educated ×YSM	-0.004	0.007	-0.017	0.018*	0.005	-0.016
	[0.007]	[0.006]	[0.012]	[0.010]	[0.018]	[0.011]
Over-educated × $YSM^2/100$	0.020	-0.020	0.065	-0.085**	-0.027	0.035
	[0.014]	[0.015]	[0.046]	[0.040]	[0.041]	[0.027]
Under-educated × YSM	-0.001	0.000	0.063	0.013	-0.023	-0.013
	[0.013]	[0.015]	[0.043]	[0.033]	[0.015]	[0.010]
Under-educated × $YSM^2/100$	0.018	0.000	-0.176	-0.028	0.027	0.028
	[0.026]	[0.036]	[0.149]	[0.112]	[0.032]	[0.021]
EXP	0.025***	0.039***	0.025***	0.038***	0.024***	0.038***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]
$EXP^2/100$	-0.048***	-0.051***	-0.047***	-0.050***	-0.046***	-0.050***
	[0.003]	[0.005]	[0.003]	[0.005]	[0.003]	[0.005]
Postgraduate	-0.096**	-0.080	-0.098**	-0.079	-0.102**	-0.080
	[0.042]	[0.103]	[0.042]	[0.104]	[0.042]	[0.103]
Bachelor	-0.038	-0.070	-0.040	-0.068	-0.043	-0.069
	[0.033]	[0.086]	[0.033]	[0.087]	[0.033]	[0.086]
Diploma	-0.146***	0.009	-0.147***	0.009	-0.149***	0.009
	[0.029]	[0.074]	[0.029]	[0.075]	[0.029]	[0.074]
Certificate	-0.134***	-0.010	-0.134***	-0.009	-0.136***	-0.010
	[0.021]	[0.055]	[0.021]	[0.055]	[0.021]	[0.054]
Postgraduate × M	-1.188	/	3.790***	0.008	/	/
	[1.091]	/	[1.128]	[0.146]	/	/
Bachelor × M	-1.184	0.064	3.049***	/	/	/
	[0.995]	[0.163]	[1.009]	/	/	/
Diploma × M	-1.133	0.258	2.793***	/	/	/
	[0.948]	[0.337]	[0.951]	/	/	/
Certificate ×M	-1.191	/	2.802***	/	/	/
	[0.876]	/	[0.886]	/	/	/
Disability or impairment	-0.072***	-0.005	-0.077***	-0.009	-0.077***	-0.007
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Poor English	0.347	0.120	-0.046	0.173	-0.247**	-0.031
	[0.233]	[0.153]	[0.109]	[0.138]	[0.097]	[0.123]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.510***	2.061***	1.508***	2.105***	1.503***	2.054***
	[0.079]	[0.172]	[0.079]	[0.172]	[0.079]	[0.176]
F-test	69.96	14.23	67.69	14.24	72.42	14.48
R^2	0.176	0.0308	0.173	0.0134	0.172	0.0281
Individuals	2072	2072	2047	2047	2048	2048
Observations	13118	13118	12979	12979	12923	12923
R^2_within	/	0.0456	/	0.0449	/	0.0435
rho	/	0.800	/	0.826	/	0.803
Hausman fe re test: Chi^2	/	82.60	/	199.7	/	89.30
Prob>chi^2=	/	3.90e-06	/	0	/	1.48e-07

Notes:

The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are natives, no qualification, being matched YSM, being matched YSM SQR/100, QLD, and Year 2009.

The models include States dummy variables (NSW, VIC, SA, WA, TAS, NT, and ACT), Unemployment, Unemployment × M and time dummy variables.

Source: HILDA-Release 9.

Table 3B. 8: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and Immigrants (Model 3 Overall Effect)

Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars

	Native (N) and ESB Immigrant			**Native (N) and NESB Immigrant**		
	(1)	(2)	(1)	(2)	(1)	(2)
	N&ESB	N&ESB	N&ESB	N&ESB	N&ESB	N&ESB
Explanatory Variables	Pooled OLS	Panel-FE	Panel-RE	Panel-FE	Pooled OLS	Panel-RE
Immigrant (M)	0.342***	/	-0.170	0.042	/	0.017
Pre-migration human capital	[0.116]	/	[0.173]	[0.162]	/	[0.234]
Education abroad	0.090***	0.061***	0.067***	0.067***	-0.019	0.035***
	[0.007]	[0.019]	[0.010]	[0.010]	[0.031]	[0.014]
Over-educated × Education abroad	-0.016**	0.001	-0.002	0.008	0.002	-0.000
	[0.007]	[0.006]	[0.006]	[0.007]	[0.007]	[0.007]
Under-educated × Education abroad	0.000	0.015*	0.013*	0.022**	0.018*	0.021**
	[0.008]	[0.008]	[0.007]	[0.010]	[0.010]	[0.009]
Experience abroad	0.016	0.043	0.000	0.036***	0.048	0.019
	[0.011]	[0.047]	[0.015]	[0.012]	[0.060]	[0.017]
Experience abroad squared/100	-0.034	0.065	-0.002	-0.125**	0.013	-0.089
	[0.048]	[0.169]	[0.065]	[0.052]	[0.149]	[0.068]
Over-educated × Experience abroad	-0.014	0.004	0.002	-0.010	-0.014	-0.011
	[0.013]	[0.013]	[0.012]	[0.015]	[0.015]	[0.014]
Over-educated × Experience abroad squared/100	0.030	0.028	0.025	-0.013	0.069	0.058
	[0.059]	[0.056]	[0.053]	[0.063]	[0.058]	[0.054]
Under-educated × Experience abroad	-0.015	-0.012	-0.011	-0.020	0.005	0.002
	[0.013]	[0.014]	[0.013]	[0.017]	[0.019]	[0.017]
Under-educated × Experience abroad squared/100	0.033	0.084	0.072	0.004	-0.056	-0.055
	[0.058]	[0.057]	[0.054]	[0.072]	[0.081]	[0.074]
Post-migration human capital						
Education in Australia (AU)	0.093***	0.034***	0.061***	0.093***	0.033***	0.054***
	[0.003]	[0.006]	[0.004]	[0.003]	[0.006]	[0.004]
Education in Australia × M	-0.001	-0.002	-0.004	0.002	-0.047	0.007
	[0.008]	[0.016]	[0.011]	[0.010]	[0.030]	[0.015]
Over-educated × Education in AU	-0.014***	-0.001	-0.004*	-0.014***	-0.001	-0.004*
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Under-educated × Education in AU	-0.008***	-0.000	-0.001	-0.008***	-0.000	-0.001
	[0.003]	[0.003]	[0.002]	[0.003]	[0.003]	[0.002]
Over-educated × Education in AU×M	-0.012*	0.002	0.000	0.018**	-0.012	-0.008
	[0.007]	[0.006]	[0.006]	[0.007]	[0.008]	[0.007]
Under-educated × Education in AU×M	-0.010	0.005	0.005	-0.003	0.009	0.005
	[0.008]	[0.007]	[0.007]	[0.011]	[0.011]	[0.011]
Experience in Australia	0.018***	0.040***	0.029***	0.018***	0.040***	0.025***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Experience in Australia squared/100	-0.040***	-0.056***	-0.056***	-0.040***	-0.056***	-0.055***
	[0.006]	[0.007]	[0.006]	[0.006]	[0.007]	[0.006]
Experience in Australia× M	-0.038***	0.027***	0.015**	0.001	-0.002	-0.005
	[0.007]	[0.008]	[0.007]	[0.009]	[0.010]	[0.009]
Experience in Australia× M squared/100	0.089***	-0.060***	-0.028*	-0.001	0.015	0.021
	[0.018]	[0.018]	[0.016]	[0.023]	[0.025]	[0.021]
Over-educated × Experience in AU	0.017***	-0.001	0.002	0.018***	-0.001	0.003
	[0.004]	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]
Over-educated × Experience in AU squared/100	-0.038***	0.007	-0.001	-0.038***	0.007	-0.002
	[0.009]	[0.008]	[0.008]	[0.009]	[0.008]	[0.008]
Under-educated × Experience in AU	0.012***	-0.003	-0.001	0.012***	-0.003	-0.001
	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Under-educated × Experience in AU squared/100	-0.007	0.011	0.009	-0.007	0.011	0.009
	[0.008]	[0.007]	[0.007]	[0.008]	[0.007]	[0.007]
Over-educated × Experience in AU×M	0.030***	-0.001	0.003	-0.025**	0.014	0.010
	[0.011]	[0.008]	[0.008]	[0.012]	[0.010]	[0.010]
Over-educated × Experience in AU squared/100×M	-0.089***	-0.010	-0.018	0.063*	-0.047	-0.038
	[0.027]	[0.021]	[0.021]	[0.034]	[0.029]	[0.027]
Under-educated × Experience in AU×M	0.011	-0.008	-0.008	-0.011	-0.015	-0.016
	[0.010]	[0.009]	[0.008]	[0.013]	[0.012]	[0.011]
Under-educated × Experience in AU squared/100×M	-0.037*	0.015	0.013	0.025	0.024	0.025
	[0.023]	[0.020]	[0.019]	[0.031]	[0.027]	[0.026]
Disability or impairment	-0.080***	-0.008	-0.015*	-0.075***	-0.006	-0.012
	[0.012]	[0.008]	[0.008]	[0.012]	[0.009]	[0.009]
Poor English	/	/	/	-0.186***	0.039	-0.021
	/	/	/	[0.069]	[0.078]	[0.072]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.873***	2.101***	2.128***	1.825***	2.246***	2.264***
	[0.044]	[0.100]	[0.064]	[0.039]	[0.103]	[0.064]
F-test	69.38	16.65	/	55.36	12.48	/
R2	0.152	0.0226	0.121	0.156	0.0172	0.132
Individuals	2313	2313	2313	2185	2185	2185
Observations	14711	14711	14711	13808	13808	13808
R2_w	/	0.0475	0.0380	/	0.0453	0.0408
rho	/	0.834	0.739	/	0.810	0.736
Hausman fe re test: Chi2	/	280.9		/	129.3	
Prob>chi2=	/	0		/	0	

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.
Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad squared/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU squared/100. Source: HILDA-Release 9.

Table 3B. 9: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and ESB Immigrants (Model 3 Age on Arrival Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars							
	Sample: Natives and ESB Immigrants							
	Native & ESB migrated at age 0-12		Native & ESB migrated at age 13-22		Native & ESB migrated at age 23-34		Native & ESB migrated at age 35-60	
Explanatory Variables	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE
Immigrant (M)	0.688***	/	-0.037	/	-0.937***	/	-1.534**	/
Pre-migration human capital	[0.168]	/	[0.298]	/	[0.258]	/	[0.740]	/
Education abroad	0.074***	0.072*	0.083***	/	0.168***	0.024	0.255***	0.402***
	[0.017]	[0.041]	[0.023]	/	[0.018]	[0.039]	[0.044]	[0.152]
Over-educated × Education abroad	0.017	-0.017	-0.013	-0.020	-0.040***	0.002	-0.101**	-0.080
	[0.019]	[0.018]	[0.023]	[0.020]	[0.014]	[0.012]	[0.049]	[0.080]
Under-educated × Education abroad	-0.014	0.004	0.019	-0.021	-0.071***	0.060**	-0.136**	-0.086
	[0.021]	[0.019]	[0.021]	[0.022]	[0.025]	[0.024]	[0.056]	[0.088]
Experience abroad	/	/	-0.006	1.228*	0.089**	0.005	-0.006	2.443***
	/	/	[0.098]	[0.691]	[0.043]	[0.075]	[0.086]	[0.503]
Experience abroad squared/100	/	/	0.369	-15.228**	-0.392	0.365	-0.029	-4.708***
	/	/	[1.862]	[6.410]	[0.284]	[0.445]	[0.229]	[0.998]
Over-educated × Experience abroad	/	/	-0.236*	-0.044	0.001	-0.008	0.093	0.150
	/	/	[0.143]	[0.123]	[0.050]	[0.045]	[0.080]	[0.124]
Over-educated × Experience abroad squared/100	/	/	6.096**	0.228	-0.016	0.085	-0.118	-0.321
	/	/	[2.785]	[2.452]	[0.329]	[0.304]	[0.217]	[0.311]
Under-educated × Experience abroad	/	/	0.105	0.050	0.160**	-0.118	0.190**	0.188
	/	/	[0.109]	[0.103]	[0.080]	[0.073]	[0.080]	[0.138]
Under-educated × Experience abroad squared/100	/	/	-1.343	-0.114	-0.803*	0.686	-0.385*	-0.412
Post-migration human capital	/	/	[1.938]	[1.779]	[0.463]	[0.431]	[0.211]	[0.342]
Education in Australia (AU)	0.094***	0.034***	0.094***	0.033***	0.093***	0.034***	0.094***	0.033***
	[0.003]	[0.006]	[0.003]	[0.006]	[0.003]	[0.006]	[0.003]	[0.006]
Education in Australia × M	-0.027**	0.002	-0.048**	0.070	0.049**	-0.049	0.140**	0.378**
	[0.012]	[0.020]	[0.021]	[0.070]	[0.023]	[0.038]	[0.069]	[0.152]
Over-educated × Education in AU	-0.014***	-0.001	-0.014***	-0.001	-0.014***	-0.001	-0.014***	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Under-educated × Education in AU	-0.008***	-0.000	-0.008***	-0.000	-0.008***	-0.000	-0.008***	-0.000
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Over-educated × Education in AU×M	0.003	-0.002	0.059**	-0.019	-0.028	0.007	-0.049	-0.102
	[0.012]	[0.010]	[0.025]	[0.023]	[0.024]	[0.022]	[0.084]	[0.095]
Under-educated × Education in AU×M	-0.016	-0.013	0.079***	0.054**	-0.070*	0.069*	-0.164*	-0.298**
	[0.012]	[0.010]	[0.026]	[0.023]	[0.036]	[0.037]	[0.091]	[0.144]
Experience in Australia	0.018***	0.040***	0.018***	0.040***	0.018***	0.040***	0.018***	0.040***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Experience in Australia squared/100	-0.041***	-0.057***	-0.040***	-0.056***	-0.040***	-0.056***	-0.040***	-0.056***
	[0.006]	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]
Experience in Australia× M	-0.030**	0.023	0.014	-0.008	-0.063***	0.031**	-0.029	0.066**
	[0.013]	[0.014]	[0.019]	[0.021]	[0.012]	[0.013]	[0.037]	[0.028]
Experience in Australia× M squared/100	0.056*	-0.051*	-0.018	-0.046	0.160***	-0.048	0.102	-0.183*
	[0.030]	[0.029]	[0.043]	[0.039]	[0.029]	[0.033]	[0.149]	[0.097]
Over-educated × Experience in AU	0.017***	-0.001	0.018***	-0.001	0.018***	-0.001	0.018***	-0.001
	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]
Over-educated × Experience in AU squared/100	-0.038***	0.007	-0.039***	0.007	-0.039***	0.007	-0.038***	0.007
	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]
Under-educated × Experience in AU	0.012***	-0.003	0.012***	-0.003	0.012***	-0.003	0.012***	-0.003
	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Under-educated × Experience in AU squared/100	-0.006	0.011	-0.007	0.011	-0.007	0.011	-0.007	0.011
	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]
Over-educated × Experience in AU×M	-0.001	0.008	0.000	0.001	0.072***	0.014	-0.020	-0.061*
	[0.019]	[0.015]	[0.025]	[0.022]	[0.016]	[0.014]	[0.051]	[0.035]
Over-educated × Experience in AU squared/100×M	-0.012	-0.027	-0.019	0.029	-0.201***	-0.066*	0.012	0.196
	[0.047]	[0.035]	[0.062]	[0.054]	[0.042]	[0.037]	[0.199]	[0.138]
Under-educated × Experience in AU×M	0.006	0.014	-0.040	-0.010	0.037*	-0.038**	0.023	-0.066*
	[0.016]	[0.014]	[0.026]	[0.020]	[0.022]	[0.019]	[0.045]	[0.035]
Under-educated × Experience in AU squared/100×M	-0.015	-0.032	0.067	0.031	-0.120**	0.086*	-0.197	0.176
	[0.036]	[0.031]	[0.056]	[0.041]	[0.056]	[0.050]	[0.180]	[0.132]
Disability or impairment	-0.075***	-0.005	-0.078***	-0.009	-0.077***	-0.006	-0.078***	-0.006
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Control for States	YES	YES	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES	YES	YES
Constant	1.825***	2.181***	1.822***	2.212***	1.831***	2.167***	1.826***	1.679***
	[0.040]	[0.092]	[0.039]	[0.096]	[0.039]	[0.104]	[0.039]	[0.149]
F-test	59.55	14.49	52.60	11.91	56.85	15.12	53.12	12.63
R2	0.148	0.0298	0.155	0.0257	0.162	0.0286	0.158	0.00346
Individuals	. 2118	2118	2045	2045	2093	2093	2018	2018
Observations	13446	13446	12956	12956	13321	13321	12806	12806
R2_w	/	0.0453	/	0.0440	/	0.0476	/	0.0481
rho	/	0.801	/	0.810	/	0.812	/	0.996
Hausman fe re test: Chi2	/	130.2	/	104.8	/	131.4	/	102.3
Prob>chi2=	/	0	/	8.36e-11	/	0	/	8.40e-08

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.
Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad squared/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU squared/100. Source: HILDA-Release 9.

Table 3B. 10: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and NESB Immigrants (Model 3 Age on Arrival Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars							
	Sample: Natives and NESB Immigrants							
	Native & NESB migrated at age 0-12		Native & NESB migrated at age 13-22		Native & NESB migrated at age 23-34		Native & NESB migrated at age 35-60	
Explanatory Variables	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE	Pooled-OLS	Panel-FE
Immigrant (M)	0.149	/	0.328	/	-1.003***		0.613	/
Pre-migration human capital	[0.302]	/	[0.362]	/	[0.336]		[1.176]	/
Education abroad	0.099***	/	0.055**	/	0.115***	-0.003	-0.015	/
	[0.026]	/	[0.025]	/	[0.022]	[0.053]	[0.057]	/
Over-educated × Education abroad	-0.021	0.033	-0.029	-0.010	0.031	-0.001	0.105*	0.020
	[0.038]	[0.036]	[0.022]	[0.021]	[0.020]	[0.023]	[0.062]	[0.062]
Under-educated × Education abroad	0.010	0.049	0.028	-0.004	-0.031	0.039	-0.172*	-0.023
	[0.032]	[0.036]	[0.025]	[0.030]	[0.028]	[0.026]	[0.091]	[0.067]
Experience abroad	/	/	0.020	/	0.133**	0.059	0.139	0.208
	/	/	[0.242]	/	[0.065]	[0.145]	[0.139]	[0.185]
Experience abroad squared/100	/	/	-4.638	/	-0.381	0.072	-0.442	-0.240
	/	/	[6.456]	/	[0.375]	[0.668]	[0.355]	[0.330]
Over-educated × Experience abroad	/	/	0.205	0.046	-0.132*	-0.001	-0.141	-0.038
	/	/	[0.309]	[0.362]	[0.077]	[0.087]	[0.113]	[0.102]
Over-educated × Experience abroad squared/100	/	/	-2.523	1.443	0.395	-0.093	0.343	0.219
	/	/	[8.538]	[9.091]	[0.437]	[0.483]	[0.303]	[0.270]
Under-educated × Experience abroad	/	/	-0.053	0.106	0.140	-0.111	0.232	0.148
	/	/	[0.256]	[0.322]	[0.093]	[0.095]	[0.169]	[0.132]
Under-educated × Experience abroad squared/100	/	/	5.375	1.734	-0.909*	0.317	-0.365	-0.429
Post-migration human capital	/	/	[6.583]	[8.482]	[0.509]	[0.509]	[0.441]	[0.366]
Education in Australia (AU)	0.094***	0.033***	0.094***	0.033***	0.093***	0.033***	0.094***	0.033***
	[0.003]	[0.006]	[0.003]	[0.006]	[0.003]	[0.006]	[0.003]	[0.006]
Education in Australia × M	0.007	0.052	-0.069***	-0.080	0.046	-0.030	-0.017	-0.007
	[0.018]	[0.072]	[0.026]	[0.061]	[0.029]	[0.054]	[0.075]	[0.125]
Over-educated × Education in AU	-0.014***	-0.001	-0.014***	-0.001	-0.014***	-0.001	-0.014***	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Under-educated × Education in AU	-0.008***	-0.000	-0.008***	-0.000	-0.008***	-0.000	-0.008***	-0.000
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Over-educated × Education in AU×M	0.007	-0.019	0.044*	-0.006	0.038	-0.013	0.105	-0.128
	[0.013]	[0.015]	[0.025]	[0.023]	[0.028]	[0.027]	[0.077]	[0.086]
Under-educated × Education in AU×M	0.010	0.013	0.100***	0.001	-0.043	0.021	-0.073	-0.189
	[0.019]	[0.027]	[0.038]	[0.037]	[0.042]	[0.033]	[0.124]	[0.177]
Experience in Australia	0.018***	0.040***	0.018***	0.040***	0.018***	0.040***	0.018***	0.040***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Experience in Australia squared/100	-0.041***	-0.056***	-0.040***	-0.056***	-0.040***	-0.056***	-0.040***	-0.056***
	[0.006]	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]
Experience in Australia× M	0.018	0.043*	0.006	-0.015	-0.038**	-0.023	0.013	-0.004
	[0.016]	[0.022]	[0.020]	[0.022]	[0.017]	[0.018]	[0.061]	[0.039]
Experience in Australia× M squared/100	-0.049	-0.090**	0.002	0.022	0.114**	0.145**	-0.072	0.027
	[0.036]	[0.045]	[0.053]	[0.058]	[0.048]	[0.057]	[0.263]	[0.160]
Over-educated × Experience in AU	0.017***	-0.001	0.018***	-0.001	0.018***	-0.001	0.018***	-0.001
	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]
Over-educated × Experience in AU squared/100	-0.038***	0.007	-0.038***	0.007	-0.038***	0.007	-0.038***	0.007
	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]
Under-educated × Experience in AU	0.012***	-0.003	0.012***	-0.003	0.012***	-0.003	0.012***	-0.003
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Under-educated × Experience in AU squared/100	-0.007	0.011	-0.007	0.011	-0.007	0.011	-0.007	0.011
	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]
Over-educated × Experience in AU×M	-0.014	0.013	0.001	0.024	0.033	0.034*	-0.128*	-0.041
	[0.024]	[0.022]	[0.033]	[0.031]	[0.023]	[0.019]	[0.069]	[0.045]
Over-educated × Experience in AU squared/100×M	0.047	-0.039	0.011	-0.089	-0.119*	-0.133**	0.555*	0.213
	[0.064]	[0.053]	[0.093]	[0.088]	[0.069]	[0.061]	[0.315]	[0.195]
Under-educated × Experience in AU×M	-0.032	-0.022	-0.045	-0.013	0.015	0.045	-0.283*	-0.123
	[0.024]	[0.028]	[0.028]	[0.027]	[0.036]	[0.029]	[0.147]	[0.094]
Under-educated × Experience in AU squared/100×M	0.075	0.034	0.077	0.033	-0.064	-0.152*	1.089*	0.313
	[0.051]	[0.055]	[0.065]	[0.067]	[0.089]	[0.086]	[0.655]	[0.402]
Disability or impairment	-0.076***	-0.006	-0.079***	-0.007	-0.076***	-0.008	-0.078***	-0.007
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Poor English	/	/	-0.083	-0.120	-0.262***	0.172	-0.377***	-0.165
	/	/	[0.241]	[0.144]	[0.096]	[0.124]	[0.144]	[0.162]
Control for States	YES	YES	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES	YES	YES
Constant	1.826***	2.190***	1.823***	2.222***	1.826***	2.212***	1.825***	2.166***
	[0.039]	[0.095]	[0.039]	[0.093]	[0.039]	[0.102]	[0.039]	[0.101]
F-test	60.11	14.12	50.24	12.11	53.24	12.14	51.04	11.79
R2	0.154	0.0294	0.153	0.0294	0.158	0.0312	0.155	0.00448
Individuals	2036	2036	2035	2035	2058	2058	2017	2017
Observations	12871	12871	12889	12889	13062	13062	12804	12804
R2_w	/	0.0450	/	0.0439	/	0.0465	/	0.0451
rho	/	0.808	/	0.805	/	0.801	/	0.850
Hausman fe re test: Chi2	/	119.3	/	98.04	/	118.7	/	100.8
Prob>chi2=	/	0	/	1.05e-09	/	5.69e-10	/	2.25e-07

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent. Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad squared/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU squared/100. Source: HILDA-Release 9.

Table 3B. 11: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and ESB Immigrants (Model 3 Year of Arrival Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars					
	Sample: Natives and ESB Immigrants					
	Native & ESB migrated between 1947 and 1979		Native & ESB migrated between 1980 and 1989		Native & ESB migrated between 1990 and 2001	
Explanatory Variables	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE
Immigrant (M)	1.433***	/	-0.305	/	-0.158	/
Pre-migration human capital	[0.212]	/	[0.290]	/	[0.296]	/
Education abroad	0.068***	0.088***	0.163***	0.035	0.127***	0.039
	[0.015]	[0.034]	[0.017]	[0.030]	[0.017]	[0.076]
Over-educated × Education abroad	0.025	-0.025	-0.080***	-0.000	-0.006	0.010
	[0.018]	[0.017]	[0.019]	[0.016]	[0.012]	[0.010]
Under-educated × Education abroad	-0.017	0.005	-0.063***	0.013	0.023	0.032**
	[0.018]	[0.016]	[0.023]	[0.019]	[0.018]	[0.015]
Experience abroad	0.032	0.093	0.015	-0.203**	0.058***	/
	[0.039]	[0.110]	[0.018]	[0.100]	[0.018]	/
Experience abroad squared/100	-0.344	/	-0.045	2.480***	-0.173**	0.097
	[0.417]	/	[0.089]	[0.866]	[0.072]	[0.223]
Over-educated × Experience abroad	-0.046	0.048	0.009	-0.005	-0.033	0.023
	[0.047]	[0.078]	[0.025]	[0.021]	[0.022]	[0.023]
Over-educated × Experience abroad squared/100	0.568	-0.483	-0.129	0.048	0.125	-0.044
	[0.459]	[1.060]	[0.127]	[0.095]	[0.086]	[0.093]
Under-educated × Experience abroad	-0.035	0.043	-0.020	-0.027	-0.028	0.005
	[0.043]	[0.072]	[0.027]	[0.025]	[0.024]	[0.027]
Under-educated × Experience abroad squared/100	0.245	-0.526	0.034	0.149	0.107	0.011
Post-migration human capital	[0.432]	[1.040]	[0.118]	[0.094]	[0.087]	[0.101]
Education in Australia (AU)	0.094***	0.034***	0.093***	0.034***	0.093***	0.034***
	[0.003]	[0.006]	[0.003]	[0.006]	[0.003]	[0.006]
Education in Australia × M	-0.034**	0.013	0.065***	-0.012	0.033	0.060
	[0.015]	[0.030]	[0.017]	[0.024]	[0.033]	[0.039]
Over-educated × Education in AU	-0.014***	-0.001	-0.014***	-0.001	-0.014***	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Under-educated × Education in AU	-0.008***	-0.000	-0.008***	-0.000	-0.008***	-0.000
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Over-educated × Education in AU×M	0.027*	-0.012	-0.069***	-0.001	-0.016	-0.045*
	[0.017]	[0.013]	[0.015]	[0.012]	[0.032]	[0.027]
Under-educated × Education in AU×M	-0.019	-0.001	-0.078***	-0.004	0.065*	-0.083
	[0.016]	[0.013]	[0.017]	[0.013]	[0.038]	[0.053]
Experience in Australia	0.018***	0.040***	0.018***	0.040***	0.018***	0.040***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Experience in Australia squared/100	-0.041***	-0.056***	-0.040***	-0.056***	-0.040***	-0.056***
	[0.006]	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]
Experience in Australia× M	-0.078***	0.027	-0.091***	0.013	0.003	0.080***
	[0.016]	[0.017]	[0.025]	[0.021]	[0.031]	[0.021]
Experience in Australia× M squared/100	0.141***	-0.056*	0.284***	-0.015	-0.217	-0.342***
	[0.033]	[0.032]	[0.076]	[0.059]	[0.168]	[0.109]
Over-educated × Experience in AU	0.017***	-0.001	0.018***	-0.001	0.018***	-0.001
	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]
Over-educated × Experience in AU squared/100	-0.038***	0.007	-0.039***	0.007	-0.038***	0.007
	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]
Under-educated × Experience in AU	0.012***	-0.003	0.012***	-0.003	0.012***	-0.003
	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Under-educated × Experience in AU squared/100	-0.007	0.011	-0.007	0.011	-0.007	0.011
	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]
Over-educated × Experience in AU×M	-0.028	0.015	0.172***	0.020	-0.015	-0.051**
	[0.022]	[0.017]	[0.033]	[0.025]	[0.039]	[0.026]
Over-educated × Experience in AU squared/100×M	0.035	-0.033	-0.578***	-0.106	0.158	0.264*
	[0.049]	[0.037]	[0.102]	[0.074]	[0.225]	[0.142]
Under-educated × Experience in AU×M	0.011	0.005	0.186***	0.005	-0.077*	-0.058*
	[0.019]	[0.016]	[0.033]	[0.024]	[0.046]	[0.031]
Under-educated × Experience in AU squared/100×M	-0.028	-0.015	-0.642***	-0.046	0.567**	0.186
	[0.039]	[0.032]	[0.106]	[0.077]	[0.269]	[0.176]
Disability or impairment	-0.074***	-0.007	-0.084***	-0.008	-0.076***	-0.006
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.825***	2.141***	1.827***	2.153***	1.833***	2.189***
	[0.040]	[0.098]	[0.039]	[0.103]	[0.039]	[0.102]
F-test	53.66	12.45	55.87	13.72	54.77	14.02
R2	0.151	0.0142	0.160	0.00795	0.159	0.0382
Individuals	2161	2161	2083	2083	2043	2043
Observations	13658	13658	13222	13222	13043	13043
R2_w	/	0.0437	/	0.0437	/	0.0510
rho	/	0.833	/	0.892	/	0.800
Hausman fe re test: Chi2	/	139.9	/	139.2	/	116.5
Prob>chi2=	/	0	/	0	/	1.19e-09

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.
Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad squared/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU squared/100. Source: HILDA-Release 9.

Table 3B. 12: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and NESB Immigrants (Model 3 Year of Arrival Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars					
	Sample: Natives and NESB Immigrants					
	Native & NESB migrated between 1947 and 1979		Native & NESB migrated between 1980 and 1989		Native & NESB migrated between 1990 and 2001	
Explanatory Variables	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE
Immigrant (M)	0.446	/	-0.742*	/	0.045	/
Pre-migration human capital	[0.403]	/	[0.399]	/	[0.297]	/
Education abroad	0.090***	/	0.147***	0.124	0.065***	-0.047
	[0.029]	/	[0.025]	[0.082]	[0.020]	[0.046]
Over-educated × Education abroad	-0.011	-0.023	-0.037	-0.063***	0.010	0.007
	[0.040]	[0.035]	[0.023]	[0.018]	[0.014]	[0.013]
Under-educated × Education abroad	-0.018	-0.016	-0.031	-0.001	-0.003	-0.000
	[0.032]	[0.030]	[0.033]	[0.023]	[0.024]	[0.024]
Experience abroad	-0.145**	/	-0.032	0.037	0.065***	0.074
	[0.063]	/	[0.038]	[0.300]	[0.018]	[0.076]
Experience abroad squared/100	1.488**	/	0.324	/	-0.227***	-0.077
	[0.625]	/	[0.216]	/	[0.069]	[0.177]
Over-educated × Experience abroad	0.048	0.117	0.064	0.017	-0.034	-0.020
	[0.096]	[0.083]	[0.042]	[0.036]	[0.022]	[0.027]
Over-educated × Experience abroad squared/100	-0.524	-0.956	-0.544**	-0.083	0.071	0.091
	[0.837]	[0.622]	[0.245]	[0.220]	[0.084]	[0.094]
Under-educated × Experience abroad	0.140*	0.237**	0.082*	0.086*	-0.082***	-0.008
	[0.076]	[0.105]	[0.044]	[0.046]	[0.030]	[0.051]
Under-educated × Experience abroad squared/100	-1.554**	-1.863**	-0.582**	-0.655**	0.231*	0.015
Post-migration human capital	[0.716]	[0.870]	[0.231]	[0.263]	[0.118]	[0.177]
Education in Australia (AU)	0.094***	0.033***	0.094***	0.033***	0.093***	0.033***
	[0.003]	[0.006]	[0.003]	[0.006]	[0.003]	[0.006]
Education in Australia × M	-0.003	-0.036	0.076***	0.104	-0.011	-0.074
	[0.029]	[0.057]	[0.022]	[0.079]	[0.021]	[0.046]
Over-educated × Education in AU	-0.014***	-0.001	-0.014***	-0.001	-0.014***	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Under-educated × Education in AU	-0.008***	-0.000	-0.008***	-0.000	-0.008***	-0.000
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Over-educated × Education in AU×M	0.011	-0.025	-0.033**	-0.058***	0.033**	-0.017
	[0.036]	[0.031]	[0.016]	[0.015]	[0.016]	[0.021]
Under-educated × Education in AU×M	-0.031	-0.007	-0.025	-0.010	0.006	-0.031
	[0.032]	[0.032]	[0.026]	[0.022]	[0.032]	[0.158]
Experience in Australia	0.018***	0.040***	0.018***	0.040***	0.018***	0.040***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Experience in Australia squared/100	-0.040***	-0.056***	-0.040***	-0.056***	-0.040***	-0.056***
	[0.006]	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]
Experience in Australia× M	-0.020	0.016	-0.085**	-0.082***	-0.001	-0.037
	[0.033]	[0.032]	[0.038]	[0.030]	[0.039]	[0.027]
Experience in Australia× M squared/100	0.026	-0.031	0.365**	0.444***	-0.104	0.177
	[0.061]	[0.058]	[0.142]	[0.109]	[0.216]	[0.146]
Over-educated × Experience in AU	0.018***	-0.001	0.018***	-0.001	0.018***	-0.001
	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]
Over-educated × Experience in AU squared/100	-0.038***	0.007	-0.038***	0.007	-0.038***	0.007
	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]
Under-educated × Experience in AU	0.012***	-0.003	0.012***	-0.003	0.012***	-0.003
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Under-educated × Experience in AU squared/100	-0.007	0.011	-0.007	0.011	-0.007	0.011
	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]
Over-educated × Experience in AU×M	-0.021	0.030	0.113**	0.176***	-0.020	0.010
	[0.044]	[0.036]	[0.045]	[0.035]	[0.043]	[0.030]
Over-educated × Experience in AU squared/100×M	0.068	-0.074	-0.504***	-0.667***	0.137	-0.061
	[0.089]	[0.070]	[0.165]	[0.129]	[0.248]	[0.168]
Under-educated × Experience in AU×M	0.014	0.003	0.078	0.088**	0.108	0.045
	[0.035]	[0.033]	[0.053]	[0.039]	[0.067]	[0.052]
Under-educated × Experience in AU squared/100×M	-0.018	-0.005	-0.320*	-0.451***	-0.342	-0.227
	[0.067]	[0.063]	[0.179]	[0.135]	[0.345]	[0.245]
Disability or impairment	-0.079***	-0.007	-0.073***	-0.007	-0.078***	-0.007
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Poor English	-0.274	-0.010	-0.326***	-0.106	-0.030	0.083
	[0.200]	[0.208]	[0.114]	[0.167]	[0.114]	[0.098]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.824***	2.209***	1.826***	2.166***	1.824***	2.243***
	[0.039]	[0.094]	[0.039]	[0.119]	[0.039]	[0.099]
F-test	51.46	12.06	52.80	13.13	51.33	11.60
R2	0.155	0.0334	0.158	0.00984	0.153	0.0180
Individuals	2052	2052	2045	2045	2062	2062
Observations	12971	12971	12970	12970	13079	13079
R2_w	/	0.0435	/	0.0493	/	0.0444
rho	/	0.798	/	0.843	/	0.819
Hausman fe re test: Chi2	/	82.83	/	113.3	/	115.7
Prob>chi2=	/	9.43e-06	/	3.53e-09	/	8.14e-09

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent. Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively. Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad squared/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU squared/100. Source: HILDA-Release 9.

Table 3B. 13: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and ESB Immigrants (Model 3 Country of Qualification Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars					
	Sample: Natives and ESB Immigrants					
	Native & ESB with Australian Qualification		Native & ESB with Overseas Qualification		Native & ESB without qualification	
Explanatory Variables	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE
Immigrant (M)	-1.047***	/	-1.298***	/	1.560***	/
Pre-migration human capital	[0.249]	/	[0.331]	/	[0.246]	/
Education abroad	0.172***	0.126	0.198***	0.118	-0.038	0.849**
	[0.017]	[0.116]	[0.020]	[0.142]	[0.035]	[0.366]
Over-educated × Education abroad	-0.025**	-0.013	-0.030***	0.007	0.038	-0.003
	[0.011]	[0.011]	[0.009]	[0.008]	[0.043]	[0.027]
Under-educated × Education abroad	0.017	-0.011	-0.034	0.037*	0.053	0.011
	[0.015]	[0.013]	[0.021]	[0.021]	[0.033]	[0.020]
Experience abroad	-0.015	/	0.040***	0.217	0.003	/
	[0.037]	/	[0.015]	[0.180]	[0.036]	/
Experience abroad squared/100	0.147	0.756	-0.106*	-0.245	-0.050	/
	[0.354]	[1.111]	[0.063]	[0.294]	[0.136]	/
Over-educated × Experience abroad	-0.001	0.089*	-0.027	-0.013	-0.008	0.003
	[0.040]	[0.051]	[0.022]	[0.026]	[0.050]	[0.031]
Over-educated × Experience abroad squared/100	0.007	-0.671	0.096	0.053	0.034	0.040
	[0.366]	[0.477]	[0.095]	[0.114]	[0.164]	[0.103]
Under-educated × Experience abroad	0.035	0.077	-0.015	-0.124**	-0.028	-0.016
	[0.050]	[0.053]	[0.035]	[0.051]	[0.037]	[0.024]
Under-educated × Experience abroad squared/100	-0.245	-0.695	0.112	0.549***	0.099	0.100
Post-migration human capital	[0.400]	[0.474]	[0.157]	[0.197]	[0.141]	[0.087]
Education in Australia (AU)	0.094***	0.034***	0.093***	0.034***	0.094***	0.033***
	[0.003]	[0.006]	[0.003]	[0.006]	[0.003]	[0.006]
Education in Australia × M	0.082***	-0.015	0.077***	0.056	-0.117***	/
	[0.017]	[0.038]	[0.029]	[0.143]	[0.031]	/
Over-educated × Education in AU	-0.014***	-0.001	-0.014***	-0.001	-0.014***	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Under-educated × Education in AU	-0.008***	-0.000	-0.008***	-0.000	-0.008***	-0.000
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Over-educated × Education in AU×M	-0.030***	0.004	-0.015	0.004	0.021	0.006
	[0.010]	[0.009]	[0.025]	[0.021]	[0.035]	[0.022]
Under-educated × Education in AU×M	0.001	-0.016	0.022	0.051	0.019	0.012
	[0.014]	[0.013]	[0.060]	[0.046]	[0.028]	[0.017]
Experience in Australia	0.018***	0.040***	0.018***	0.040***	0.018***	0.040***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Experience in Australia squared/100	-0.040***	-0.056***	-0.040***	-0.056***	-0.040***	-0.056***
	[0.006]	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]
Experience in Australia× M	-0.019*	0.016	-0.039***	0.047***	-0.016	0.008
	[0.011]	[0.012]	[0.010]	[0.013]	[0.028]	[0.020]
Experience in Australia× M squared/100	0.036	-0.060**	0.112***	-0.085***	0.052	-0.013
	[0.028]	[0.027]	[0.025]	[0.032]	[0.058]	[0.040]
Over-educated × Experience in AU	0.018***	-0.001	0.018***	-0.001	0.017***	-0.001
	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]
Over-educated × Experience in AU squared/100	-0.038***	0.007	-0.039***	0.007	-0.038***	0.007
	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]
Under-educated × Experience in AU	0.012***	-0.003	0.012***	-0.003	0.012***	-0.003
	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]	[0.003]
Under-educated × Experience in AU squared/100	-0.007	0.011	-0.007	0.011	-0.007	0.011
	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]
Over-educated × Experience in AU×M	0.039**	-0.005	0.043***	0.010	-0.037	0.006
	[0.016]	[0.013]	[0.016]	[0.014]	[0.037]	[0.023]
Over-educated × Experience in AU squared/100×M	-0.097**	0.011	-0.134***	-0.060	0.060	-0.031
	[0.039]	[0.031]	[0.041]	[0.039]	[0.085]	[0.053]
Under-educated × Experience in AU×M	-0.005	0.017	0.073**	0.028	-0.026	-0.004
	[0.019]	[0.017]	[0.036]	[0.030]	[0.029]	[0.018]
Under-educated × Experience in AU squared/100×M	-0.011	-0.027	-0.239**	-0.110	0.016	-0.002
	[0.045]	[0.040]	[0.109]	[0.092]	[0.060]	[0.037]
Disability or impairment	-0.080***	-0.006	-0.080***	-0.005	-0.072***	-0.010
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.819***	2.187***	1.833***	2.049***	1.827***	1.967***
	[0.039]	[0.109]	[0.039]	[0.189]	[0.040]	[0.138]
F-test	56.14	12.42	56.55	13.67	51.04	12.71
R2	0.158	0.0291	0.162	0.0161	0.149	3.85e-05
Individuals	2129	2129	2083	2083	2090	2090
Observations	13486	13486	13231	13231	13206	13206
R2_w	/	0.0441	/	0.0503	/	0.0439
rho	/	0.819	/	0.922	/	0.971
Hausman fe re test: Chi2	/	109.0	/	121.7	/	103.5
Prob>chi2=	/	5.09e-09	/	1.07e-10	/	6.13e-09

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent.
Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad squared/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU squared/100. Source: HILDA-Release 9.

Table 3B. 14: The Effect of Over-education on Earnings via Pre-migration and Post-migration Human Capital for Natives and NESB Immig*ran*ts (Model 3 Country of Qualification Effect)

	Dependent Variable : The natural logarithm of hourly wage from main job in 2009 dollars					
	Sample: Natives and NESB Immigrants					
	Native & NESB with Australian Qualification		Native & NESB with Overseas Qualification		Native & NESB without qualification	
Explanatory Variables	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE	Pooled OLS	Panel-FE
Immigrant (M)	-1.596***	/	-1.073***	/	0.825**	/
Pre-migration human capital	[0.397]	/	[0.379]	/	[0.366]	/
Education abroad	0.163***	0.135	0.151***	0.026	0.043	/
	[0.025]	[0.104]	[0.024]	[0.026]	[0.054]	/
Over-educated × Education abroad	-0.024**	-0.017	0.029**	0.022	-0.023	0.034
	[0.011]	[0.012]	[0.012]	[0.014]	[0.063]	[0.044]
Under-educated × Education abroad	0.030	0.008	0.005	0.084**	0.022	0.057
	[0.029]	[0.021]	[0.051]	[0.034]	[0.051]	[0.042]
Experience abroad	0.024	/	0.095***	-0.027	0.014	/
	[0.017]	/	[0.021]	[0.147]	[0.072]	/
Experience abroad squared/100	-0.081	0.271	-0.341***	0.875	-0.053	/
	[0.069]	[0.214]	[0.097]	[0.617]	[0.288]	/
Over-educated × Experience abroad	0.028	-0.012	-0.130***	-0.060*	0.003	-0.032
	[0.021]	[0.021]	[0.029]	[0.036]	[0.093]	[0.069]
Over-educated × Experience abroad squared/100	-0.120	0.050	0.424***	0.299**	-0.316	0.342
	[0.083]	[0.078]	[0.131]	[0.144]	[0.475]	[0.349]
Under-educated × Experience abroad	0.093	0.117	0.028	-0.083	-0.026	0.002
	[0.066]	[0.129]	[0.110]	[0.074]	[0.073]	[0.053]
Under-educated × Experience abroad squared/100	-0.440*	-0.672	-0.161	0.180	0.081	-0.001
Post-migration human capital	[0.239]	[0.740]	[0.362]	[0.237]	[0.295]	[0.201]
Education in Australia (AU)	0.094***	0.033***	0.093***	0.033***	0.094***	0.033***
	[0.003]	[0.006]	[0.003]	[0.006]	[0.003]	[0.006]
Education in Australia × M	0.088***	0.044	0.103***	/	-0.011	/
	[0.024]	[0.057]	[0.031]	/	[0.061]	/
Over-educated × Education in AU	-0.014***	-0.001	-0.014***	-0.001	-0.014***	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Under-educated × Education in AU	-0.008***	-0.000	-0.008***	-0.000	-0.008***	-0.000
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Over-educated × Education in AU×M	0.021**	-0.028***	0.016	0.032	-0.063	0.055
	[0.009]	[0.011]	[0.024]	[0.025]	[0.068]	[0.043]
Under-educated × Education in AU×M	0.028	0.021	-0.017	0.070*	-0.024	0.080*
	[0.026]	[0.021]	[0.067]	[0.042]	[0.058]	[0.047]
Experience in Australia	0.018***	0.040***	0.018***	0.040***	0.018***	0.040***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Experience in Australia squared/100	-0.040***	-0.056***	-0.040***	-0.056***	-0.040***	-0.056***
	[0.006]	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]
Experience in Australia× M	0.032***	-0.003	-0.051***	-0.027	-0.002	0.053
	[0.012]	[0.014]	[0.017]	[0.019]	[0.044]	[0.040]
Experience in Australia× M squared/100	-0.068**	-0.013	0.136***	0.174***	-0.013	-0.089
	[0.031]	[0.034]	[0.047]	[0.064]	[0.085]	[0.076]
Over-educated × Experience in AU	0.017***	-0.001	0.018***	-0.001	0.018***	-0.001
	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]
Over-educated × Experience in AU squared/100	-0.038***	0.007	-0.038***	0.007	-0.038***	0.007
	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]
Under-educated × Experience in AU	0.012***	-0.003	0.012***	-0.003	0.012***	-0.003
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Under-educated × Experience in AU squared/100	-0.007	0.011	-0.007	0.011	-0.007	0.011
	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]
Over-educated × Experience in AU×M	-0.024	0.050***	0.008	0.003	0.027	-0.047
	[0.017]	[0.016]	[0.023]	[0.021]	[0.059]	[0.037]
Over-educated × Experience in AU squared/100×M	0.063	-0.140***	-0.049	-0.062	-0.041	0.086
	[0.048]	[0.045]	[0.072]	[0.061]	[0.124]	[0.081]
Under-educated × Experience in AU×M	-0.052	-0.027	-0.019	-0.036	-0.020	-0.066*
	[0.033]	[0.026]	[0.067]	[0.046]	[0.045]	[0.037]
Under-educated × Experience in AU squared/100×M	0.106	0.059	0.039	0.037	0.053	0.115
	[0.069]	[0.061]	[0.214]	[0.153]	[0.089]	[0.071]
Disability or impairment	-0.073***	-0.005	-0.078***	-0.009	-0.077***	-0.007
	[0.012]	[0.009]	[0.012]	[0.009]	[0.012]	[0.009]
Poor English	0.259	0.110	-0.083	0.153	-0.244**	-0.067
	[0.240]	[0.151]	[0.109]	[0.137]	[0.118]	[0.124]
Control for States	YES	YES	YES	YES	YES	YES
Control for unemployment	YES	YES	YES	YES	YES	YES
Control for time periods	YES	YES	YES	YES	YES	YES
Constant	1.824***	2.164***	1.828***	2.181***	1.824***	2.200***
	[0.039]	[0.103]	[0.039]	[0.102]	[0.039]	[0.094]
F-test	54.01	12.56	51.67	12.26	50.62	12.37
R2	0.160	0.0175	0.155	0.00993	0.153	0.0301
Individuals	2072	2072	2047	2047	2048	2048
Observations	13118	13118	12979	12979	12923	12923
R2_w	/	0.0468	/	0.0462	/	0.0437
rho	/	0.829	/	0.834	/	0.804
Hausman fe re test: Chi2	/	109.0	/	116.2	/	116.7
Prob>chi2=	/	1.53e-08	/	1.31e-09	/	5.36e-11

Notes: The Hausman test rejects the random effects result and accepts the fixed effects result. The result is consistent. Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively. Base-categories are native, Matched × Education abroad, Matched × Experience abroad, Matched × Experience abroad squared/100, Matched × Education in AU, Matched × Experience in AU, Matched × Experience in AU squared/100. Source: HILDA-Release 9.

Appendix 3C: Derivation of Years since Migration (YSM)

Following the approach from Friedberg (2000), YSM is defined as the following:

(3C.1) $$Age\_arAu+YSM= EXP+edhighy+6$$

Where EXP denotes years of potential work experience; edhighy is years of actual education; Age_arAu is the age on arrival in Australia. It is defined as the age of a person born overseas when he first enters Australia from another country, with the intention of staying in Australia. Immigrant age at the time of interview is presented by the addition of age on arrival in Australia and years of residence in Australia. Different from native Australians, immigrants accumulate their human capital across countries. ED_2 and EXP_2 are immigrants' education and experience acquired after migration, Subscript 2 signifies 'domestic' country (Australia). Thus, ED_2 and EXP_2 represent the post immigration human capital. Similarly, Subscript 1 signifies 'original' country. ED_1 and EXP_1 denote education and experience obtained from their original country before migration and they represent pre-migration human capital.

After replacing total years of experience and education with pre-migration and post-migration experience and education, the Equation (3C.1) can be written as:

(3C.2) $$Age\_arAu+YSM= EXP_1+ED_1+EXP_2+ED_2+6;$$ then we have

(3C.3) $$YSM= EXP_2+ED_2 + (EXP_1+ED_1+6-Age\_arAu);$$

If the age on arrival in Australian is over 6 years old, immigrants are more likely to have attended overseas schooling and have initial stock of human capital which is presented by overseas experience (EXP_1) and overseas education (ED_1), then their pre-migration human capital investment equation is $Age\_arAu= EXP_1+ED_1+6$, that is $(EXP_1+ED_1+6-Age\_arAu) =0$. Thus,

(3C.4) $YSM= EXP_2+ED_2;$

If the age on arrival is between 1 and 6[30], then this young group of immigrants is more likely to come to Australia with their Adult parents who are migration-decision maker. This young arrival group is assumed to have no initial stock of human capital and accumulate their human capital after migration to Australia, thus years of migration is expressed by

(3C.5) $YSM= EXP_2+ED_2+ (6-Age\_arAu);$

Years since Migration (YSM) = hgage –Age_arAu;

Where hgage is the age last birthday at June 30 immediately preceding the fieldwork for that wave; Age_arAu denotes age at migration which is constructed by year first came to Australia to live (anyoa) minus year of birth (hgyob). That is

(3C.6) Age_arAu=anyoa-hgyob;

(3C.7) YSM=hgage-Age_arAu=hgage-anyoa+hgyob;

(3C.8) $EXP=hgage-edhighy-6;\ EXP=EXP_1+EXP_2;\ edhighy =ED_1+ED_2$

Years of education and years of experience are derived from relevant variables (edcoq, edcly and anyoa). Edcoq presents country where completed highest qualification, edcly is country where completed school education; anyoa is the year first came to Australia to live. Based on this information, I derive education and experience which are obtained abroad and domestically for immigrants.

[30] For this data, there is 16 per cent of immigrants migrate to Australia when their age is less than 6 years old. Among them, 13 per cent is ESB immigrants and 3 per cent is NESB immigrants. Total 109/704 (16 %); ESB 82/539 (13%); NESB 27/165 (3%).

Appendix 3D: Definition of Variables

Personal Characteristics	
age	Continuous age variable, expressed in years
married	Dummy variable, 1 if married(or de facto), zero otherwise
Has children aged 14orless	Dummy variable, 1 if has any children aged 14 or less, zero otherwise
Disability or impairment	Dummy variable, 1 if has Long term health condition, disability or impairment, zero otherwise
Poor English	Dummy variable, 1 if immigrant speaks English poorly, zero otherwise
Year of Arrival	
Arrived 1947-1979	Dummy variable, 1 if immigrant arrived between 1947 and 1979, zero otherwise
Arrived 1980-1989	Dummy variable, 1 if immigrant arrived between 1980 and 1989, zero otherwise
Arrived 1990-2001	Dummy variable, 1 if immigrant arrived between 1990 and 2001, zero otherwise
Age on Arrival	
Age 0-12	Dummy variable, 1 if immigrant migrated at age 0 to 12, zero otherwise
Age 13-22	Dummy variable, 1 if immigrant migrated at age 13 to 22, zero otherwise
Age 23-34	Dummy variable, 1 if immigrant migrated at age 23 to 34, zero otherwise
Age 35-60	Dummy variable, 1 if immigrant migrated at age 35 to 60, zero otherwise
Years since Migration-YSM	Continuous variable, expressed in years of duration in Australia for immigrants
Country of birth	
Natives	Dummy variable,1 if born in Australia, zero otherwise
Immigrant	Dummy variable,1 if born overseas, zero otherwise
ESB immigrant	Dummy variable,1 if born in an English speaking country, zero otherwise
NESB immigrant	Dummy variable,1 if born in an non-English speaking country, zero otherwise
Job Characteristics	
Jbmo6s	AUSEI06 occupational status scale, current main job
Unemployment	Unemployment rate annually, refer to 6202.0 - Labour Force, Australia, Australian Bureau of Statistics
Employed	Dummy variable,1 if employed, zero otherwise
Unemployed	Dummy variable,1 if unemployed, zero otherwise
FT	Dummy variable,1 if full-time employed, zero otherwise
PT	Dummy variable,1 if part-time employed, zero otherwise
Hourly Wage	Continuous variable, expressed in current weekly gross wages and salary from main job divided by combined hours per week usually worked in main job in 2009 dollars
Log Hourly Wage	Continuous variable, expressed in the natural logarithm of hourly wages from main job
Human Capital	
Years of experience (total)-EXP	Continuous variable, expressed in potential years of work experience, calculated by hgage-edhighy-6
Years of Domestic experience-EXP_2	Continuous variable, expressed in potential years of work experience obtained in Australia
Years of experience abroad-EXP_1	Continuous variable, expressed in potential years of work experience obtained in overseas
Years of actual education (total)-ED	Continuous educational attainment variable, expressed in years
Years of domestic education-ED_2	Continuous domestically educational attainment variable, expressed in years
Years of education abroad-ED_1	Continuous abroad educational attainment variable, expressed in years
Based on degree type	
Post-graduate	Dummy variable, 1 if highest qualification is Doctorate, Masters, grad diploma, grad certificate or Bachelor with honours, zero otherwise
Bachelor	Dummy variable, 1 if highest qualification is Bachelor without honours, zero otherwise
Advanced diploma	Dummy variable, 1 if highest qualification is Advanced diploma or diploma, zero otherwise
Certificate	Dummy variable, 1 if highest qualification is certificate I II III or IV, zero otherwise
Based on country achieved	
Australian qualification	Dummy variable, 1 if highest qualification is obtained in Australia, zero otherwise
Overseas qualification	Dummy variable, 1 if highest qualification is obtained in overseas, zero otherwise
No Qualification	Dummy variable, 1 if highest qualification is year12 or below, zero otherwise
Educational Mismatched	
Under cross -wave Mode measure	
Over-educated	Dummy variable, takes the value 1 if over-educated, zero otherwise
Under-educated	Dummy variable, takes the value 1 if under-educated, zero otherwise
Matched	Dummy variable, takes the value 1 if adequately educated, zero otherwise
Years of over-education	Continuous variable, the years of over-education
Years of under-education	Continuous variable, the years of under-education
Years of required education	Continuous variable, the years of adequate education

4. Essay Three:

Dynamic Effects of Over-education and Over-skilling

Abstract

In this paper, a dynamic random effects probit model is employed with Mundlak correction to re-test the theory of career mobility among job mismatched workers using longitudinal HILDA data. The existence of an upward career path is inferred from wage growth data. Career mobility theory hypothesises that over-education leads to a higher level of occupational rank and wage growth over time. I find that there is no empirical support for using career mobility to explain over-education in the Australian labour market. In particular, over-educated and over-skilled workers do not seem to gain any advantage from quitting their employment. Over the course of time, this type of workers who quit has significantly less wage growth than do their counterparts who continued their employment. Moreover, downward wage growth is found among over-educated workers. In contrast, over-skilled workers have a temporary disadvantage from job movement but there are no significant effects during a three-year period. Furthermore, the empirical results show that over-education and over-skilling are persistent over time. The evidence shows that they are self-perpetuating from initial state and persistent from previous state.

Keywords: over-education, over-skilling, career mobility, upward occupational mobility, upward wage growth

4.1 Introduction

Over-education measures the deviation between the formal education obtained by workers and education required to perform a job. Over-education has been shown to impact wages. By contrast, over-skilling provides a more direct measure between knowledge and skills accumulated by workers and the actual skill requirements of their jobs. Over-skilling has been shown to impact satisfaction and job mobility (Allen & van der Velden, 2001; Kostas Mavromaras, McGuinness, O'Leary, Sloane, & Wei, 2010b; Kostas. Mavromaras, McGuinness, O'Leary, Sloane, & Fok, 2009c). It is argued in previous studies that skill matching better controls for the effects of unobserved ability than education matching. Skill matching has also been used to explain job satisfaction and job mobility.

Pay penalty and job satisfaction are theoretically expected to motivate over-educated workers to move to jobs in upward occupational ranks, resulting in greater post-move wage growth. In this paper, these predications of career mobility theory are tested. This analysis further reveals whether over-education is temporary or persistent.

The existing literature only examines the effects of job mismatches on job leaving (involuntarily and voluntarily), but it lacks further research on the consequences of job leaving. For example, a very important question for studying job mismatches is the answer to the question of whether or not voluntary job leavers experience upward occupational mobility and wage growth through re-employment. If job leavers are able to achieve a good skills match in their new positions, then these mismatches may be temporary and only a part of the career process. In addition, this movement may not involve any actual cost to them. This paper will contribute to the literature by providing further evidence in terms of upward occupational mobility as reflected by wage growth for over-educated workers.

This paper addresses workers' mobility resulting from the under-utilisation of skills in a dynamic setting. The study has two objectives: the first objective is to re-test career mobility theory in relation to the Australian labour market. Over-educated workers may

optimally choose a lower level employment for their future promotion opportunities. This theory was previously examined by Linsley (2005a) based on the data from the 1997 wave of the Negotiating the Life Course (NLC) survey. However, the analyses did not examine career mobility theory from wage growth or upward career mobility aspects directly. The information collected by the NLC survey does not allow to trace an individual's job match history. Thus, Linsley (2005a) proposed three models to examine career mobility theory indirectly. The relationships between promotion expectations and job match, between tenure and job match were examined, respectively, in first two models. The third model tested whether over-educated workers are more or less likely to have previously moved to a higher level occupation. The empirical evidence did not support career mobility theory.

However, this conclusion was disputed by Miller (2007) who argued that Linsley's results came from a small sample size which limited the power of the tests undertaken. Miller suggested that alternative datasets should be used to test career mobility theory in Australia. Compared with Linsley's study, this study will provide a comprehensive analysis on the effects of both education mismatches and skill mismatches using longitudinal panel data. The second objective is to investigate whether over-education and over-skilling are part of the career mobility process, and if these mismatches are temporary or persist overtime.

Furthermore, in comparison with the study of Mavromaras et al. (2009c) and Mavromaras et al. (2010b) in which a graduate sample was used, this current study expands the sample range from graduates to all working-age employees. The existing literature concentrates on the effect of over-education on labour market performance. I look also at the effect of under-education and this may afford additional insights.

The following questions are addressed:

> *To what extent do mismatches influence a worker's decision to quit (voluntary job leaving)?*
>
> *To what extent do mismatches influence workers' upward occupational mobility?*

To what extent do mismatches account for workers' upward wage growth?

Does career mobility theory explain the education mismatch and skill mismatch in the Australian labour market?

Are these mismatches temporary or persistent?

Thus, in consideration of the above analyses and under the framework of career mobility theory, the effects of job mismatches on job satisfaction, decisions to quit, training, upward occupational mobility and upward wage growth are examined, based on the HILDA panel data.

This essay extends the Australian literature as follows:

This is the first study to examine career mobility theory directly in Australia. Following the international literature, Büchel and Mertens (2004) and Rubb (2006) have examined career mobility theory from both upward occupational mobility and upward wage growth perspectives. This paper examines career mobility theory from these two aspects in the Australian labour market based on longitudinal data.

Both over-education and over-skilling are considered in this study. The analysis addresses heterogeneity of workers precisely through longitudinal data and econometric modelling.

This essay makes contributions as follows. Previous research employed static models to evaluate the impact of job mismatch. I extend the literature by using a panel data, and constructing a dynamic random effects probit model, controlling for the initial conditions, to examine the impact of job mismatch. I define job mismatch as the combination of education mismatch and skill mismatch. This combined variable is used to better control for workers heterogeneity than only an education mismatch or skill mismatch variable. Several important impacts of job mismatch are examined as a supplement of explanation of career mobility.

The next section provides a literature review concerning the theory, concept, and

empirical evidence with respect to over-education and over-skilling. The hypotheses and an analytical framework are given in Sections 4.3 and 4.4. Section 4.5 includes the HILDA Survey information and the variables used in my study. The empirical results and interpretations are discussed in Section 4.6. A summary of this section is provided in Section 4.7.

4.2 Literature review

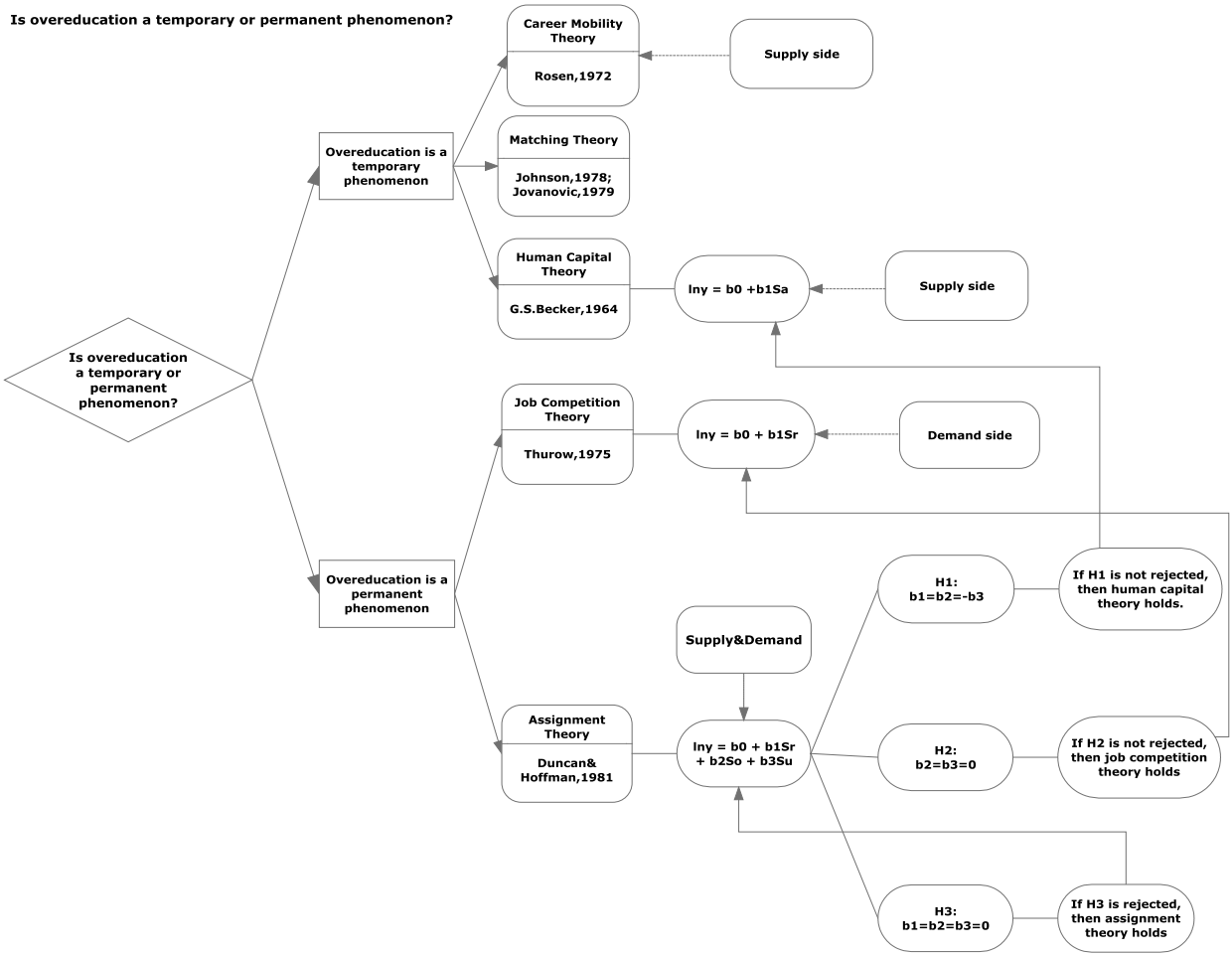
4.2.1 Is over-education a temporary or permanent phenomenon? (the theoretical perspective and empirical results)

Three major theories (human capital theory (Becker, 1964), matching theory (Johnson, 1978; Jovanovic, 1979) and career mobility theory (Rosen, 1972)) suggest over-education as a short-run phenomenon. In contrast, job competition theory and assignment theory support the idea that over-education is a persistent phenomenon.

Figure 4.1 describes two explanations of over-education from a theoretical perspective. It further reveals the associations between various theories by using earnings models. For example, based on assignment theory, Duncan and Hoffman (1981) proposed a standard Over-education, Required-education, Under-education (ORU) earnings model to analyse the effects of education mismatches on earnings. There are three hypotheses on the coefficient of over-education, required education and under-education. Each of these coefficients reflects a different theory perspective. Moreover, in considering labour supply and demand in the labour market, job competition theory supports the explanation of over-education from the demand side, whereas; assignment theory provides the explanation of over-education from both supply and demand sides. Human capital theory and career mobility theory explain over-education from the supply side and they consider over-education as a temporary phenomenon.

In this essay, the focus is on the first theory in Figure 4.1, that is, career mobility theory from the supply side to explain over-education.

Figure 4. 1: Is Over-education a Temporary or a Permanent Phenomenon?



4.2.1.1 Over-education as a temporary phenomenon:

Human Capital Theory (Becker, 1964) supports over-education as a short-run dis-equilibrium. An oversupply of educated labour leads to a reduction in labour market wages, which, in turn leads to organisations substituting cheaper educated labour with less educated workers. Next, individuals decrease their investment in education because of lower return. As time passes, organisations and individuals adjust the demand and supply respectively. Therefore, over-education is, at most, a short run phenomenon as

work experience increases.

Both matching theory and career mobility theory, described in the following section, are the extension of human capital theory. They also present over-education as a transient process and a temporary phenomenon.

Matching Theory (Johnson, 1978; Jovanovic, 1979) suggested that over-education is a temporary phenomenon for the individual, but a permanent occurrence in the economy. In this framework, over-education represents a poor match. Workers may temporarily accept jobs in which the educational requirement is lower than the workers' actual qualifications due to the cost of searching for employment. As time passes by, however, such workers are likely to leave their current position after searching for a position that offers a match for the quality of their skills and education level.

Career Mobility Theory was proposed by Rosen (Rosen, 1972). This theory was extended to occupational mobility, established by Sicherman and Galor (1990), and as an extension of human capital theory. Career mobility theory provides a persuasive explanation for the existence of over-education. Over-education may be a part of the career mobility process and it is part of a phase of insertion and adaptation in the early stages of the working life (Groot & Maassen van den Brink, 2003). Over-educated workers may optimally choose a lower level employment, if the effect of education on the probability of being promoted for these jobs is higher than for other jobs. Over-educated workers may sacrifice a wage premium in their current jobs to gain specific skills, or other types of human capital, enabling them to move to higher- level jobs and higher wages. In this model, total human capital, not just the number of years of education, has impact on productivity. Therefore, the years of over-education may compensate for a lack of work experience, training and tenure. Also, employers may save on training costs by the recruitment of over-educated workers. As a result, in this model, over-education can be an optimal choice for both employers and employees where no resource inefficiency is involved.

To test career mobility theory, Sicherman (1991) conducted an empirical analysis on the

1976 and 1978 waves of the Panel Study of Income Dynamics (PSID). The empirical results confirmed career mobility theory in which over-educated workers have higher turnover rates and higher upward occupational mobility than other workers with similar characteristics. On average, over-educated workers have less experience and they receive lower amounts of on-the-job training than workers with the required level of schooling. There is a negative relationship between the schooling effect on wages within occupations and the schooling effect on the probability of moving to a higher-level occupation.

Using the same PSID data but with 1976, 1978 and 1985 waves, Robst (1995) re-examined Sicherman's (1991) analysis. Robst argued that controlling for the workers' actual education may not clearly test for the validity of career mobility hypothesis that over-educated workers are more likely to have upward mobility than adequately educated workers in similar jobs. The reason is that if an over-educated worker has the same level of education as that of an adequately educated worker, he/she must work in a job that requires a lower level of education than that of the adequately educated worker. To solve this problem, Robst studied the labour market performance of both over-educated workers, and adequately-educated workers (controlling for actual education or controlling for required education). Robst found that over-educated workers, over time, are more likely to move to better jobs that require a higher level of education in both cases. Generally speaking, because jobs requiring a higher level of education usually demand a higher level of human capital and they pay higher wages, these positions are the superior ones in relation to those positions requiring a lower level of education. Robst suggests that comparing jobs rather than occupations is a more meaningful way to examine the question of how education affects job movement. For a given job he finds that over-educated workers are more likely to move to a job requiring higher education.

Hersch (1995) supported career mobility theory and suggested that mismatch seems to be optimal. According to Hersch, from an employer's perspective, the training cost is lower for over-qualified workers, than for their less qualified colleagues, despite the fact that over-qualified workers have a higher turnover rate. From the perspective of the worker, over-qualified workers sacrifice temporary mismatches to gain opportunities for future promotion. Empirical evidence suggests that initially employed over-qualified workers

receive less training but greater opportunities for promotion than their well-matched colleagues. Job matching processes take place within a firm instead of changing firms. However, over-qualified workers who do not receive promotion in their current jobs are more likely to quit.

In Spain, Alba-Ramirez (1993) conducted an empirical study and the results are in line with occupational mobility theory. Over-educated workers have less experience, less chance to access on-the-job training, a higher turnover rate than other comparable workers, and their mismatch is improved with age and mobility. Conversely, some different results are found in Alba-Ramirez and Blazquez (2003) that over-educated workers, whose formal training or education is closely related to their jobs, are more likely to receive on-the-job training and to be promoted within the firm than the other two types of over-educated workers. This group has a significant probability of quitting if they are not promoted in their study.

In addition, Büchel and Mertens (2004) argued that career mobility model should be tested in a wage growth approach, which is the basic indicator of upward mobility. They pointed out that moving to a better job should be observed, not only in moving to a higher occupational level, but also with an accompanying wage growth. Using the German Socio-Economic Panel (1984-1997), both upward occupation mobility and wage growth for over-educated workers were tested. In contrast with career mobility theory, over-educated workers in Germany are less likely to move to a higher occupational level or to experience above average wage growth than adequately educated workers over both two-year and five-year time durations. Büchel and Mertens (2004) explained that the reason is country-specific where the United States and Germany have differing allocation mechanisms. Additionally, job mobility is freer in the U.S. than in Germany. However, this interpretation was disputed by Rubb (2005). Nevertheless, Rubb (2005) commented that Büchel and Mertens (2004) provided a theoretically sound list of plausible weaknesses in the career mobility theory and also applied empirical tests; although the analyses and interpretation of their results were potentially flawed because they controlled for educational attainment and not for occupational level. As for the opportunity of training and promotion, in line with the findings by Robst (1995) and

Hersch (1995), German over-qualified workers are less likely to gain on-the-job training opportunities, and less likely than their well-matched counterparts to gain knowledge that could lead to a superior position or to promotion.

Furthermore, a similar empirical testing approach has been applied to the United States labour market where both occupational mobility and earnings growth of over-educated and under-educated workers were examined by Rubb (2006) based on U.S. CPS (1994-2000). The results differ from the findings of Büchel and Mertens (2004). According to Rubb (2006), over-educated workers have a greater likelihood of upward occupational mobility and faster earnings growth in their occupations than adequately educated and under-educated workers. These findings are not only in line with occupational mobility theory but they also extend this theory by supporting the earnings growth aspect. Rubb (2006) also predicted that employers are likely to provide more training for under-educated workers compared to over-educated workers, due to the higher transiency rate among over-educated workers. The tenure and training effects on the earnings of over-educated workers would provide some useful information to explain whether intra-firm or inter-firm activities cause the wage growth and upward occupational mobility of over-educated workers. However, these hypotheses were not been tested due to lack of data.

Similarly, Groeneveld and Hartog (2004) applied a standard ORU model for a large firm producing energy, and a telecommunication firm to analyse the effects of over-education. They found that over-educated workers have a higher probability of job promotion and wage growth than do under-educated workers in an internal labour market, in particular, amongst younger employees. However, in relation to the firm's external labour market, only the effect on job promotion for over-educated workers was observed.

By using two waves of a Dutch longitudinal survey, Groot and Maassen van den Brink (2003) found over-education to be a transitional phenomenon and that only a small proportion of worker could not exit from over-education over a period of time. Over-educated workers would obtain education matched jobs through job-to-job mobility across the firm instead of internal mobility within the firm. Empirical evidence was found that over-education compensates for lack of experience and tenure.

In Britain, the results from Sloane et al. (1999) are mixed. In the opinion of that study, over-educated workers experience higher rates of job mobility and have shorter employment duration in their current job, and a higher likelihood of involuntary job separations. Rather than being promoted to move into higher occupational level positions, over-educated workers do not improve their mismatched status by changing jobs, on the contrary, they may become unemployed. The implication of this result is that over-educated workers may be stuck in the secondary sector with minimal access to a successful employment match or they may have lesser ability or an inferior quality education, which impede to achieve a good match.

4.2.1.2 Over-education as a permanent phenomenon:

Contrary to the perspectives of the previously mentioned theories, both the job competition model and the screening model consider over-education to be a long-term phenomenon, which produces a serious inefficiency in human capital resource allocation.

Job Competition Theory (Thurow, 1975) suggested that when there is a queue of workers in the labour market who are competing for jobs. Those at the head of the queue are hired first. A worker's position in the queue is determined by their training cost. It is assumed that highly educated workers are more able and productive and require less training than those who are less well educated. Remuneration is fixed to the position of employment. Over-educated workers receive the same wage as those who are in jobs with the required level of education.

The increase in the educational attainment of workers causes a shift in the distribution of workers in the labour queue; organisations will employ people with higher education which forces low-skilled workers into lowly paid jobs or into being unemployed. People with higher education pay a penalty since they are forced to accept lower level jobs rather than matched jobs in the job queue. Even though over-educated workers have lower returns on their educational investment than matched workers, in order to secure a job or to keep a position, rational individuals still will invest in education. The job competition theory explains that over-education is a suboptimal investment in education, a form of

allocation inefficiency.

Assignment Theory (Sattinger, 1993) encompasses both the Mincer earnings human capital model and Thurow's (1975) job competition model in a general equation which is referred to as the ORU model (Duncan & Hoffman, 1981). A mismatch problem exists in cases where workers who differ in human capital are allocated jobs of levels of complexity which do not match the degree of human capital that they possess. According to the assignment theory, the heterogeneity between workers and jobs may impede the match between workers and jobs in a dynamic economy; in such a situation, over-education would be a permanent feature of the labour market. A few studies have showed that assignment theory outperforms both the human capital and job competition models (J. Hartog & Oosterbeek, 1988; P. J. Sloane et al. 1999).

Dolton & Vignoles (2000) using a one in six sample of the year 1980, found that the over-education rate was 38% for graduates who work in their first job and six years later, for U.K graduates who were surveyed in 1986, it was 30%. The researchers suggested the assignment model is the best for explaining the phenomenon of over-education in the U.K. market.

In Canada, similar results were found by Frenette (2004). After examining the incidence of over-qualification in the labour market of Canadian graduates, he reported little evidence of any decline in the incidence of over-qualification over a 3-year period. This finding indicates that over-qualification is a highly state-dependent and persistent phenomenon.

4.2.2 Over-education and over-skilling

Most previous studies have been concerned with over-education, defined by the extent of mismatch between workers' actual educational attainment and the educational requirements of their positions of employment. Since over-education does not offer direct evidence about the extent of skills mismatch, it cannot distinguish whether or not the

penalty paid by over-educated workers is due to a form of market failure, or whether it can be attributed to the inferior quality of over-educated workers. In addition, according to McGuinness & Wooden (2009), a measure of education might produce the following problems. (1) Formal education, on-the-job-training and experience as well as other abilities accumulate human capital which would determine productivity. Measures of over-education ignore unobserved heterogeneity, which would bias estimation results. (2) Simply comparing education levels, rather than the types of education, could mean that a measure for over-education would not account for the degree of fit between type of education acquired and that required. (3) In order to screen potential employees, employers may increase formal job entry requirements; these may considerably exceed the level of education required to perform the job. Under this circumstance, workers undertaking such jobs would be over-skilled but would not be categorised for over-education (Seamus McGuinness & Wooden, 2009).

To overcome the failure of controlling for unobserved ability from the measure of over-education, researchers have started to use an over-skilling variable instead of one for over-education. This is because, conceptually, over-skilling more seemingly reflects the presence of skills that could easily be related in the employment context. It further includes some components that could not be represented by formal education (Kostas Mavromaras, McGuinness, & Wooden, 2007). Specifically, for some datasets, skilling variable may directly assess workers' utilisation of 'ability and skills'. In contrast, over-education measures the deviation between the formal education obtained by the worker and the education required by the employer in order for the worker to perform a job.

Empirical evidence has shown that over-skilling is different from over-education (Allen & van der Velden, 2001; F. Green & McIntosh, 2007); over-skilling is most likely to capture unobserved individual ability, thus providing some further insight into the quality of match (Kostas Mavromaras, McGuinness, O'Leary, Sloane, & Fok, 2010a). Allen and van der Velden (2001) reported there was "relatively weak" relationship between responses to a subjective question on skills utilisation and education mismatch. Similarly, there was only a 0.2 correlation between measures of over-skilling and over-education in the UK data that was reported by Green and McIntosh (2007).

Few studies included in the literature have used over-skilling variables. This is principally due to data limitations on this type of information. While more data has become available, some recent studies have placed increased focus on the relationship between over-education and over-skilling as an instrument for the evaluation of theoretical models for the labour market (Mavromaras et al. (2009c) and Mavromaras, Sloane & Wei (2012)).

Recently, in Australia, several studies have focused on the skills relating to employment mismatches based on the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Over-skilling is measured by the degree to which employees state that they are making adequate use of their skills and abilities in their jobs. In detail, over-skilling is derived from HILDA by using the responses, scored on a seven point scale, to the statement; "I use many of my skills and abilities in my current job", with a response of 1 corresponding with strongly disagree, and 7 with strongly agree. A similar question was employed in the studies of both Allen and van der Velden (2001) and Green and McIntosh (2007)[31]. In Mavromaras, et al. (2010b), individuals with responses of 1,2,3 or 4 on the scale were classified as over-skilled and those with responses of 5,6 or 7 as skill-matched. These two classification categories of 'over-skilling' differ from previous studies (Kostas Mavromaras, McGuinness, O'Leary, Sloane, & Fok, 2010a; Kostas. Mavromaras, Séamus. McGuinness, Nigel. O'Leary, et al., 2009c; Seamus McGuinness & Wooden, 2009) in which over-skilling was classified in three categories: (1) the severely over-skilled (individuals with responses of 1, 2, or 3 on this scale); (2) the moderately over-skilled (those with responses of 4 or 5); (3) the well-matched (those selecting 6 or 7). These cut-off points for extreme and moderate over-skilling were appropriate; this was confirmed by the sensitivity tests in the work of McGuinness and Wooden (2009)[32]. Moreover, in

[31]In the data used by Allen and van der Velden (2001), responses scored on a five point scale to the question: "My current job offers me sufficient scope to use my knowledge and skills" were addressed as a measure of skills underutilisation. To define the over-skilled, Green and McIntosh (2007) combined the answers from two items: (1) In my current job, I have enough opportunity to use the knowledge and skills that I have (2) How much of your past experience, skill and abilities can you make use of in your present job?

[32] McGuinness and Wooden (2009) cross-tabulated the over-skilling variable with a measure of job complexity (responses to "my job is complex or difficult" which scored on the same 7 point scale used to measure over-skilling) to confirm that the more over-skilled the worker, the less difficult they consider their job to be. They further refined that either the severely or moderately over-skilled must not report high levels (a score of more than 5) of job complexity. They claimed that this association showed that the over-skilling

Mavromaras, et al. (2009b), in which moderately over-skilled workers were excluded from the analysis, the inclusion of workers in this category tended to give rise to a sharp contrast between the severely over-skilled and the well-matched workers.

After applying the preceding definition of over-skilling to the study, based on these empirical results, McGuinness and Wooden (2009) summarised that the over-skilling variable provides a more direct measure between worker accumulated knowledge and skills, and the actual skill requirements of their jobs, therefore, that over-skilling is the preferable variable for estimation purposes than the over-education variable.

Further empirical evidence was also found in Mavromaras, et al. (2010b). The researchers compared the over-skilling variable, which was directly given in the HILDA Survey with the over-education variable, which was based on an empirical method. They found that about 50 percent of over-educated workers were classified as over-skilled and the other half as over-educated workers who are skill matched. Using an occupational mode measure of over-education, less than 25 percent of severely over-skilled workers are over-educated. After examining the effects of over-skilling and over-education on wages, both respectively and jointly, and accounting for some of the unobserved individual differences, the researchers found that over-education and over-skilling contain different information; the over-skilling variable was the most preferred as it offered a direct control of the quality of the employer-employee match.

4.2.3 Empirical findings in the Australian labour market

The results from international literature regarding the effect of over-education on career mobility are mixed. A numbers of studies in U.S. (Sicherman & Galor ,1990; Sicherman, 1991; Robst ,1995; Rubb, 2006), in Dutch (Groot & Maassen van den Brink, 2003) and in Spain(Alba-Ramirez , 1993) supported career mobility theory to explain the existence of over-education. These studies suggested that over-education is a temporary

responses would not be biased by respondents having incorporated non-labour-market-relevant skills and abilities into these responses.

phenomenon. In contrast, the Australian Linsley (2005a)'s study did not support career mobility theory, which aligned with the German evidence found by Büchel and Mertens (2004).

Using occupation mobility and wage growth to examine career mobility theory have been done in U.S. (Rubb, 2006) and Germany (Büchel & Mertens, 2004). My study will extend the international literature to examine career mobility theory from a dynamic upward occupation mobility, and wage growth perspective in Australia based on longitudinal data.

4.2.3.1 The effect of over-education on job mobility

In Australia, Linsley (2005a) proposed three career mobility models to test career mobility theory based on the data from the 1997 wave of the Negotiating the Life Course (NLC) survey. The empirical results are mixed. (1) Contrary to career mobility theory, over-educated workers have lower promotion expectations than adequately educated workers who have similar education, but work in jobs allocated in higher level occupations. This effect is significant for women, not for men. This finding implies that over-education persists for women. (2) In line with the career mobility theory, over-educated women are less likely to have had five or more years of tenure with their current employer; under-educated men are more likely to stay with current jobs and to experience upward mobility. Due to these results, Linsley concluded that over-education is persistent and it brings substantial cost by not only reducing an individual's current and future earnings, but also impeding his or her career prospects. This empirical evidence does not support the career mobility theory, but is in line with the predictions of the job competition model. However, this conclusion was disputed by Miller (2007), who argued that Linsley's results come from a small sample size which limits the power of the tests undertaken and he suggested that alternative datasets should be used to test the career mobility theory in Australia.

4.2.3.2 The effect of over-skilling on job mobility

Based on the same dataset, McGuinness and Wooden (2009) examined the extent to which

over-skilling is a transitory phenomenon. Their results are in line with Sloane et al. (1999). Some over-skilled workers have greater job mobility due to involuntary job separations. Even though over-skilled workers have voluntarily left their previous employer, the majority do not improve their employment match in order to fully use their skills through re-employment. Instead, most remain either over-skilled for their employment role or exit from the workforce entirely.

Also using the same dataset, but extended from the first four waves to the first six waves of the HILDA survey, Mavromaras et al. (2009b) adopted dynamic panel econometric methods to estimate the dynamic process of over-skilling, and the state dependence[33] of over-skilling. They pointed out that: "The presence of state dependence in over-skilling is important for policy reasons, as the cost of labour market mismatches for individuals depends on both the size of the wage penalty and on how long that penalty persists." Referring to previous findings[34], Mavromaras et al. (2009b) excluded the moderately over-skilled from the analysis and focused on the sharp comparison between the severely over-skilled and well-matched workers. Their study found that degree-level education remained significant whilst vocational education became statistically insignificant. This is contrary to findings of Mavromaras et al. (2009a) in which, both vocational and degree-level educational variables are significant in an over-skilling incidence equation. Mavromaras et al. (2009b) pointed out that these two results are not contradictory because they are answering different questions based on the differing nature of data and estimation methods[35] between each of the studies. The results of Mavromaras et al. (2009b) suggested that this over-skilling state dependence varied strongly according to education pathway. Over-skilling is more likely to be a short-term phenomenon for vocational education graduates, but is persistent for degree-level graduates due to state dependence

[33] State dependence is defined as the degree to which the effect of any initial endowments on an outcome may be attenuated or accentuated by the continued presence of that outcome (Heckman 1981; 1991).

[34] Moderately over-skilling has no significant effect on the wage penalty (Mavromaras et al. 2009b) and on adverse mobility (McGuinness & Wooden, 2007).

[35] Rather using the nature of longitudinal HILDA data, Mavromaras et al. (2009a) applied pooled regression estimation method based on the cross-sectional data. Hence, the results reflected the difference in over-skilling between people with and people without a particular type of qualification, all observed at the same point in time.

in the labour force.

Furthermore, Mavromaras and McGuinness (2012) employed the Wooldridge (2005) method with Mundlak (1978) correction approach based on the same dataset (the first six waves of the HILDA survey) to examine whether over-skilling is a self-perpetuating labour market state and whether state dependence differs by education pathway. They found higher degree graduates suffer the greatest over-skiing state dependence, and also suffer the highest over-skilling wage penalty compared to vocationally qualified workers.

Moreover, Mavromaras, Mahuteau, Sloane and Wei (2013) employed the Wooldridge method with Mundlak correction approach to examine the persistence of over-skilling in over-skilling dynamics models. They used unbalanced panel of the first nine waves of the HILDA survey. Results showed that although university graduates have lowest persistence of over-skilling mismatch but they suffer the highest over-skilling per person losses than workers who are in other education category. By contrast, VET graduates who hold Certificates showed high persistence but low wage losses.

These studies have employed a dynamic panel approach to examine the state dependence of over-skilling. However, they did not examine the effects of over-skilling on upward occupation mobility and upward wage growth. My study does examine these effects and therefore extends the literature.

4.2.3.3 The effect of over-education and over-skilling on job mobility

The studies of both Mavromaras et al. (2009c) and Mavromaras et al. (2010b) explore the relationship between job mobility and mismatch, disaggregated by male and female. Their studies have used a graduate sample, and the empirical mode method to define the required education. They also used the same cut-off point to define over-skilled and skill matched categories and the same random effect estimates. The difference between the studies is the data being extended <u>from six waves in the 2009 study to seven waves in the 2010 study.</u> Empirical results from Mavromaras et al. (2009c) imply that either over-education is a consequence of choice in many types of employment, or it compensates

some workers with lower ability or bad quality of education. Over-skilling, in contrast, imposes real costs on individuals and it is one form of market failure. This conclusion is further confirmed in the follow up of the Mavromaras et al. (2010b) study which shows that over-education is a matter of choice or necessity, whereas over-skilling is a matter of regret. These results are in line with (Allen & van der Velden, 2001) in which over-education was shown to have an impact on wages, but over-skilling affects satisfaction and job mobility.

Mavromaras, Sloane and Wei (2012) used a random effects model with the Mundlak (1978) correction to examine the outcome of over-skilling and over-education on wages, and a random effects probit model to estimate the effect of job mismatch on job satisfaction for full-time employees in Australia. They used an unbalanced panel, which was taken from the first eight waves of the HILDA survey. They used four job mismatch groups of well-matched, only over-educated, only over-skilled, and both over-educated and over-skilled. They found difference in satisfaction and wage by type of mismatch, education pathway, gender and age. Many instances where a mismatch is correlated to reduce wages and job satisfaction are found, therefore, a good job match would benefit both employers and employees.

4.3 Hypotheses

Career mobility theory suggests that over-education is temporary for individuals and that it is a phase of insertion and adaptation in the early stages of the working life (Groot & Maassen van den Brink, 2003). Based on the prediction of the career mobility theory, I use the longitudinal HILDA data to test the following hypotheses:

- Over-skilling on its own, or jointly with over-education, has a significant effect, in terms of quitting (voluntary job leaving).
- Career mobility theory predicts that individuals currently in positions for which they are over-educated are likely to have higher rates of upward occupational mobility than other workers with similar characteristics.

- Career mobility theory predicts that individuals currently in positions for which they are over-educated have higher rates of upward wage growth mobility than other workers with similar characteristics.

4.4 Analytical framework

The theoretical framework of career mobility theory has been tested in different countries. For example, the US labour market was examined by Sicherman and Galor (1990); the labour market in Germany was evaluated by Büchel and Mertens (2004); and the Australian labour market was examined by Linsley (2005a). These studies have used different perspectives and factors to test the theory of career mobility; their results are mixed.

In the current study, I test the theory of career mobility in the Australian labour market. Due to low job satisfaction in their current employment, over-educated workers or workers whose skills are under-utilised, may desire to leave their current employment to search for positions that are better suited to their individual strengths and capabilities. Meanwhile, employers may not be willing to risk training these categories of workers due to their high turnover rate. Human capital theory explains the substitution relationship between education and other types of human capital. Thus, workers who use their surplus education to compensate for their lack of work experience or on-the-job training are likely to be hired. Employers are inclined to hire this type of worker because of the savings made on not having to provide on-the-job training. Thus, over-education is only a temporary phase. Once workers enhance their experience and equip themselves with specific skills, they are likely to be offered higher, more responsible, positions and thus experience wage growth. Following this analysis, the relationship between job mismatch and upward mobility, is tested. The results not only shed light on the question of whether or not the theory of career mobility can be used to explain the over-education phenomenon in the Australian labour market, but also reveal whether over-education and over-skilling are merely temporary or are persistent. Furthermore, the state dependency of over-education and over-skilling are respectively evaluated as a complementary examination of the findings.

In order to make better use of the longitudinal features of the data; the dynamic standard random effects probit models with varying specifications[36] are applied. Two problems occur with dynamic models. The first problem comes from the possibility of correlation between the lagged-dependent variable on the right hand side and the error terms. This issue is addressed as an initial conditions problem. The Wooldridge (2005) approach is employed in order to solve this problem. Wooldridge's Conditional Maximum Likelihood (CML) estimator is generated by setting up the distribution of individual effects, conditional on both the initial value of the dependent and explanatory variables. Heckman's (1981) estimator requires a specification of the joint probability of the observed sequence of explanatory variables. By conditioning on the initial value of dependent variables, the Woodridge approach avoids the requirement of Heckman's estimator, and also it defines an estimator that is easier to compute.

Arulampalam and Stewart (Arulampalam & Stewart, 2009) evaluated some estimators proposed by Heckman, Orme[37] and Wooldridge. They found that none of these estimators dominated the others, and that three estimators performed almost equally, except in the instances where time periods were short.

A second potential problem arises from the biases occurring in the correlation between explanatory variables and error terms; this problem is solved by using the Mundlak (1978) correction.

In the following latent model, β is unbiased if explanatory variables x_{it} and individual

[36] So far, most previous research employed static models to evaluate the impact of job mismatch. Static models are special instances of dynamic models, which constrain that the coefficients on lags of dependent variables and coefficients on initial status of dependent variables are zero. If both coefficients are significant, then static model exist some omitted variable problems. However, static models may reveal some information, in particular, when analysing the upward mobility, the dynamic models are not applicable for a five-year period due to the deletion information. Instead, static models are used to estimate these effects. Thus, both dynamic models and static models are employed in this study. The results for the static models are in the Appendix 4B.

[37] Orme (1997) used an approximation to substitute individual effects with another unobservable component that is uncorrelated with the initial observation.

specific effects μ_i are independent, that is

(4.1) $$y_{it}^{*} = x_{it}\,\beta + \mu_i + \varepsilon_{it}\text{ , Where } E[\mu_i|X_i] = 0, and\ \varepsilon_i|\ X_i \sim \mathrm{N}\ (0,\sigma_{\varepsilon}^{2}).$$

To relax this assumption, the Mundlak (1978) model proposes individual effects μ_i as a function of individual means, that is $\mu_i = \bar{X}_\iota\ \delta + \eta_i$, where $\eta_i|\ X_i \sim \mathrm{N}(0,\sigma_{\eta}^{2})$. It assumes zero correlation between $\bar{X}_\iota$ and η_i.

Thus, we have $E[\mu_i|X_i] = \bar{X}_\iota\delta$, where $\bar{X}_\iota$ is an average of x_{it} over time for individual i, and it is time invariant.

We rewrite the above latent model as

(4.2) $$y_{it}^{*} = x_{it}\,\beta + \bar{X}_\iota\delta + \left[\varepsilon_{it} + \mu_i - E[\mu_i|X_i]\right] = x_{it}\,\beta + \bar{X}_\iota\delta + u_{it}\quad ,$$

where

u_{it} is new error term for the whole model, based on construction, we have

(4.3) $$E[u_{it}|X_i] = E[\varepsilon_{it} + \mu_i - E[\mu_i|X_i]\ \ |X_i] = 0$$

Mundlak's approach is used to control for endogeneity effects due to unobserved individual effects. It is considered as a compromise between the fixed and random effects models. It also provides a test for adjustment for endogeneity as an alternative to the Hausman test--If the coefficient on group mean δ is non-zero, that suggests that individual effects are not to be ignored (Greene, 2010).

Combining Wooldridge's (2005) approach and the Mundlak (1978) correction, the unobserved individual effect μ_i is conditional on the initial observed dependent variable y_{i0} and the means of time varying explanatory variables.

(4.4) $$\mu_i = \Upsilon_0 y_{i0} + \bar{X}_\iota \delta + \eta_i \;\; where\; \eta_i | X_i, y_{i0} \sim \mathrm{N}\left(0, \sigma_\eta^2\right)$$

Thus, the dynamic model is written as:

(4.5) $$y_{it}^* = \Upsilon y_{it-1} + x_{it}\,\beta + \Upsilon_0 y_{i0} + \bar{X}_\iota \delta + \eta_i + \varepsilon_{it}$$

It is noted that coefficients δ and Υ_0 will differ between panels of different lengths T and they are specific to the particular sample. The estimates of β approximate the fixed effects estimators, as approved by Wooldridge (2009). The estimates of Υ examine the state dependence of the dependent variable.

These random effects probit models with Mundlak correction were used by Mavromaras and McGuinness (2012) to examine whether over-skilling is a self-perpetuating labour market state and whether state dependence differs by education pathway. The same approach was also used by Mavromaras, Sloane and Wei (2012) to examine the outcome of over-skilling and over-education on wages and the job satisfaction of full-time employees in Australia. The Wooldridge method with Mundlak correction approach was used by Mavromaras, Mahuteau, Sloane and Wei (2013) to estimate the persistence of over-skilling in over-skilling dynamics models.

However, none of these studies used random effects probit models to examine the impacts of job mismatch on upward occupation mobility and upward wage growth in Australia. The study will provide new evidence on examine career mobility theory in a dynamic setting, and reveal whether over-education or over-skilling, or jointly lead to future upward career mobility. This will extend the literature.

Random effects probit models are proposed to estimate the effects of job mismatch on quitting and upward job mobility. All models are tested not only by controlling for educational attainment, but also for occupational levels.

In addition, two random effects probit models are used to examine the state dependence of over-education and over-skilling, respectively.

4.5 Data and variables

4.5.1 Data

The data used in this research is sourced from the first nine waves of the HILDA Survey. The sample is restricted to an unbalanced panel of all working-age male full-time employees (23-64). The HILDA survey provides information on job separation from wave 2 onwards. Workers who have changed jobs since the last interview were asked the main reason that they stopped working in the job that they had held at the time of the previous interview. To test the effect of job mismatch on job separation, this research matches this variable with previous job mismatch status by using individual id as a key. Thus, wave 9 data is excluded after transferring the information relating to job separation to wave 8. Job training information is available from wave 3 onwards. In combining job separation and training, wave 3 to wave 8 data is used. Because the focus is on the comparison of upward job mobility between workers who stay in their current job and workers who leave voluntarily, workers who leave involuntarily or leave for other reasons are excluded from the test. In addition, self-employed workers and; fulltime or part-time students, are excluded. Time periods and unemployment are included as explanatory variables.

4.5.2 Variables

The earnings variable used in this study is logged hourly wage from main job. To derive the hourly wage for main jobs, the first step is to convert nominal earnings to real earnings. 2009 is used as the base year, reference ABS CateNo6345.0 labour price index, and the real earnings for each year are generated by taking the nominal earnings and dividing the data by the wage price index. To account for an absence of response to questions relating

to employment (in the responding households), wages are presented as missing data, thus, the variable chosen is imputed weekly gross wages and salary for main jobs[38]. After converting the imputed nominal weekly gross wages and salary from main job to real imputed weekly gross wages and salary, hourly wage from main job are derived by using the imputed real weekly gross wages and salary from main jobs is divided by the weekly average number of hours worked per week in main job. Then the hourly wage is converted into logged hourly wage.

On-the-job training is a dummy variable, derived from the responses to the question relating to part taken in any work related training in the past 12 months [excludes those employed but not employees], with value 1 labels, yes and 2 labels, no. Variables are available from wave 3 to wave 8.

Job scale variable is based on AUSEI06 occupational status scale of current main job, which is used to control for job level. McMillan, Beavis & Jones (McMillan, Beavis, & Jones, 2009) introduces the Australian Socioeconomic Index 2006, which assigns sociologically occupational status scores to the official occupational classifications of the Australian Bureau of Statistics (ABS). AUSEI06 is generated based on the 2006 Census of Population and Housing data. AUSEI06 reports that medical practitioners are at the top of the scale (100), then other health professionals (94), university lecturers and tutors (92) and legal professionals (91). Laborers are placed at the bottom of the scale.

Required education is measured with the empirical Mode measure based on the results[39] from Mavromaras et al. (2010b), and then over-skilling is defined by following their

38 Imputation methods are used to deal with missing cases. Since income is a sensitive issue for some people who do not report their income in interview, thus missing data occurs. Nearest Neighbour Regression imputation & the Little and Su imputation are applied to the imputation of data for responding persons. A full description of the imputation process for the income variables is provided by Hayes and Watson (2009).

39 After comparing using the 'objective method' as used by Kler (2005), the 'empirical method' was selected to define over-education because, even though the minimum required qualifications obtained from ANZSCO are generally consistent with the mode of education from 'empirical method', they are questionable(e.g. for degree for farmers). In addition, both measures to define over-education lead to similar results.

approach[40].

The HILDA survey does not provide any questions on over-education; and also worker's self-reported (SR) is not applicable. Thus, in this research, the required years of education to do a job are defined with a cross-wave Mode measure, in varying waves; this measures the number of years of education to undertake particular employment positions. Variable jbmo62 provides 2-digit ANZSCO 2006 occupations category for employed workers for each wave. First, the cross-wave Mode measures the required years of education to take on an employment position varying by waves. Then, the amount of education that most commonly occurs within an occupational category is calculated for each wave. The required years of education for the whole nine waves are derived by combining all the waves of Mode education and grouping them together. Then years of over-education and years of under-education are obtained by comparing the actual years of education with the required years of education.

Spearman's rank correlation coefficient between the over-educated and the over-skilled is 0.0142 and the test for null hypotheses cannot reject the independence of over-education and over-skilling. This is consistent with the results of Green and McIntosh (2007), and Allen and van der Velden (2001). Over-skilling is more likely to capture unobserved individual ability, thus providing some further insight into the quality of match (Kostas Mavromaras, McGuinness, O'Leary, Sloane, & Fok, 2010a). Green and McIntosh (2007) found a 0.2 of correlation between measures of over-skilling and over-education in UK data. Allen and van der Velden (2001) reported there was a "relatively weak" relationship between the responses to a subjective question on skills utilisation and educational mismatch.

[40] In detail, over-skilling is derived from HILDA by using the responses, scored on a seven point scale, to the question "I use many of my skills and abilities in my current job", with a response of 1 corresponding with strongly disagree, and 7 with strongly agree. Individuals with responses of 1, 2, 3 or 4 on the scale were classified as over-skilled and those with responses of 5, 6 or 7 as skill-matched. The sensitivity tests confirm the cut-off points for over-skilled and skill-matched are appropriate.

4.5.3 Other variables

This section introduces the variables and relationships in the research. Firstly, six types of mismatched groups are defined. Secondly, the relationship between overall job satisfaction and over-skilling, over-education is examined. Thirdly, job mobility by education and skill matches is evaluated. Finally, upward occupation mobility and upward wage growth variables are defined.

1. **Education and skill mismatch**

According to the definition of required education and over-skilling, and considering both education mismatch and skill mismatch, the entire sample is divided into six job-matching groups[41]. Figure 4.2 describes these combinations.

Well-matched: the individual works in a job where both education and skills are matched the job requirements.

Individuals holding a professional degree (e.g. law or medicine) or a skill-specific certificate work in their particular field, such as, the legal profession or plumbing.

Only Over-educated: the individual works in a job for which he/she is over-educated but skill- matched.

Individuals with less ability or with an education of lower quality are forced into lower level positions which are more commensurate with their actual level of skill; individuals work in a position with a lower educational requirement but which utilises their skills.

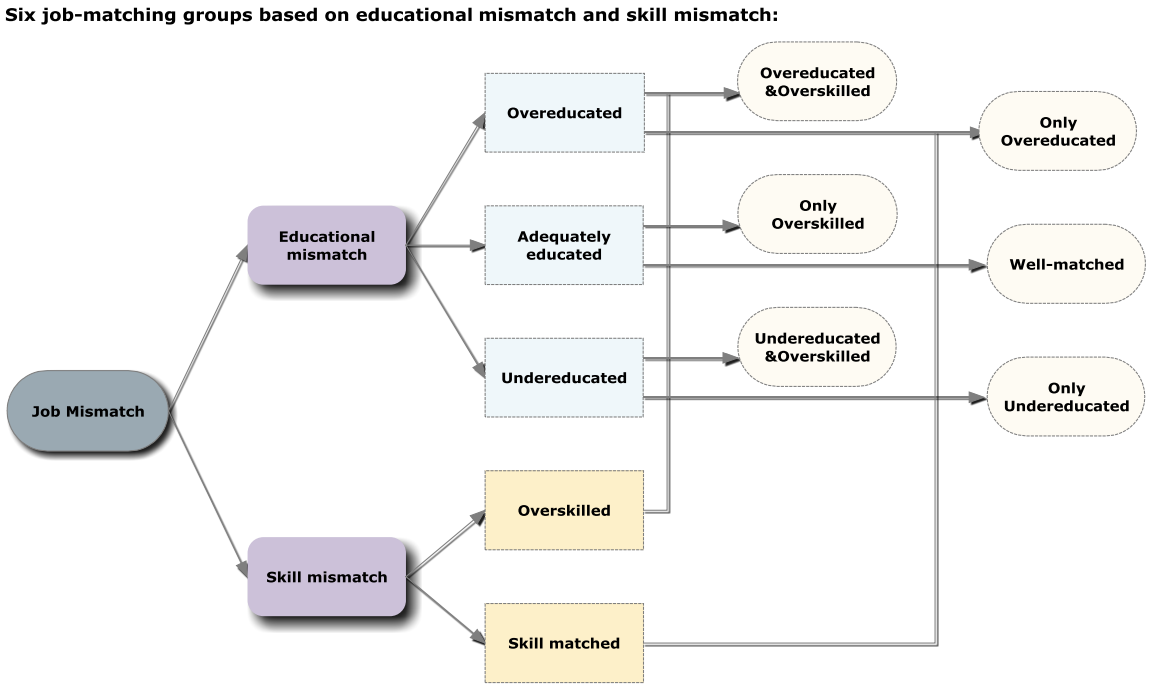
Only Over-skilled: the individual works in a job for which he/she is over-skilled but not over-educated. His or her educational level is matched to his or her work requirement.

With the increasing supply of educated workers, employers may be expected to raise their hiring requirements in relation to education standard, but have not necessarily

[41] In Mavromaras et al. (2010), the sample is limited to working-age (16-64 for males, 16-59 for females) employees holding a university degree or equivalent qualification. It is not possible for this graduate group holding the highest level of education to be under-educated. Therefore, in their sample, there are four worker-job matching categories (the first four groups in this study).

updated their actual technological working conditions. The individual employed under this hiring standard, is over-skilled but not over-educated.

Figure 4. 2: Construction of Six Types of Educational and Skill Mismatched Groups



Over-educated & Over-skilled: the individual works in an employment position where both his education and skill level exceeds those required by that position.

Individuals, who have difficulty in locating jobs, genuinely underuse both education and skill. Examples of this are, women with children and part-time workers who are susceptible to both mismatches.

Only Under-educated: the individual works in a job for which he is under-educated but skill matched.

Individuals work in jobs where the skills requirements are commensurate with their actual level of skills, but the educational requirement of which exceeds their

educational attainment. Usually under-educated workers have a long tenure with their current employer, a long period of work experience and a considerable amount of on-the-job training.

Under-educated & Over-skilled: the individual works in a position for which he/she is under-educated and over-skilled.

Individuals work in jobs where their actual level of skill exceeds the skills requirement for the position, but their educational attainment is lower than educational requirements. Usually this type of worker is very capable, stays with the same job for a length time period, receives on-the-job training, and has a considerable amount of work experience.

In this research, the Mavromaras et al. (2010b) sample is expanded, from graduates to the entire range of working-age employees. Thus, under-education information is also available in this study, and worker-job matching categories have been extended from four to six groups. The existing literature does not provide the effect of mismatch on job mobility for under-educated groups.

Table 4. 1: Combinations of Educational and Skill Mismatch

VARIABLES	Types of Educational and Skill mismatch (percentage)					
	Over-educated & Over-skilled	**Only Over-educated**	**Under-educated & Over-skilled**	**Well-matched**	**Only Over-skilled**	**Only Under-educated**
Over-educated	19.55	80.45	/	/	/	/
Under-educated	/	/	20.21	/	/	79.79
Education matched	/	/	/	83.37	16.63	/
Total	5.40	22.23	6.86	32.04	6.39	27.08

Table 4.1 reveals the difference between educational and skill mismatch. Overall, 27.62 per cent of workers are employed in positions which require a lower level of education than that which they possess and 18.35 per cent of them report that they have not fully

used their skills and abilities in their current job. These over-skilled workers are quite evenly distributed into three education mismatch groups, in which there are around 6 per cent of workers within each group. Workers are fortunate to find an educationally matched position. However, 16.63 of them consider their skills are under-utilised. This evidence further suggests that over-education and over-skilling are different concepts. A combination of education mismatch and skill mismatch would provide a better analysis of the quality of match (Mavromaras, McGuinness, O'Leary, Sloane, & Fok, 2010a).

2. Overall job satisfaction

Overall job Satisfaction is derived from the responses to the question: "When all things are considered, how satisfied you with your job are?" The answers are scored on a 10 point scale, in which 0 represents totally dissatisfied, 10, totally satisfied. Job satisfaction is recoded into a dummy variable with a value of 1 if a respondent has responses of 7, 8, 9 or 10 on the scale.

Table 4. 2: Overall Job Satisfaction by Types of Job Mismatch

Overall job satisfaction	**Types of Educational and Skill Match (percentage)**						
	Over-educated & Over-skilled	Only Over-educated	Under-educated & Over-skilled	Well-matched	Only Over-skilled	Only Under-educated	Total
	Col %	Col %	Col %	Col %	Col %	Col %	Col %
0 (Totally dissatisfied)	1.0	0.0	0.6	0.1	0.1	0.3	0.2
1	0.9	0.2	1.5	0.3	0.7	0.5	0.5
2	1.9	0.7	1.8	0.7	1.0	0.7	0.9
3	4.0	0.9	3.0	1.1	3.1	0.8	1.4
4	4.8	1.6	3.7	1.7	4.5	1.4	2.1
5	9.1	4.2	8.8	4.4	10.9	4.7	5.4
6	14.2	7.2	11.7	7.6	12.3	6.1	8.0
7	27.7	23.3	23.7	21.5	22.6	19.0	21.8
8	22.6	34.3	25.9	33.8	25.0	33.3	32.1
9	10.0	21.2	11.5	20.8	13.3	22.0	19.5
10 (Totally satisfied)	3.8	6.3	7.9	8.0	6.6	11.1	8.1
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mean of job satisfaction	6.7	7.7	7.0	7.7	7.0	7.8	7.6
Observations	682	2807	866	4045	807	3419	12626

Table 4.2 presents overall job satisfaction by types of job mismatch. Overall, the average job satisfaction is around 7.6 out of 10 for males aged 23 to 64; this implies that most workers are satisfied with their jobs. When the whole sample is split by job mismatch, the difference in satisfaction levels among different types of job mismatch is found. Over-skilling on its own, or jointly with other education mismatch, is associated with the lower number, or less satisfaction. Over-educated and over-skilled workers have the lowest average job satisfaction level, at a level of 6.7 out of 10. Over-skilled workers have the same level of 7 out of 10 as under-educated and over-skilled workers. Their levels of satisfaction are below the average level of 7.6 and less than that of well-matched workers (7.7) or workers who are only mismatched in terms of their level of education (7.7 for over-educated and 7.8 for under-educated). This evidence may imply that skill under-utilisation, rather than education mismatch matters in the area of job satisfaction.

Table 4. 3: Correlations between Over-educated, Over-skilled and Overall Job Satisfaction

VARIABLES		Over-educated	Over-skilled	Overall job satisfaction
Over-educated		1.00		
	(p)	(0.00)		
Over-skilled		0.01	1.00	
	(p)	(0.46)	(0.00)	
Overall job satisfaction		-0.01	-0.18	1.00
	(p)	(0.44)	(0.00)	(0.00)

The Spearman correlation is used to test the relationship between over-skilling, over-education and overall job satisfaction. Results are reported in Table 4.3. The Spearman correlation test shows that it is skill under-utilisation that has a significant negative effect on overall job satisfaction, however, over-education is not associated with overall job satisfaction. This statistical result is consistent with the evidence from Allen and van der Velden (2001) and Green and McIntosh (2007). Chevalier (Chevalier, 2003) who combined the over-education and satisfaction variables to create two types of over-education: ‘apparent over-education’ and ‘genuine over-education’. The less satisfied workers are genuinely over-educated and suffer a considerable pay penalty of 22%-26%.

Due to the negative relationship between over-skilling and satisfaction, for the over-educated and over-skilled workers in this study, the results are similar to those of Chevalier's (2003) genuinely over-educated workers.

3. Job mobility

The HILDA survey contains information in regard to job separation. In this study, in the 'responding person' file, workers who have changed their job since the previous interview are asked: "What was the main reason you stopped working in that job (or business) that you held on [date of last interview]?" The 'individual job leaving' is altered to: no change, quit, involuntary and other categories[42].

a) No change: if workers still work in the same job.
b) Quit (Voluntary leaving): (1) not satisfied with job, (2) to obtain a better job/just wanted a change/to start a new business, (3) retired/did not want to work any longer, (4) to study at home to look after children, house or someone else, (5) travel/have a holiday, (6) returned to study/started study/needed more time for study, (7) too much time spent in travel/too far from public transport, (8) change of lifestyle, or (9) immigration.
c) Involuntary leaving: (1) Got laid off, (2) No work available, (3) Retrenched, or (4) Made redundant.
d) Others: including temporary or seasonal work, spouse transferred pregnancy, sickness or disability, and any other reasons that cannot be classified.

As expected, Table 4.4 reports that over-educated and over-skilled workers have the highest incidence of job separation; 18.8 per cent for all reasons, and 11.1 per cent experience voluntary job leaving or quit. This is about 4 per cent lower than the results of Mavromaras, K., McGuinness, S., O'Leary, N., Sloane, P., and Fok, Y. K. (2009c); they reported on15 per cent of over-educated and over-skilled workers who left their current employment. It is unsurprising that the results differ; on the one hand graduates were the only group in their sample, and on the other, there were four types of job mismatch in

[42] The approach for defining job separation variables follows McGuinness and Wooden (2009).

their sample rather than six; the study of Mavromaras, K., McGuinness, S., O'Leary, N., Sloane, P., and Fok, Y. K. (2009c) did not include a category for under-education.

Table 4. 4: Job Mobility by Education and Skill Mismatches

Job status	Types of Educational and Skill match (percentage)					
	Over-educated & Over-skilled	Only Over-educated	Under-educated & Over-skilled	Well-matched	Only Over-skilled	Only Under-educated
No change	81.1	89.2	85.2	89.4	81.5	90.2
Quit	11.1	4.7	8.6	5.3	9.9	5.4
Layoff	4.4	3.6	6.2	3.1	4.9	3.4
Other	3.3	2.5	0.0	2.2	3.7	1.0

The over-skilled, or jointly with the under-educated group, account for a higher proportion of voluntary job separation compared to the rest of the groups, ranging from 9.9 per cent to 8.6 per cent. The incidence of layoff is from 3.1 to 6.2 per cent among six groups. Job separation for other reason is only a small proportion of the sample.

As noted in 4.2.1.1, career mobility theory provides a persuasive explanation for the existence of over-education from a supply side perspective. Over-education may be a part of the career mobility process and it is part of a phase of insertion and adaptation in the early stages of the working life (Groot & Maassen van den Brink, 2003). Over-educated workers may optimally choose a lower level employment, if the effect of education on the probability of being promoted for these jobs is higher than for other jobs. Over-educated workers may sacrifice a wage premium in their current jobs to gain specific skills, or other types of human capital, enabling them to move to higher- level jobs and higher wages. Thus, it should be tested by comparing differences between workers who experience a voluntary separation (quit) and workers who experience job ‘no changes’ rather than those experiencing involuntary separation (lay off). Therefore, in this study, the focus is on these two groups of workers (who stay or who quit their jobs voluntarily) to test career mobility theory. Workers who are laid off or who leave their jobs for other reasons are excluded.

4. Upward occupational mobility and upward wage growth

Upward career mobility is tested by upward occupational mobility and upward wage growth models for a one-year period and a three-year period, respectively.

In this research, the method of Büchel and Mertens (2004) is followed, to define dummy variables for upward occupational mobility and upward wage growth .

Workers experience upward occupational mobility if they have experienced to a higher occupational rank between two time periods (t-k and t). In the HILDA survey, Variable jbmo6s provides AUSEI06 (Australian Socioeconomic Index 2006) occupational status scale of current main job. A larger number of jbmo6s represents a higher occupational rank. Thus, jbmo6s is used here as an index of occupational rank. The AUSEI06 is generated based on the 2006 Census of Population and Housing data.

An issue arises when upward occupational mobility and upward wage growth variables are defined. Workers in some occupations experience greater mobility than others. As a result, average wages, along with occupational scale in some occupations experience larger increases than those in other occupations. Thus, it is ambiguous when workers experience wage growth or occupational upward mobility as to whether it is due to their own attributes, or to occupational growth.

Figures 4.3 and 4.4 present occupational mobility and wage growth within 2-digit occupations between 2001 and 2009. In Figure 4.3, occupational mobility is relatively stable with the exception of a small upward or downward movement for professionals, operators, or labourers during this nine-year period. There are straight lines for most of occupations. Thus, dummy variables are used to define upward occupational mobility as 1, in cases where workers move to a higher occupational rank between t-k and t, and 0, if otherwise. It is worth noting that individual occupational rank and group occupational rank were not compared in this study because of the relatively small occupational mobility within occupations.

In contrast, in Figure 4.4, the group occupational average log hourly wage has moved dramatically upward or downward in some occupations during this period. Sports and Personal service workers experienced an earnings increase; this reached 3.6 in 2003. After a moderate fall in 2004, earnings started to increase again and reached 3.75 in 2005. Then followed a sharp fall to 3.25 in 2006; this was lower than the rate for 2001. However, workers' earnings experienced a sharp increase in grow after 2006, reaching 4.1 in 2009. Farmers and Farm Managers, Arts and Media Professionals, Health and Welfare Support Workers, Sales Support Workers, amongst other groups of workers, to some extent, all experienced something of a fluctuation in earnings between the years 2001 to 2009. This evidence suggests that some occupational groups experience a significant growth in wages. And that the wage growth of individuals in these groups may stem from growth of average wages for that group as a whole rather than any individual change.

Büchel and Mertens (2004) have considered this issue, and have stated that workers experience upward wage growth, if their wage growth during some specific period exceeds that of the mean plus one standard deviation of wage growth in their same occupation group during the same period. The same approach is employed in this research to define dummy variables for upward wage growth. That is, workers experience upward career mobility if their wage growth during a one year or three-year period exceeds the mean plus one standard deviation of wage growth in the same occupation group during that period. In this study, mean and standard deviation of wage within occupations is based on the 2-digit ANZSCO 2006 occupations category for each wave; this variable is then matched with each individual in every wave. A comparison between individual wage growth and group wage growth within occupations produces dummy variables which are used to define wage growth for a one-year period and a three-year period.

Figure 4.4 also reports that Chief Executives, General Managers and Legislators, Specialist Managers and Health Professionals have higher earnings than those who work in the other occupations. Farms, Forestry and Garden workers, Food Preparation Assistants and other labourers have the lowest wage rate.

The means of the main variables used in the analysis are reported in Table 4.5[43]. The full definition of variables is available in Appendix 4C. In general, workers who quit, or workers who stay in their jobs, predictably, between six different job mismatched groups there are differing job characteristics. Younger workers with less experience, less occupational tenure, less current job tenure and less earnings than their older counterparts, are more likely to experience leaving their employment, voluntarily. With the exception of over-skilled workers; among the other five types of mismatched workers, there were 8 to 10 per cent fewer workers who left their employment in order to have on-the-job training than workers who remained in their employment.

The overall job satisfaction is lower among workers who quit than workers who did not quit among all groups.

Workers on a higher occupational scale are less likely to quit among all groups, with the exception of under-educated and over-skilled workers, who are on a lower occupational scale.

With the exception of over-skilled workers, workers among the other five groups of job mismatch who leave their employment are shown to have fewer opportunities for on-the-job training than workers who did not quit in the same type of job mismatch.

Only the group of over-educated workers are shown to have the highest earnings, the highest occupational ranking, and more actual years of education, when compared to the other five types of group.

[43] The mean and standard deviations for the whole sample are reported in Appendix 4A.

Figure 4. 3: Occupational Scales (Rank) by 2-digit Occupations from 2001 to 2009

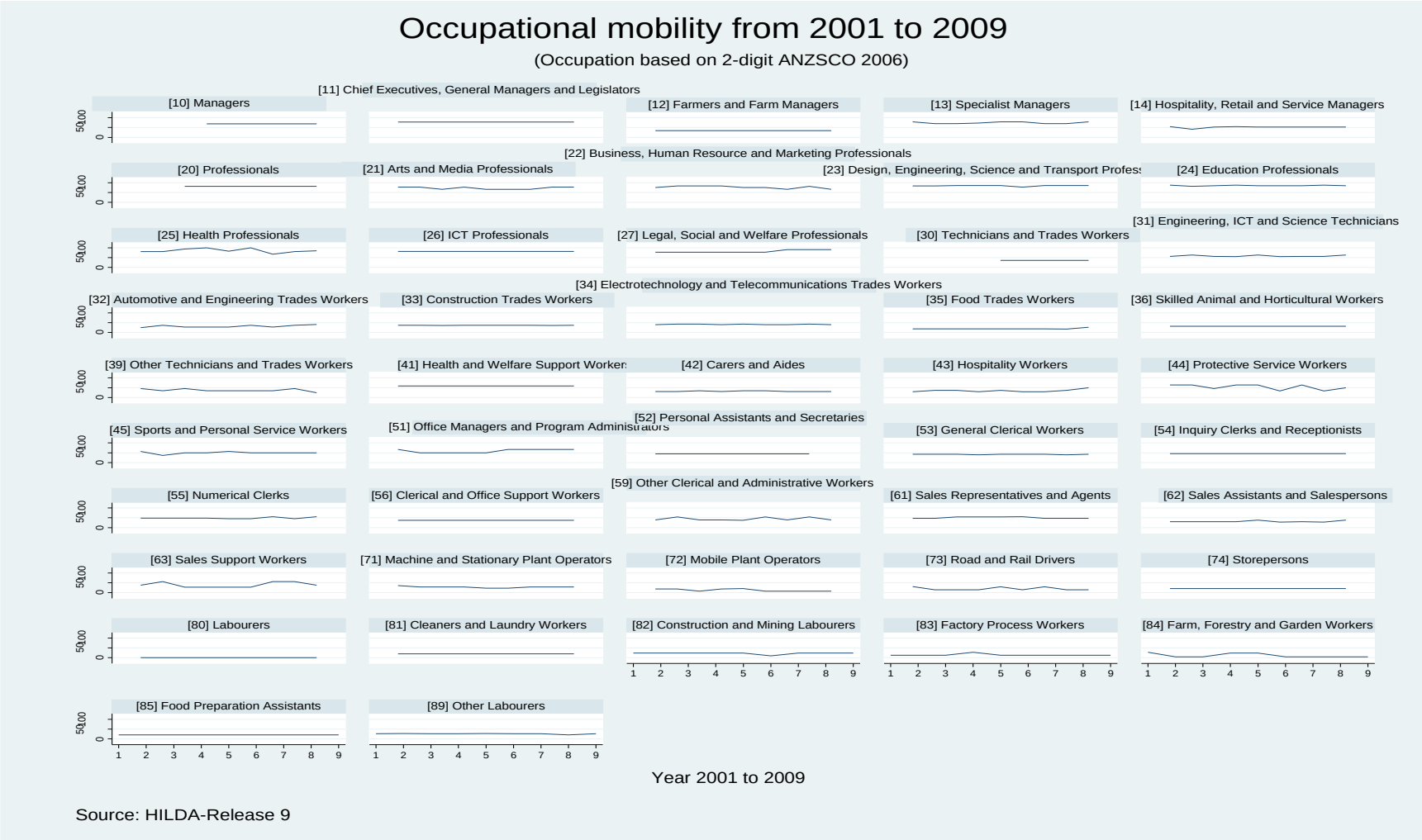


Figure 4. 4: Mean Plus One Standard Deviation of Log Hourly Wage for 2-digit Occupational Group from 2001 to 2009

Table 4. 5: Means of Main Variables Used in the Analysis by Quit Status

	Types of Educational and Skill match (percentage)											
	Over-educated & Over-skilled		Only Over-educated		Under-educated & Over-skilled		Well-matched		Only Over-skilled		Only Under-educated	
VARIABLES	*Job no change* mean	*Quit* mean	*Job no change* mean	*Quit* mean	*Job no change* mean	*Quit* mean	*Job no change* mean	*Quit* mean	*Job no change* mean	*Quit* mean	*Job no change* mean	*Quit* mean
Age	40.71	34.19	42.77	37.90	42.06	36.08	41.41	36.46	40.43	35.90	43.19	38.28
Years of experience	20.05	13.81	20.78	16.08	24.99	18.68	20.91	15.98	20.48	15.97	25.32	20.40
Occupation tenure	8.11	3.70	10.93	6.75	10.64	6.15	13.15	9.88	11.33	8.26	11.63	7.77
Job Tenure	6.86	2.99	9.71	4.67	9.19	3.89	9.29	4.06	8.86	3.88	9.76	4.45
Training	0.35	0.27	0.50	0.42	0.25	0.16	0.47	0.41	0.33	0.38	0.44	0.34
Overall job satisfaction	0.67	0.41	0.86	0.67	0.70	0.58	0.86	0.71	0.71	0.50	0.87	0.68
Log hourly wage (2009 $)	3.19	3.10	3.46	3.34	3.14	3.07	3.37	3.29	3.28	3.14	3.29	3.16
Job occupational scale	40.35	32.74	60.36	55.16	37.79	37.81	50.43	46.13	42.43	40.05	51.80	49.39
Years of actual education	14.66	14.38	15.99	15.82	11.07	11.40	14.50	14.48	13.95	13.93	11.88	11.88
Years of required education	11.96	11.34	13.87	13.55	14.23	14.13	14.50	14.48	13.95	13.93	14.85	14.78
Occupational mobility during a one-year period	0.41	0.38	0.48	0.37	0.46	0.51	0.48	0.43	0.47	0.33	0.51	0.45
Occupational mobility during a three-year period	0.40	0.53	0.49	0.43	0.48	0.45	0.48	0.44	0.46	0.32	0.55	0.46
Occupational mobility during a five-year period	0.41	0.40	0.48	0.43	0.51	0.67	0.50	0.39	0.43	0.33	0.57	0.51
Wage growth during a one-year period	0.55	0.54	0.51	0.53	0.51	0.55	0.51	0.56	0.54	0.40	0.52	0.52
Wage growth during a three-year period	0.51	0.47	0.57	0.58	0.54	0.52	0.55	0.62	0.50	0.42	0.52	0.54
Wage growth during a five-year period	0.56	0.40	0.62	0.57	0.50	0.87	0.57	0.63	0.55	0.50	0.53	0.46
Observations	515	58	2,227	171	659	72	3,190	283	599	86	2,700	238

Source: HILDA-Release 9

4.6 Estimations and empirical results

This section aims to examine career mobility theory and the state dependence of over-education and over-skilling. Random effects probit models are proposed for the estimation of the dynamic effects of education mismatches and skill mismatches on the following; quitting, upward occupational mobility, and upward wage growth during one-year and three-year periods. Two additional random effects probit models are employed to examine the persistence of over-education and over-skilling. The dynamic impacts of job mismatch are examined by two approaches: one is to examine the effects of over-education and over-skilling on upward mobility from quitting or subsequent job mismatch status; the other is to demonstrate whether or not over-education and over-skilling are permanent or temporary phenomenon.

Both initial condition problem and endogeneity in a dynamic model can be controlled for by random effects probit models with some additional corrections. Thus, this study employs random effects probit estimations, using a Wooldridge (2005) approach to solve the initial condition problem. The Mundlak (1978) correction is applied in order to adjust for biases from endogeneity of the correlation between explanatory variables and error terms. Combining education mismatch and skill mismatch, six types of mismatch groups are constructed for examining the effects of job quitting, upward occupational mobility, and upward wage growth. Based on the literature pertaining to over-education literature, the effects, from both within occupations and across occupations, are evaluated. Results are given in Table 4.6 through to Table 4.10. In addition, state dependence of over-education and over-education, are examined, respectively and the results are presented in Tables 4.11 and 4.12.

All the results are given by coefficients or marginal effects. The sign of coefficient explains the positive or negative relationship between dependent variable and explanatory variable. The extent of its impact is interpreted by marginal effects, which are calculated for the average person who has all characteristics at mean values.

These dynamic effects results are different from the static regression results[44]. The static models are special instances of dynamic models; these constrain that the coefficients on the lags of the dependent variables and coefficients on the initial status of the dependent variables are zero. If both coefficients are significant, then static model could suffer from some omitted variables problems. However, I also examine effects of job mismatch from static models due to two purposes. One aims to compare previous evidence in the literature which mostly were based on static models. The other is to obtain additional information from upward career mobility model within a five-year period. Because, in the dynamic model, with a longer lagged period, more observations are dropped, this does not allows me to estimate the dynamic effects of job mismatch on upward job mobility for a five-year period.

This section is organised as follows. Career mobility theory is examined in Section 4.6.1 in three sub-sections. Both upward occupation mobility and upward wage growth are examined with random effects probit models with Mundlak correction. Further evidence on the persistence of over-education and over-education is provided in Section 4.6.2.

4.6.1 Career mobility theory

Career mobility theory explains over-education as a temporary phenomenon. An over-educated worker may optimally choose a lower level employment to gain other human capital for future promotion. Therefore, career mobility theory hypotheses that over-education leads to a higher level of occupational ranks and wage growth over time. In this section, the question of whether or not mismatch leads workers to leave their current jobs voluntarily is answered in Section 4.6.1.1 Furthermore, after leaving their current jobs, whether workers experience upward occupational mobility or upward wage growth. This is examined in Section 4.6.1.2 and 4.6.1.3, respectively.

[44] The static results are in Appendix 4B.

4.6.1.1 Voluntary leaving (quitting) and mismatch

The actual quits model is written as:

Model 1: Voluntary leaving (quitting) and mismatch

$$(4.6)\quad quit_{it}^{*} = \gamma quit_{i(t-1)} + x_{it}\,\beta + \sum_{j=1}^{5} \alpha_j MTYP_{it} + \gamma_0 quit_{i0} + \overline{\sum_{J=1}^{5} \alpha_J MTYP_{it}} + \overline{X}_i\,\delta + \eta_i + \varepsilon_{it}$$

$quit_{i(t-1)}$ is a dummy variable, takes the value 1 if individual has actually left his or her job held on the date of last interview, zero otherwise. $MTYP_{it}$ contains six types of job mismatch dummy variables, namely over-educated, over-educated & over-skilled, under-educated & over-skilled, over-skilled, well-matched and under-educated for individual i at time t. The reference category is well-matched. X is a set of other personal or job characteristics likely to affect individual's quitting behaviour, such as current occupational scales, on-the-job training, and current job hourly wage and so on.

The determinants of job leaving in a dynamic setting are reported in Table 4.6 by controlling for both across occupations and within occupations.

Firstly, the results from within occupations are similar to those from across occupations. Secondly, there is state dependence but no initial condition effect on job leavers. This implies that the original leaving action does not affect future instances of job quitting, but previous employment leaving behaviour does affect the likelihood of job leaving in future employment.

The coefficients for the overall satisfied workers are negative and significant in both specifications, which indicates that employment satisfaction dominates the attitude of

workers in regard to job leaving behaviour. This result is robust when controlling for both across occupations and within occupations.

Contrary to expectations, the results for both over-educated & over-skilled and over-educated but skill matched seemingly play a small role in job quitting actions. The previous literature suggests that over-educated workers are more likely to leave their current jobs if they have not experienced promotion (Hersch, 1995). This can be explained by three reasons. One reason is that previous regressions have examined these effects by using cross-sectional data; thus, there is an 'unobserved heterogeneity issue'. The second reason is that previous regressions evaluated the aggregate effects of education mismatch. The third reason is that static models were employed for the studies in previous literature.

In this study, the features of panel data are used to examine the dynamic effects of job mismatch on job leaving. 'Unobserved heterogeneity' plays an important role among these two types of over-educated workers. Over-educated and over-skilled workers have the propensity to stay in their current jobs. On the one hand, they are less satisfied with their jobs than their well-matched counterparts; on the other hand, they are less likely to resign from such a situation. Perhaps, it is that 'some unobserved heterogeneity' that attracts them to stay in their employment, or else provides a barrier to finding other positions elsewhere. These facts require further investigation.

The results from dynamic models in Columns (1) and (2) are different from those in static models[45]. Educationally matched but over-skilled workers are not shown to be more likely to leave their current employment position significantly.

As expected, workers with higher earnings and those in occupations that are highly ranked are less likely to leave their current employment due to the higher opportunity cost.

[45]See Appendix Table 4B.1. Static results found that educationally-matched and over-skilled workers are more likely to experience leaving their employment than are well-matched workers across occupations or within occupations. Skill under-utilisation is the main cause of workers leaving their employment.

Table 4. 6: Dynamic Random Effect Probit Estimations of Job Mismatch on Voluntary Leaving-Quitting With Controls for Initial Conditions
(Model 1: Quitting and Mismatch)

	Dependent variable =1 if workers experience voluntary leaving-quit at t		
	Across Occupations	**Within Occupations**	Pr(quit=1|u_i=0)=3.2 %
	(1)	(2)	
VARIABLES	Quit at t	Quit at t	
	Marginal Effects	Marginal Effects	Mean of X
Lagged dependent variable			
Quit at t-1	0.064***	0.064***	0.075
Initial condition	(0.018)	(0.018)	
Quit at t=0	-0.000	-0.000	0.062
	(0.007)	(0.007)	
Overall satisfied	-0.070***	-0.070***	0.833
	(0.013)	(0.013)	
Over-educated and Over-skilled	-0.012	-0.008	0.045
	(0.010)	(0.012)	
Only Over-educated	0.001	0.007	0.235
	(0.009)	(0.013)	
Under-educated and Over-skilled	0.024	0.017	0.066
	(0.019)	(0.018)	
Only Over-skilled	0.020	0.020	0.066
	(0.014)	(0.014)	
Only Under-educated	0.015	0.010	0.261
	(0.012)	(0.012)	
Well-Matched	Ref.	Ref.	
Log Hourly wage (**2009$**)	-0.030***	-0.031***	3.361
	(0.010)	(0.010)	
Job occupational scale	-0.000*	-0.000**	51.328
	(0.000)	(0.000)	
Actual years of education	-0.011	/	13.900
	(0.051)	/	
Required years of education	/	0.002	14.281
	/	(0.003)	
Log likelihood	-1460	-1459	
Wald chi-squared	451.0	452.8	
Individuals	1,699	1,699	
Observations	6624	6624	

Notes:
Standard errors in parentheses.

***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are; Australian, Not Union member, healthy, No training, Well-matched, year 2008, and QLD.

The models Include Time periods Dummies, states Dummies, unemployment, Immigrant status, Union and membership, Healthy status, Work experience, Current job tenure, Current occupational tenure, Job occupational scale, On-the-job training and Current job hourly wage. The full set of results are available upon request.

Source: HILDA-Release 9

4.6.1.2 Upward occupational mobility and mismatch

Upward career mobility predicts that over-educated workers experience higher upward occupational mobility than their counterparts. Two random effects probit models are used to estimate effects. The first one is a basic probit model, as given in Equation (4.7). The second model, as shown in Equation (4.8), is based on the basic probit model with the addition of the interaction terms of between quit and various types of mismatch. This model is used to examine the effects of the employment quitting of different types of mismatched groups of workers on upward occupational mobility. Both models are examined across occupations (controlling for the actual years of education) and within occupations (accounting for required years of education), during one-year and three-year periods, respectively. These two models are as follows:

Model 2: Upward occupational mobility and mismatch

(4.7) $$UOCM^*_{i,t} = \gamma UOCM_{i,t-k} + x_{i,t}\,\beta + \sum_{j=1}^{5} \alpha_j MTYP_{it} + \gamma_0 UOCM_{i,0} + \overline{\sum_{J=1}^{5} \alpha_J MTYP_{\iota,t}} + \bar{X}_\iota \delta + \eta_i + \varepsilon_{i,t}$$

And

(4.8) $$UOCM^*_{i,t} = \gamma UOCM_{i,t-k} + x_{i,t}\,\beta + \sum_{j=1}^{5} \alpha_j MTYP_{it} + \sum_{j=1}^{6} \xi_j (quit * MTYP_{it}) + \gamma_0 UOCM_{i,0} + \overline{\sum_{J=1}^{5} \alpha_J MTYP_{\iota,t}} + \overline{\sum_{J=1}^{6} \xi_J (quit * MTYP_{\iota t})} + \bar{X}_\iota \delta + \eta_i + \varepsilon_{i,t}$$

The dummy variable $UOCM_{i,t-k}$ indicates whether worker i has moved into a higher ranked occupation between t-k and t, and takes the value 1 if he or she has moved to a more highly ranked occupation than those held in previous years. $x_{i,t}$ is personal characteristics and job characteristics which have impacts on occupational mobility for worker i at year t. $MTYP_{i,t}$ denotes the various types of mismatch occurring. Each type of mismatch is dummy variable. In Equation (4.8), ξ_j reveals the effects of job quitting associated with their original job mismatch status on future upward occupational mobility when compared to workers who have same original job mismatch status but do not quit. If career mobility theory holds, then the coefficients ξ_j are expected to be positive on over-educated & over-skilled and on over-educated. The variable η_i is an individual specific effect and is not correlated with the covariates. The variable $\varepsilon_{i,t}$ is the error term.

The state dependence of upward occupational mobility is found for both the one-year and three-year periods. However, the effects are in contrast. If workers with average characteristics experience upward occupational mobility in the previous year, this is more likely to reduce the chances of promotion to a higher occupational rank in current year; however, such workers are more likely to move upwards occupational rank in a three-year period than are other workers. The endowment of initial occupational rank has a significant and positive impact on future upward occupational mobility, although these impacts become weaker as the time period lengthens. It is reasonable that a worker once allocated to an occupation has the motivation to increase his occupational rank when he seeks new employment.

The magnitude of the coefficients found on job mismatch when controlling for the educational attainment is larger than those found when accounting for the required amount of education to perform jobs. This evidence shows that job mismatch has a stronger impact on upward occupational mobility across occupations than it does within occupations.

Across occupations, contrary to career mobility theory, both over-educated & over-skilled and only over-educated workers are less likely to move upwards in both the one-year and

three-year periods. In particular, 'average' over-educated & over-skilled workers have a 14 per cent lower probability to move to an upper level of occupational rank than do well-matched workers (who have the same number of years of education but work in matched jobs) in a one-year period; this probability increases to 26 per cent in a three-year period. By contrast, 'average' under-educated & over-skilled workers and 'average' only under-educated workers enjoy around a 22 per cent to 34 per cent higher probability of moving to a higher occupational rank than 'average' well-matched workers.

Within occupations, 'average' only under-educated workers experience a 23 to 25 per cent greater opportunity to move up than their Well-matched colleagues with more years of education but whose skills and education better match their positions of employment.

With reference to the effects, on future upward occupational mobility, of the type of job quitting associated with the status of original job mismatch and comparing them with the effects on future upward occupational mobility of workers who have same original job mismatch status but who, nonetheless, chose to remain in the same employment position, it is evident from Columns (2) and (4) of Tables 4.7 and 4.8, that job quitting plays a small role in upward occupational mobility. Workers with positions that require high levels of education, or workers with more years of education than others, enhance their upward career mobility. In most previous literature a static model was applied when examining the effects of job mismatch on career mobility. Due to the omission of information caused by dropping observations in the dynamic models, a five-year period of analysis is not applicable. However, this may be available in static models[46].

[46] Thus, as a supplement to the dynamic models and to provide a comparison to previous literature, static models analyses are included in Appendix 4B[46]. The results for the static models reveal the same picture. Refer to Tables 4B.2 and 4B.3.Using a five-year period, across or within occupations, Only Under-educated workers seemingly experience moves higher occupational levels relative to Well-matched workers. There is no evidence to show that job leaving, gives workers greater upward occupational mobility.

Table 4. 7: Dynamic Random Effect Probit Estimations of Job Mismatch on one-year Upward Occupational Mobility with Controls for Initial Conditions across and within Occupations
(Model 2: Mismatch and Upward Occupational Mobility within a one-year Period)

Dependent variable=1 if moved to a higher ranked occupation during a one-year period at t					
	Across Occupations		**Within Occupations**		
		With interaction effects		***With interaction effects***	
	(1)	(2)	(3)	(4)	
VARIABLES	PDUS1[+] at t	PDUS1 at t	PDUS1 at t	PDUS1 at t	Pr(PDUS1=1|u_i=0)=45%
Main panel estimation results	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Mean of X
Lagged dependent variable					
Upward Occupation Mobility at t-1	-0.055**	-0.054**	-0.058**	-0.057**	0.482
Initial condition	(0.025)	(0.025)	(0.025)	(0.025)	
Upward Occupation Mobility at t=0	0.556***	0.557***	0.560***	0.560***	0.493
	(0.027)	(0.027)	(0.027)	(0.027)	
Over-educated and Over-skilled	-0.136**	-0.131**	0.012	0.016	0.044
	(0.055)	(0.057)	(0.068)	(0.069)	
Only Over-educated	-0.153***	-0.150***	-0.009	-0.005	0.239
	(0.039)	(0.040)	(0.050)	(0.051)	
Under-educated and Over-skilled	0.271***	0.262***	0.154**	0.143**	0.064
	(0.051)	(0.053)	(0.061)	(0.063)	
Only Over-skilled	-0.010	0.001	-0.006	0.005	0.065
	(0.047)	(0.049)	(0.047)	(0.049)	
Only Under-educated	0.339***	0.343***	0.230***	0.234***	0.258
	(0.038)	(0.039)	(0.046)	(0.047)	
Log Hourly wage (**2009$**)	-0.074	-0.077	-0.070	-0.072	3.378
	(0.050)	(0.050)	(0.050)	(0.050)	
Quit	-0.045	/	-0.046	/	0.074
	(0.038)	/	(0.038)	/	
Quit x Over-educated and Over-skilled	/	-0.069	/	-0.068	0.002
	/	(0.171)	/	(0.171)	
Quit x Only Over-educated	/	-0.060	/	-0.066	0.016
	/	(0.079)	/	(0.079)	
Quit x Under-educated and Over-skilled	/	0.067	/	0.067	0.006
	/	(0.123)	/	(0.124)	
Quit x Well-matched	/	-0.007	/	-0.009	0.024
	/	(0.067)	/	(0.067)	
Quit x Only Over-skilled	/	-0.123	/	-0.126	0.007
	/	(0.115)	/	(0.115)	
Quit x Only Under-educated	/	-0.080	/	-0.075	0.019
	/	(0.070)	/	(0.070)	
Mean of actual years of education	0.027**	0.027**	/	/	13.913
	(0.011)	(0.011)	/	/	
Mean of required years of education	/	/	-0.027	-0.028*	14.292
	/	/	(0.017)	(0.017)	
Required years of education	/	/	0.058***	0.058***	14.288
	/	/	(0.011)	(0.011)	
Log likelihood	-3113	-3111	-3099	-3097	
Wald chi-squared	515.8	517.6	532.8	534.7	
Individuals	1,506	1,506	1,506	1,506	
Observations	5750	5,750	5,750	5,750	

Notes: [+] PDUS1 is a dummy variable, takes value of 1 if moved to a higher ranked occupation during a one-year period at t; 0 otherwise. Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are: Australian, Not Union member, healthy, Well-matched, Year 2008, and QLD.
The models include Time periods Dummies, States Dummies, unemployment, immigrant status, Union membership, Health status, Work experience, Current job tenure, Current occupational tenure, on-the-job training and Base year hourly wage rates. Workers on the highest occupational scale at base year are excluded because they cannot move any further upward. Source: HILDA-Release 9.

Table 4. 8: Dynamic Random Effect Probit Estimations of Job Mismatch on three-year Upward Occupational Mobility with Controlling for Initial Conditions across and within Occupations (Model 2: Mismatch and Upward Occupational Mobility within a three-year Period)

Dependent variable=1 if moved to a higher ranked occupation during a three-year period at t					
	Across Occupations		Within Occupations		
		With interaction effects		*With interaction effects*	
	(1)	(2)	(3)	(4)	
VARIABLES	PDUS3[1] at t	PDUS3 at t	PDUS3 at t	PDUS3 at t	**Pr(PDUS3=1|u_i =0)=49%**
Main panel estimation results	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Mean of X
Lagged dependent variable					
Upward Occupation Mobility at t-3	0.314***	0.313***	0.319***	0.319***	0.496
Initial condition	(0.032)	(0.032)	(0.032)	(0.032)	
Upward Occupation Mobility at t=0	0.281***	0.284***	0.278***	0.280***	0.507
	(0.039)	(0.039)	(0.038)	(0.038)	
Over-educated and Over-skilled	-0.257***	-0.269***	-0.147	-0.164*	0.044
	(0.070)	(0.070)	(0.090)	(0.090)	
Only Over-educated	-0.161***	-0.164***	-0.041	-0.043	0.246
	(0.054)	(0.054)	(0.068)	(0.068)	
Under-educated and Over-skilled	0.216***	0.215***	0.113	0.109	0.058
	(0.069)	(0.072)	(0.082)	(0.086)	
Only Over-skilled	0.026	0.046	0.029	0.048	0.062
	(0.062)	(0.065)	(0.062)	(0.065)	
Only Under-educated	0.337***	0.343***	0.245***	0.249***	0.253
	(0.048)	(0.049)	(0.060)	(0.060)	
Log hourly wage $2009	0.063	0.060	0.068	0.064	3.406
	(0.071)	(0.071)	(0.070)	(0.070)	
Quit	-0.075	/	-0.073	/	0.072
	(0.054)	/	(0.054)	/	
Quit x Over-educated and Over-skilled	/	0.137	/	0.169	0.003
	/	(0.218)	/	(0.210)	
Quit x Only Over-educated	/	-0.016	/	-0.017	0.013
	/	(0.113)	/	(0.113)	
Quit x Under-educated and Over-skilled	/	-0.036	/	-0.026	0.007
	/	(0.166)	/	(0.167)	
Quit x Well-matched	/	-0.048	/	-0.056	0.024
	/	(0.096)	/	(0.096)	
Quit x Only Over-skilled	/	-0.226*	/	-0.224	0.007
	/	(0.136)	/	(0.136)	
Quit x Only Under-educated	/	-0.147	/	-0.138	0.019
	/	(0.093)	/	(0.094)	
Mean of actual years of education	0.034***	0.034***	/	/	13.953
	(0.011)	(0.011)	/	/	
Mean of required years of education	/	/	-0.013	-0.013	14.287
	/	/	(0.020)	(0.020)	
Required years of education	/	/	0.048***	0.049***	14.273
	/	/	(0.016)	(0.016)	
Log likelihood	-1676	-1673	-1672	-1668	
Wald chi-squared	585.6	590.6	598.7	604.9	
Individuals	1,152	1,152	1,152	1,152	
Observations	3,142	3,142	3142	3,142	

Notes: 1 PDUS3 is a dummy variable, takes value of 1 if moved to a higher ranked occupation during a three-year period at t; 0 otherwise. Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are: Australian, Not Union member, healthy, Well-matched, Year 2008, and QLD. The models include Time periods Dummies, states Dummies, unemployment, immigrant status, Union membership, Health status, Work experience, Current job tenure, Current occupational tenure, on-the-job training and Base year hourly wage rates. Workers on the highest occupational scale at base year are excluded because they cannot move any further upward. Source: HILDA-Release 9.

4.6.1.3 Upward wage mobility and mismatch

Upward career mobility is accompanied by wage growth. To test this prediction, a binary wage growth model has been constructed, based on one-year period and three-year periods, respectively. The approach of Büchel and Mertens (2004) is followed in this study but controls for both required years of education (within occupations) and actual years of education (across occupations).

Workers experience upward career mobility if their wage growth from year t to t+1 is higher than the mean wage growth during that period plus one standard deviation in their status group (g) in the pair of years under investigation(y), that is $\Delta \ln(w_{i,y}) > mean(\Delta \ln(w_{g,y})) + std(\Delta \ln(w_{g,y}))$. $w_{i,y}$ is log hourly wage for worker i at year y. $w_{g,y}$ is log hourly wage for the group of workers who have same mismatch status as worker i.

Model 3: Upwards wage mobility and mismatch

$$(4.9) \quad wagegrowth^{*}_{i,t} = \Upsilon wagegrowth_{i,t-k} + x_{i,t}\beta + \sum_{j=1}^{5} \alpha_j \, MTYP_{i,t} + \Upsilon_0 wagegrowth_{i,0} + \overline{\sum_{j=1}^{5} \alpha_j \, MTYP_{i,t}} + \bar{X}_i\delta + \eta_i + \varepsilon_{i,t}$$

Where $wagegrowth_{i,t-k}$ is the dummy variable, takes the value 1 if worker i has experienced a wage growth during k years. $x_{i,t}$ represents the personal characteristics and job characteristics for worker i at year t. $MTYP_{i,t}$ is the dummy variable for five types of mismatch, respectively and well-matched is excluded as a reference type. η_i is the individual specific effect which is included in the error term only when η_i is not correlated with the covariates. $\varepsilon_{i,t}$ is error term. The panel probit model is applied to estimate the

parameters.

To test the job upward wage growth mobility as a result of job quitting, Equation (4.9) is extended to Equation (4.10) by adding interaction items between job leaving and various types of job mismatch.

$$
\begin{aligned}
(4.10) \qquad & wagegrowth_{i,t}^{*} \\
& = \gamma wagegrowth_{i,t-k} + x_{i,t}\,\beta + \sum_{j=1}^{5} \alpha_j MTYP_{it} \\
& + \sum_{j=1}^{6} \xi_j (quit * MTYP_{it}) + \gamma_0 wagegrowth_{i,0} + \overline{\sum_{j=1}^{5} \alpha_j MTYP_{i,t}} \\
& + \overline{\sum_{j=1}^{6} \xi_j (quit * MTYP_{it})} + \overline{X_i}\delta + \eta_i \\
& + \varepsilon_{i,t}
\end{aligned}
$$

Coefficients ξ_j examine the effects on upward wage growth caused by job leaving in varying types of job mismatch. If the career mobility theory holds, then coefficients are expected to be positive among the over-educated & over-skilled and the over-educated.

Upward wage growth is examined during one-year and three-year periods, respectively. Workers with valid data for occupation variable in two consecutive years and three consecutive years are included in the analysis. It takes time for workers to settle down in their new jobs if they leave voluntarily from their current positions. The first year is a transitory period for them, and they are more likely to suffer a wage reduction in comparison to their previous job. However, after a three-year period, some workers may change their mismatched status to a matched status and may thus achieve wage growth.

In accordance with the models in Equations (4.9) and (4.10), the dynamic random

effects[47] estimations results are given in Tables 4.9 and 4.10.

In general, the estimation results when controlling for the actual years of education are close to those achieved when controlling for the required years of education for both a one-year period and a three-year period.

Within a one-year period, the results from the dynamic models are consistent with the results from the static models. The reason for this is that the coefficients of the lagged dependent variable in both the dynamic and static models are both significant and negative, and the coefficients of initial status of dependent variable are not significant in dynamic models. This evidence in dynamic models shows that 'average' workers who have experienced previous year wage growth are less likely to have wage growth in the current year. Their initial wage growth does not have impact on their wage growth in the current year. 'Average' only over-educated workers have a 6 per cent lower probability of experiencing wage growth than do Well-matched workers who have the same number of years of education but who are in matched jobs. A 12 per cent higher chance of enjoying wage growth is found among 'average' under-educated & over-skilled workers both across occupations and within occupations. Although job quitting has no impact on upward occupational mobility, it does have an impact on wage growth among different types of workers. On average, the act of job quitting lowers by 8 per cent of probability the likelihood for 'average' workers of being able to enjoy any wage growth due to reasons related to settlement. Specifically, 'average' only over-skilled workers and 'average' only under-educated workers suffer 22 per cent and 14 per cent lower probability of experiencing wage growth than those workers who have same characteristics but who remain in their current employment.

A three-year period of estimation offers different results from those of a one-year period. The coefficients of lagged dependent variables are positive and significant; this implies

[47] Likewise, the previous upward occupational mobility analyses and the static models with results are reported in Tables 4B.4 and 4B.5 for a one-year period and a five-year period, respectively. In static models, the previous hourly wages are included into the explanatory variables. The negative significant effects are found with these variables.

that 'average' workers who have experienced previous three-year period wage growth would be able to enjoy a 13.4 per cent higher likelihood of wage growth for the following three-year period relative to 'average' workers who have not experienced such wage growth. Workers who have experienced wage growth in the previous year are less likely to have a wage increase in the current year, but if they have experienced wage growth three years previously then they are more likely to have a wage increase during the current year. The length of the time period has varying effects on wage growth.

Because the initial status of dependent variables is negative and significant for a three-year period in dynamic models and no such variables are estimated for a five-year period in static models, results from the dynamic for three-year periods are not comparable with those of static models for a five-year time period. 'Average' only over-educated workers are found to have a 9 to 13 per cent less probability of experiencing wage growth than 'average' well-matched workers across occupations and within occupations for a three-year period. 'Average' over-educated & over-skilled workers who leave their current employment have a 33 per cent lower probability of having a wage growth relative to the same types of workers who do not leave their current employment. This evidence is in line with the results found in quitting models. Even though this type of worker may be dissatisfied with their job; nonetheless they have no intention of leaving their employment. Once they leave their current job, their future jobs are not guaranteed to provide them with an increase in financial remuneration. Under-educated & over-skilled workers are the other types of workers who suffer a loss from quit action in a three-year period. 'Average' under-educated & over-skilled workers who leave their employment have a 33 to 34 per cent lower probability experiencing wage growth than those workers who remain in the same employment. In addition, workers with more years of education are more likely to experience a wage growth.

Among workers who do not change their jobs, over-educated workers, have a, temporarily lower, probability to experience wage growth within one year, and this disadvantage worsens over three years in comparison with well-matched workers. This result is contrary to career mobility theory, which explains that over-educated workers have a higher probability of wage growth in comparison to well-matched workers.

Only over-skilled workers and only under-educated workers who quit their jobs have a temporary disadvantage in wage growth over a one year time period. Despite this, there appears to be no wage loss over a three-year period. Although over-educated & over-skilled workers and under-educated & over-skilled workers are unlikely to experience significant effects from leaving their employment within one year, it may lower the probability of experiencing wage growth within three years. The findings suggest that workers who are over-skilled and are either over-educated or under-educated suffer significant less wage growth during a three-year period than their counterparts who continued employment. Relevant data information on job satisfaction reveals that workers in these categories of mismatch are associated with lower job satisfaction. Thus, a compensating differential theory could be applied into explanations. Workers quit and move to another job that they are happier with, even if the pay prospects are not good. In this sense it may be an "upward movement" if job satisfaction is considered and not just pay. This needs to be further investigated.

In summary, in an explanation of over-education, evidence from the dynamic random effect probit estimation of job mismatch and upward wage mobility during one-year and three-year periods reveals that over-education is not a temporary career pathway phenomenon, and that the career mobility theory is not applicable to the Australian labour market. Resignation from employment has significant negative impacts on wage growth among educationally mismatched and over-skilled workers within a three-year period but has no such effect within a one-year period.

This result implies that over-education is not seen as a pathway to a better ranking or paid job. Over-educated workers are trapped into this suboptimal situation. Therefore, policy should be implemented to help over-educated workers to find a matched job. For example, policies may be designed to subsidise firms to re-locate workers where they could better utilise their skills. Likewise, over-educated workers could be encouraged to negotiate with their employers to re-assign them to jobs where skill allocation efficiency can be achieved.

Table 4. 9: Dynamic Random Effect Probit Estimations of Job Mismatch on one-year Upward Wage Mobility with Controls for Initial Conditions across and within Occupations
(Model 3: Mismatch and Upward Wage Growth within a one-year Period)

Dependent variable=1 if wage growth > mean plus standard deviation during a one-year period at time t					
	Across Occupations		**Within Occupations**		
		With interaction effects		***With interaction effects***	
	(1)	(2)	(3)	(4)	
VARIABLES	DUWG1ˆ at t	DUWG1 at t	DUWG1 at t	DUWG1 at t	**Pr(DUWG1=1| u_i=0)=52%**
Main panel estimation results	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Mean of X
Lagged dependent variable					
Upward wage growth at t-1	-0.258***	-0.258***	-0.258***	-0.258***	0.532
Initial condition	(0.013)	(0.013)	(0.013)	(0.013)	
Upward wage growth at t=0	-0.012	-0.011	-0.011	-0.011	0.506
	(0.014)	(0.014)	(0.014)	(0.014)	
Over-educated and Over-skilled	-0.058	-0.049	-0.062	-0.053	0.044
	(0.051)	(0.052)	(0.057)	(0.058)	
Only Over-educated	-0.061*	-0.057	-0.064	-0.060	0.239
	(0.035)	(0.036)	(0.042)	(0.043)	
Under-educated and Over-skilled	0.120***	0.119**	0.122**	0.121**	0.064
	(0.046)	(0.047)	(0.049)	(0.051)	
Only Over-skilled	0.016	0.037	0.016	0.037	0.065
	(0.037)	(0.039)	(0.037)	(0.039)	
Only Under-educated	0.028	0.038	0.030	0.041	0.258
	(0.036)	(0.037)	(0.041)	(0.041)	
Job occupational scale	-0.001	-0.001	-0.001	-0.001	51.621
	(0.001)	(0.001)	(0.001)	(0.001)	
Quit	-0.078**	/	-0.077**	/	0.074
	(0.032)	/	(0.032)	/	
Quit x Over-educated and Over-skilled	/	-0.132	/	-0.131	0.002
	/	(0.152)	/	(0.152)	
Quit x Only Over-educated	/	-0.070	/	-0.070	0.016
	/	(0.067)	/	(0.067)	
Quit x Under-educated and Over-skilled	/	-0.012	/	-0.012	0.006
	/	(0.109)	/	(0.109)	
Quit x Well-matched	/	0.004	/	0.004	0.024
	/	(0.054)	/	(0.054)	
Quit x Only Over-skilled	/	-0.222**	/	-0.222**	0.007
	/	(0.090)	/	(0.090)	
Quit x Only Under-educated	/	-0.141**	/	-0.141**	0.019
	/	(0.058)	/	(0.058)	
Mean of actual years of education	-0.000	-0.000	/	/	13.912
	(0.007)	(0.007)	/	/	
Mean of required years of education	/	/	0.004	0.004	14.291
	/	/	(0.013)	(0.013)	
Required years of education	/	/	-0.001	-0.001	14.287
	/	/	(0.010)	(0.010)	
Log likelihood	-3726	-3722	-3726	-3722	
Wald chi-squared	481.3	489.5	481.4	489.6	
Individuals	1,505	1,505	1,505	1,505	
Observations	5,742	5742	5,742	5742	

Notes: ˆDUWG1 is a dummy variable, takes value of 1 if wage growth > mean plus standard deviation during a one-year period at time t; 0 otherwise. Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are: Australian, Not Union member, healthy, and Well-matched.
The models include Time periods Dummies, states Dummies, unemployment, Immigrant status, Union membership, Health status, Work experience, Current job tenure, Current occupational tenure, Job scale, On-the-job training and Base year hourly wage rates. Source: HILDA-Release 9

Table 4. 10: Dynamic Random Effect Probit Estimations of Job Mismatch on three-year Upward Wage Mobility with Controls for Initial Conditions across and within Occupations (Model 3: Mismatch and Upward Wage Growth within a three-year Period)

Dependent variable=1 if wage growth > mean plus standard deviation during a three-year period at time t

	Across Occupations		Within Occupations		
		With interaction effects		*With interaction effects*	
	(1)	(2)	(3)	(4)	
VARIABLES	DUWG3˘at t	DUWG3 at t	DUWG3 at t	DUWG3 at t	**Pr(DUWG3=1|u_i=0)=54%**
Main panel estimation results	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Mean of X
Lagged dependent variable					
Upward wage growth at t-3	0.134***	0.136***	0.136***	0.138***	0.554
Initial condition	(0.019)	(0.019)	(0.019)	(0.019)	
Upward wage growth at t=0	-0.057***	-0.059***	-0.059***	-0.060***	0.559
	(0.019)	(0.019)	(0.019)	(0.019)	
Over-educated and Over-skilled	-0.075	-0.049	-0.113	-0.089	0.044
	(0.073)	(0.075)	(0.079)	(0.081)	
Only Over-educated	-0.087*	-0.087*	-0.124**	-0.126**	0.246
	(0.048)	(0.049)	(0.058)	(0.058)	
Under-educated and Over-skilled	-0.013	0.032	0.022	0.069	0.058
	(0.066)	(0.069)	(0.072)	(0.073)	
Only Over-skilled	-0.058	-0.044	-0.059	-0.045	0.062
	(0.052)	(0.054)	(0.052)	(0.054)	
Only Under-educated	-0.075	-0.064	-0.044	-0.030	0.253
	(0.049)	(0.050)	(0.056)	(0.057)	
Job occupational scale	-0.000	-0.000	0.000	0.000	51.978
	(0.001)	(0.001)	(0.001)	(0.001)	
Quit	-0.075	/	-0.076	/	
	(0.047)	/	(0.047)	/	
Quit x Over-educated and Over-skilled	/	-0.333**	/	-0.344**	0.003
	/	(0.148)	/	(0.143)	
Quit x Only Over-educated	/	0.010	/	0.005	0.013
	/	(0.099)	/	(0.099)	
Quit x Under-educated and Over-skilled	/	-0.341***	/	-0.340***	0.007
	/	(0.107)	/	(0.107)	
Quit x Well-matched	/	0.027	/	0.030	0.024
	/	(0.079)	/	(0.079)	
Quit x Only Over-skilled	/	-0.118	/	-0.119	0.006
	/	(0.140)	/	(0.141)	
Quit x Only Under-educated	/	-0.117	/	-0.117	0.019
	/	(0.084)	/	(0.084)	
Mean of actual years of education	0.023**	0.022**	/	/	13.953
	(0.009)	(0.010)	/	/	
Mean of required years of education	/	/	0.025	0.026	14.286
	/	/	(0.018)	(0.018)	
Required years of education	/	/	-0.016	-0.017	14.273
	/	/	(0.014)	(0.014)	
Log likelihood	-2090	-2085	-2092	-2087	
Wald chi-squared	149.8	159.2	146.0	155.9	
Individuals	1,152	1,152	1,152	1,152	
Observations	3,140	3,140	3,140	3,140	

Notes: ˘DUWG3 is a dummy variable, takes value of 1 if wage growth > mean plus standard deviation during a three-year period at time t; 0 otherwise.
Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are: Australian, Not Union member, healthy, and Well-matched.
The models include Time periods Dummies, states Dummies, unemployment, Immigrant status, Union membership, Health status, Work experience, Current job tenure, Current occupational tenure, Job scale, On-the-job training and Base year hourly wage rates.
Source: HILDA-Release 9

4.6.2 State dependence of over-education and over-skilling

Previous parts of this paper have shown that career mobility theory is not applicable for the explanation of the phenomenon of over-education in Australia. An implication of this result is that potentially over-education was permanent. In this section, a direct dynamic model is used to examine the persistence of over-education based on Models 4 and 5 below.

To further evaluate dynamic effects by qualification category, I use four sub-samples of Graduate, Diploma, Certificate, and Without Qualification. Graduate includes Doctorate, Masters, graduate diploma, graduate certificate and Bachelor, and requires over 16 years of education to achieve. Diploma includes Advanced diploma and diploma, and needs 15 years of education. Certificate includes certificate I, certificate II, certificate III or certificate IV which require above 13 years of education. 'Without qualification' covers workers without qualifications, representing less than 13 years of education.

Model 4: Over-education and state dependence

The effect of past over-education on current over-education is estimated using the following equation:

$$(4.11) \quad Overeducation_{it}^{*} = \Upsilon Overeducation_{it-1} + x_{it}\,\beta + \Upsilon_0 Overeducation_{i0} + \overline{X}_{\iota}\delta + \eta_i + \varepsilon_{it}$$

Model 5: Over-skilling and state dependence

The effect of past over-skilling on current over-skilling can be written as:

$$(4.12) \qquad Overskilling_{it}^{*} = \Upsilon Overskilling_{it-1} + x_{it}\,\beta + \Upsilon_0 Overskilling_{i0} + \overline{X}_i\delta + \eta_i + \varepsilon_{it}$$

Based on Equations (4.11) and (4.12), the extent of state dependence of over-education and over-skilling are reported in Tables 4.11 and 4.12. Overall, for the whole sample, state dependence is found for both over-education and over-skilling. The positive and significant coefficients of first lag of over-education and over-skilling in Column (1) of Tables 4.11 and 4.12 demonstrate that both over-education and over-skilling are self-perpetuating. Furthermore, the magnitude of lagged over-education is three times larger than that of lagged over-skilling which implies a stronger state dependence for over-education than over-skilling.

The coefficient of initial over-education and over-skilling in Column (1) of Tables 4.11 and 4.12 are positive and significant statistically. This remains true for the coefficient of initial over-skilling. In addition, their magnitude is quite similar. This evidence reveals that initial conditions of over-education and over-skilling do matter for their future states, respectively.

Over-skilling has stronger impact from initial over-skilling state rather than previous over-skilling state. In contrast, over-education has stronger impact from previous over-education state rather than initial over-education state. However, the whole sample is separated into subsamples by qualification, the results are different.

Columns (2) to (5) in Table 4.11 report the estimations for over-education among Graduates, Diploma holders, Certificate holders and Without Qualifications, respectively. Likewise, Columns (2) to (5) in Table 4.12 present the estimations for over-skilling among these four types of qualification groups, respectively.

Table 4. 11: Dynamic Random Effect Probit Estimations of Over-education Status with Controls for Initial Condition (Model 4: Over-education and State Dependence)

	Dependent variable =1 if workers are observed to be over-educated at t				
	Whole Sample	**By Qualification**			
	(1)	(2)	(3)	(4)	(5)
	Overall	**Graduate**	**Diploma**	**Certificate**	**Without Qualification**
VARIABLES	Over-education at t coefficient	Over-education at t coefficient	Over-education at t coefficient	Over-education at t coefficient	Over-education at t coefficient
Lagged dependent variable					
Over-education at t-1	1.390***	1.322***	1.055***	1.236***	0.259
Initial condition	(0.087)	(0.245)	(0.196)	(0.138)	(0.159)
Over-education at t=0	1.006***	0.278	0.875***	0.229*	0.239
	(0.108)	(0.291)	(0.219)	(0.139)	(0.155)
Quit at t	-0.149	0.243	0.434	-0.436**	-0.290
	(0.115)	(0.369)	(0.369)	(0.209)	(0.218)
Hourly wage (**2009$**)	-0.183	-0.342	0.174	-0.075	-0.389
	(0.138)	(0.452)	(0.435)	(0.260)	(0.276)
Job occupational scale	-0.060***	-0.148***	-0.125***	-0.026***	-0.032***
	(0.004)	(0.018)	(0.012)	(0.005)	(0.007)
Log likelihood	-1819	-236.7	-155.0	-517.6	-451.4
Wald chi-squared	1427	154.7	209.5	223.6	125.7
rho	0.316	0.543	1.66e-06	0.0719	0.146
Individuals	1,699	488	178	545	529
Observations	6624	1893	675	2,125	1931

Notes:

Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively. Base-categories are: Australian, Not Union member, healthy, No training, Well-matched, year 2008 and QLD.

The models include Time periods Dummies, States Dummies, unemployment, Immigrant status, Union membership, Health status, Years of education, Work experience, Current job tenure, Current occupational tenure, Job occupational scale, On-the-job training and Current job hourly wage rates. Full results are available upon request.

Source: HILDA-Release 9

Graduates seemingly become severely trapped into over-education or over-skilling once they reach such a status. Graduates who are presently over-educated for their positions of employment are more likely to find themselves over-educated in the future than their currently well-matched counterparts. Graduates who are currently over-skilled are more likely to be over-skilled in the next stage of their employment. Compared to other groups, education mismatch and skill under-utilisation have strong state dependence and are self-perpetuating; this can be shown by the larger magnitude of coefficient of the next lagged over-education and over-skilling among Graduates. Initial over-education does not influence future over-education status, but initial over-skilling does have a positive impact on future over-skilled status.

These results of over-skilling for Graduates in Column (2) of Table 4.12 are consistent with those of Mavromaras et al. (2009b). These researchers adopted dynamic panel econometric methods to estimate the dynamic properties of over-skilling and the possible presence of the state dependence[48] of over-skilling based on the first six waves of the HILDA survey. Heckman's method was used to control for initial condition. They found that over-skilling is persistent for degree-level graduates due to state dependence in the labour force.

In Column (3) of Table 4.11, workers who hold Diplomas are found to have significant state dependence and initial impact for over-education. However, in Column (3) of Table 4.12, among workers who hold Diplomas, there is no evidence to show state dependence for over-skilling, but it has a strong impact on the initial over-skilling.

The significant state dependence of over-education and over-skilling are found among workers who hold Certificates. Compared to Graduates, the magnitude of coefficients for over-skilling is half of that for graduates; this reflects, a relatively lower incidence of state dependence effects for Certificate holding workers.

[48] State dependence is defined as the degree to which the effect of any initial endowments on an outcome may be attenuated or accentuated by the continued presence of that outcome (Heckman 1981; 1991).

There are a small number of workers without Qualification who are over-educated for their current employment positions, so there is no significant effect from previous over-education or initial over-education. However, both their initial over-skilling and previous over-skilling affect their future over-skilling states.

Table 4. 12: Dynamic Random Effect Probit Estimations of Over-skilling with Controls for Initial Conditions (Model 5: Over-skilling and State Dependence)

	Dependent variable =1 if workers are observed to be over-skilled at t				
	Whole Sample	**By Qualification**			
	(1)	(2)	(3)	(4)	(5)
	Overall	**Graduate**	**Diploma**	**Certificate**	**Without Qualification**
VARIABLES	Over-skilled at t coefficient	Over-skilled at t coefficient	Over-skilled at t coefficient	Over-skilled at t coefficient	Over-skilled at t coefficient
Lagged dependent variable					
Over-skilling at t-1	0.409***	0.823***	0.348	0.428***	0.282**
Initial condition	(0.075)	(0.175)	(0.238)	(0.132)	(0.126)
Over-skilling at t=0	0.974***	0.883***	1.189***	0.812***	1.005***
	(0.092)	(0.191)	(0.313)	(0.154)	(0.156)
Quit at t	0.162	-0.073	-0.287	0.140	0.452***
	(0.099)	(0.220)	(0.362)	(0.162)	(0.173)
Job occupational scale	-0.007***	-0.009*	-0.011	-0.007	-0.005
	(0.003)	(0.005)	(0.008)	(0.005)	(0.005)
Log likelihood	-2403	-461.3	-224.2	-797.9	-837.8
Wald chi-squared	530.6	210.6	66.64	135.1	191.4
rho	0.370	0.252	0.356	0.286	0.398
Individuals	1,699	488	178	545	529
Observations	6624	1,893	675	2125	1,931

Notes:

Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Base-categories are: Australian, Not Union member, healthy, No training, Well-matched, year 2008 and QLD.

The models include Time periods Dummies, States Dummies, unemployment, Immigrant status, Union membership, Health status, Years of education, Work experience, Current job tenure, Current occupational tenure, Job occupational scale, On-the-job training and Current job hourly wage rates. Full results are available upon request.

Source: HILDA-Release 9

Binary Quit variable is equal to 1 if they leave their current job, 0 otherwise.

For the entire sample, contrary to expectations, current education mismatch and skill mismatch do not have significant effects on job quitting behaviour. This is consistent with result from the previous job quitting model, in which it was found that overall job dissatisfaction drives workers to leave their jobs.

Both over-education and over-skilling have no significant effect on job quitting behaviour for Graduates and those who hold Diplomas. Positive effects are found between over-education and job quitting for Graduates and Diploma holders; however, statistically, these effects are not significant. On the contrary, over-educated workers who have certification in their field of employment are less likely to leave their current jobs when compared to their counterparts. Workers without Qualifications are the only group who are more likely to leave their current employment if their skills are under-utilised.

Overall, the higher the position on the occupational scale, the less chance there is of being over-educated or over-skilled. The reason for this being that positions on that are high on the occupational scale require a higher level of education and a more advanced skill set than do positions lower down the occupational scale. Thus, workers whose positions are high on the occupational scale are less likely to be over-educated or over-skilled. Strong negative significant effects between job occupational scale and over-education are found among workers with different types of qualifications. However, negative significant effects between job occupational scale and over-skilling are found among Graduates.

4.7 Summary

This essay examines the effect of job mismatch on upward occupational mobility and upward wage growth during one-year and three-year periods in a dynamic setting. Career mobility theory is examined. The analysis leads to the following findings:

(1) Skill under-utilisation motivates workers to move out of their current employment

positions; whereas, education mismatches do not.

(2) When controlling for the actual years of education, during one-year and three-year time periods, upward occupational growth is found among under-educated and over-skilled workers and also among the under-educated but skilled-matched workers. By contrast, downward occupational growth is found among over-educated and over-skilled workers and also among the over-educated but skill-matched workers. These findings do not support career mobility theory's explanation for over-education.

(3) When accounting for the actual years of education, upward wage growth is found among under-educated and over-skilled workers during a one-year period. Downward wage growth is found among Over-educated workers during both a one-year period and a three-year period. Over-educated and over-skilled workers who leave their current jobs seemingly suffer a great disadvantage with respect to wage growth, compared to those similar over-educated workers who do not leave their employment during a three-year period.

(4) The empirical results are not in line with career mobility theory. There is no evidence for over-educated workers experiencing upward wage growth throughout their career path. Even when they resign from their current employment, they appear to suffer considerable disadvantage in wage payment in their new employment. This is in line with findings of Linsley (2005a), based on a different data set.

(5) Skill under-utilisation affects quit behaviour. Education mismatch explains wage effects. These results are consistent with the previous findings in Mavromaras et al. (2010b), and Allen and Van der Velden (2001).

The analytical contributions are summarised as follows:

(1) Using dynamic models I examine job mismatch impacts on upward mobility. These are areas that are under-researched. The results and analyses in this study will add to current knowledge concerning job mismatches.

(2) Career mobility theory provides a persuasive explanation for the existence of over-education from a supply side perspective. Thus, this should be tested to compare differences between workers who experience a voluntary separation (voluntary resignation) and workers who experience no change of employment

position, rather than those experiencing involuntary separation (lay off). In this paper, I focus on these two groups of workers who stay and workers who quit voluntarily to test Career mobility theory.

(3) In Australia, this has been the first use of longitudinal data to examine career mobility theory from a dynamic upward occupational mobility and upward wage growth perspective. A Mundlak correction model is used to adjust for unobserved heterogeneity effects.

(4) An improved performance is found for under-educated workers; this includes those workers whose skills are under-utilised in the Labour market. It is only this group that experiences upward occupational mobility and upward wage growth. Previous research has ignored this group when testing career mobility theory.

Appendix 4 A: Mean and Standard Deviation for the Whole Sample

Table 4A. 1: Sample Statistics

VARIABLES	(1) mean	(2) sd	(3) Observations
Age	42.122	9.890	7987
ESB immigrant	0.126	0.331	7987
NESB immigrant	0.071	0.258	7987
Married	0.776	0.417	7987
Not healthy	0.133	0.339	7987
Graduate	0.283	0.348	7978
Diploma	0.100	0.301	7987
Certificate	0.319	0.466	7987
No qualification	0.298	0.457	7987
Years of education	13.866	2.429	7987
Years of required education	14.242	1.795	7987
Union member	0.369	0.482	7987
Unemployment rate (per cent)	4.776	0.647	7987
Hourly wage (2009$)	31.008	15.552	7987
Log hourly wage (2009$)	3.335	0.444	7987
Overall satisfaction	0.825	0.380	7987
Quit	0.088	0.283	7987
Years of experience	22.256	10.276	7987
Job Tenure	8.960	8.847	7987
Occupation Tenure	11.455	10.075	7987
Job occupational scale	50.721	24.338	7987
training	0.433	0.496	7987
Over-skilled	0.185	0.388	7987
Over-educated	0.280	0.449	7987
Under-educated	0.330	0.470	7987
Over-educated & Over-skilled	0.050	0.218	7987
Only Over-educated	0.230	0.421	7987
Under-educated & Over-skilled	0.069	0.253	7987
Well-matched	0.325	0.468	7987
Only Over-skilled	0.065	0.247	7987
Under-educated	0.261	0.439	7987
Occupational mobility during a one-year period	0.476	0.499	6633
Occupational mobility during a three-year period	0.491	0.500	5073
Occupational mobility during a five-year period	0.499	0.500	2786
Wage growth during a one-year period	0.521	0.500	6625
Wage growth during a three-year period	0.545	0.498	5070
Wage growth during a five-year period	0.568	0.495	2787

Source: HILDA-Release 9

Appendix 4B: Static Models of Job Mismatch on Job Quitting and Upward Mobility

Random logit models are applied to estimate the static effects of job mismatch on job quitting and upward mobility.

The section is structured as follows. First, the static impact of job mismatch on job quitting is examined in Model 4B1. Second, the static impacts of job mismatch on upward occupation mobility and upward wage growth are examined, respectively, during a one-year and a five-year period in Models 4B2 and 4B3.

Model 4B1: Job mismatch and voluntary leaving (Quitting)

The actual quits model is written as:

$$(4B.1) \qquad quit_{i,t}^{*} = x_{i,t}\,\beta + \sum_{j=1}^{6} \alpha_j MTYP_{i,t} + \overline{\sum_{J=1}^{6} \alpha_J MTYP_{\iota,t}} + \overline{X}_{\iota}\delta + \eta_i + \varepsilon_{i,t}$$

According to the model in Equation (4B.1), Table 4B.1 presents random effect estimations of job mismatch on voluntarily leaving within and across occupations separately. Contrary to the hypothesis, there is no significant negative effect of over-education and over-skilling on job-quitting.

Across occupations, with or without controlling for time periods and unemployment, in columns (1) and (3), without Mundlak correction to adjust unobserved heterogeneity, Over-educated & Over-skilled workers are less likely to experience voluntarily leaving

their current jobs than workers with the same years of education but who work in higher occupational level jobs that demand the same education and skill as they have. However, once the Mundlak correction models are applied, in columns (2) and (4), the negative significant coefficients for over-educated & over-skilled become positive and non-significant. The coefficients of only over-skilled and only under-educated are changed to be positive and significant. This evidence shows that unobserved heterogeneity plays an important role in quitting. Over-educated & over-skilled workers have a propensity to remain in their current jobs. Under-educated workers are more likely to quit. This is in line with the results in Sicherman (1991) and Robst (1995). Sicherman (1991) found job mobility among under-educated workers but gave no further explanation. Robst (1995) offered two explanations of the greater mobility of under-educated workers: being laid off or fired and leaving due to retirement. These are two reasons for accounting for the mobility of under-educated workers. Unfortunately, both explanations do not apply to this study. Firstly, the sample used here does not include workers who experience involuntary leaving; that is being laid off or fired. Secondly, according to Table 4.5, the mean age of under-educated workers who resign from their employment is around 38 years; these workers still have a long period of time before reaching the retirement age of 65 years. In the final column of Table 4.5, those under-educated workers who leave their employment have a greater number of years of experience, lower actual years of education, higher than required years of education for their jobs and less earning power than well-matched workers. Thus, they may more likely to leave to search for better jobs due to less opportunity cost.

Within occupations, the Mundlak correction in column (6) shows the positive significant coefficient for only over-skilled; and this result is not sensitive to adding time periods and unemployment variables.

The common result in Table 4B.1 is found that educationally-matched and over-skilled workers are more likely to experience leaving their employment than are well-matched workers across occupations or within occupations. Skill under-utilisation is the main cause of workers leaving their employment.

Table 4B. 1: Random Effect Estimations of Job Mismatch on Voluntary Leaving-Quitting within and across Occupations

Dependent variable =1 if workers experience voluntary leaving-quit

	Control educational attainment Across Occupations				**Control occupational level Within Occupations**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RE	CRE	RE	CRE	RE	CRE	RE	CRE
	xtlogit RE	xtlogit RE *(with Mundlak correction)*	xtlogit RE	xtlogit RE *(with Mundlak correction)*	xtlogit RE	xtlogit RE *(with Mundlak correction)*	xtlogit RE	xtlogit RE *(with Mundlak correction)*
Explanatory Variables	Quit	Quit	Quit	Quit	Quit	Quit	Quit	Quit
Main panel estimation results			***Control time periods***				***Control time periods***	
Over-educated & Over-skilled	-0.365*	0.0545	-0.394*	0.0236	-0.301	0.299	-0.308	0.192
	(0.209)	(0.299)	(0.212)	(0.301)	(0.218)	(0.338)	(0.221)	(0.343)
Only Over-educated	-0.137	0.155	-0.154	0.120	-0.0721	0.402	-0.0713	0.278
	(0.134)	(0.215)	(0.135)	(0.216)	(0.138)	(0.260)	(0.140)	(0.267)
Under-educated & Over-skilled	0.110	0.449	0.130	0.472	-0.0168	0.224	-0.0188	0.344
	(0.204)	(0.285)	(0.207)	(0.288)	(0.185)	(0.306)	(0.188)	(0.313)
Only Over-skilled	0.181	0.489**	0.203	0.523**	0.176	0.497**	0.199	0.536**
	(0.169)	(0.225)	(0.171)	(0.227)	(0.169)	(0.225)	(0.171)	(0.227)
Only Under-educated	0.221	0.394*	0.243	0.455**	0.0939	0.162	0.0961	0.330
	(0.151)	(0.223)	(0.153)	(0.224)	(0.124)	(0.248)	(0.125)	(0.255)
Well-Matched	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Actual years of education	0.0504	0.309**	0.0575	0.0316	/	/	/	/
	(0.0370)	(0.139)	(0.0375)	(0.0506)	/	/	/	/
Required years of education	/	/	/	/	0.0136	0.0800	0.0226	0.0594
	/	/	/	/	(0.0359)	(0.0591)	(0.0365)	(0.0602)
Mundlak correction	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Control for States	YES	YES	YES	YES	YES	YES	YES	YES
Control for unemployment	NO	NO	YES	YES	NO	NO	YES	YES
Control for time periods	NO	NO	YES	YES	NO	NO	YES	YES
Log likelihood	-2092	-1971	-2078	-1927	-2093	-1973	-2079	-1926
Wald chi-squared	378.2	478.5	391.8	508.7	377.2	477.8	390.5	510.1
Number of individuals	1977	1977	1977	1977	1977	1977	1977	1977
Observations	7,972	7972	7972	7972	7,972	7972	7972	7972

Notes:
Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are Australian, Not Union member, healthy, No training, Well-matched, year 2008, and QLD.
The models include Immigrant status, Time periods Dummies, States Dummies, Unemployment, Union membership, Healthy status, Work experience, Current job tenure, Current occupational tenure, Job scale, on-the-job training and current job hourly wage.

Source: HILDA-Release 9

Model 4B2: Job mismatch and upward occupational mobility

$$(4B.2) \qquad UOCM^{*}_{i,t} = x_{i,t}\,\beta + \sum_{j=1}^{6} \alpha_j MTYP_{it} + \overline{\sum_{J=1}^{6} \alpha_J MTYP_{\iota,t}} + \bar{X}_\iota \delta + \eta_i + \varepsilon_{i,t}$$

And

$$(4B.3) \qquad UOCM^{*}_{i,t} = x_{i,t}\,\beta + \sum_{j=1}^{6} \alpha_j MTYP_{it} + \sum_{j=1}^{6} \xi_j\left(quit * \alpha_j MTYP_{it}\right) + \overline{\sum_{J=1}^{6} \alpha_J MTYP_{\iota,t}} + \overline{\sum_{J=1}^{6} \xi_J\left(quit * \alpha_J MTYP_{\iota t}\right)} + \bar{X}_\iota \delta + \eta_i + \varepsilon_{i,t}$$

Based on Equations (4B.2) and (4B.3), Tables 4B.2 and 4B.3 present the random effect logit estimations of job mismatch on one-year and five-year upward occupational mobility, respectively.

In comparison with the structure of significance produced by different models in Tables 4B.2 and 4B.3, such as in column (1) and (1)*[49], they report identical results for the effects of job mismatch. Furthermore, the magnitude of the coefficients reported in Table 4B.3 is greater than the corresponding ones in Table 4B.2. This explains the strength of the estimation results when extending the time period from a one-year period to a five-year

[49] The superscript * reports results from random effect logit estimations of job mismatch during a five-year period. This also applies to results based on Model 4B3.

period; the effects are stronger in a longer time periods.

Career mobility theory predicts the over-educated workers are more likely to move to a higher occupational rank. However, the results of this study cast doubts on the use of the career mobility theory to explain the over-education phenomenon. In particular, across occupations, with Mundlak correction to account for unobserved heterogeneity, the coefficient of over-educated & over-skilled and only over-educated in columns (2) and (2)*; columns (4) and (4)* are significantly negative, which suggests these two types of workers are less likely to experience a move to positions in higher level occupations either, within a one-year, or, within a five-year period. Within occupations and without correction of individual effects, the coefficients of the first two rows in columns (5) and (5)*; columns (7) and (7)* are positive and significant. This is in line with career mobility theory in which over-educated workers are more likely to experience upward occupational mobility. However, with the addition of the group means variables to the models, the sign becomes no more significant. The evidence shows that unobserved heterogeneity is not trivial issue. Without adjustment, the results are biased upward or downward.

All the coefficients of Only Under-educated in Tables 4B.2 and 4B.3 are positive and significant which proves the robustness of the result. Across or within occupations, relative to well-matched workers, Only Under-educated workers seem to experience moves to a higher level occupations.

Under-educated & over-skilled workers are the other groups who are most likely to move to higher level occupational jobs than are well-matched workers across occupations or within occupations. Workers with jobs requiring a high degree of educational achievement enhance their upward career mobility.

There is no evidence to show that quitting their occupation assists workers in moving upward in occupational mobility.

Table 4B. 2: Random Effect logit Estimations of Job Mismatch on One-year Upward Occupational Mobility

	Dependent variable=1 if moved to a higher ranked occupation during a one-year period							
	Control educational attainment (Across Occupations)				Control occupational level (Within Occupations)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explanatory Variables	RE	CRE	RE	CRE	RE	CRE	RE	CRE
Main panel estimation results			***With interaction effect***				***With interaction effect***	
Over-educated & Over-skilled	-0.625***	-0.994***	-0.655***	-0.973***	0.885***	-0.0969	0.838***	-0.0929
	(0.213)	(0.290)	(0.222)	(0.303)	(0.217)	(0.330)	(0.226)	(0.341)
Only Over-educated	-0.211*	-0.817***	-0.222*	-0.859***	1.042***	0.0442	1.031***	0.00367
	(0.126)	(0.197)	(0.130)	(0.200)	(0.129)	(0.244)	(0.132)	(0.246)
Under-educated & Over-skilled	1.772***	1.872***	1.729***	1.877***	0.0233	1.131***	-0.0494	1.131***
	(0.190)	(0.256)	(0.198)	(0.266)	(0.162)	(0.286)	(0.171)	(0.295)
Only Over-skilled	-0.208	-0.250	-0.227	-0.265	-0.193	-0.240	-0.205	-0.250
	(0.177)	(0.221)	(0.187)	(0.231)	(0.173)	(0.223)	(0.184)	(0.233)
Only Under-educated	2.077***	1.971***	2.080***	1.952***	0.435***	1.283***	0.422***	1.259***
	(0.144)	(0.202)	(0.147)	(0.206)	(0.108)	(0.233)	(0.113)	(0.237)
Quit x Over-educated & Over-skilled	/	/	-0.152	-0.512	/	/	0.126	-0.376
	/	/	(0.668)	(0.726)	/	/	(0.669)	(0.739)
Quit x Only Over-educated	/	/	-0.349	0.109	/	/	-0.293	0.0972
	/	/	(0.325)	(0.374)	/	/	(0.326)	(0.377)
Quit x Under-educated & Over-skilled	/	/	0.128	-0.252	/	/	0.324	-0.275
	/	/	(0.426)	(0.496)	/	/	(0.413)	(0.496)
Quit x Well-matched	/	/	-0.411	-0.504	/	/	-0.409	-0.528*
	/	/	(0.261)	(0.316)	/	/	(0.255)	(0.317)
Quit x Only Over-skilled	/	/	-0.183	-0.234	/	/	-0.228	-0.306
	/	/	(0.480)	(0.588)	/	/	(0.475)	(0.596)
Quit x Only Under-educated	/	/	-0.349	-0.145	/	/	-0.252	-0.152
	/	/	(0.254)	(0.305)	/	/	(0.247)	(0.305)
Actual years of education	0.580***	1.183	0.582***	1.159	/	/	/	/
	(0.0395)	(1.094)	(0.0397)	(1.099)	/	/	/	/
Required years of education	/	/	/	/	0.695***	0.373***	0.697***	0.375***
	/	/	/	/	(0.0417)	(0.0585)	(0.0418)	(0.0586)
Mundlak correction	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Control for States	YES	YES	YES	YES	YES	YES	YES	YES
Control for time periods and unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Log likelihood	-2829	-2378	-2826	-2376	-2781	-2354	-2778	-2352
Wald chi-squared	441.5	866.4	442.5	864.6	534.5	883.4	536.2	881.4
Number of individuals	1728	1728	1728	1728	1728	1728	1728	1728
Observations	6,823	6,823	6823	6823	6823	6,823	6823	6823

Notes: Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are Australian, Not Union member, healthy, Well-matched, year 2008 and QLD.
The models include Immigrant status, Time periods Dummies, States Dummies, Unemployment, Union membership, Health status, Work experience, Current job tenure, Current occupational tenure, On-the-job training and Base year hourly wage are included. Workers with the highest occupational scale at base year are excluded because they cannot move further upward.
Source: HILDA-Release 9

Table 4B. 3: Random Effect Estimations of Job Mismatch on Five-year Upward Occupational Mobility

	Dependent variable=1 if moved to a higher ranked occupation during a five-year period							
	Control educational attainment Across Occupations				Control occupational level Within Occupations			
	(1)*	(2)*	(3)*	(4)*	(5)*	(6)*	(7)*	(8)*
Explanatory Variables	RE	CRE	RE	CRE	RE	CRE	RE	CRE
Main panel estimation results			*With interaction effect*				*With interaction effect*	
Over-educated & Over-skilled	-1.197***	-2.105***	-1.324***	-2.116***	0.815**	-0.953	0.617	-1.006
	(0.381)	(0.532)	(0.402)	(0.558)	(0.387)	(0.595)	(0.406)	(0.618)
Only Over-educated	-0.195	-0.920***	-0.182	-0.938***	1.563***	0.293	1.549***	0.270
	(0.217)	(0.341)	(0.223)	(0.348)	(0.234)	(0.446)	(0.240)	(0.451)
Under-educated & Over-skilled	2.433***	2.393***	2.401***	2.472***	0.0730	1.369***	0.0151	1.451***
	(0.355)	(0.462)	(0.368)	(0.482)	(0.304)	(0.517)	(0.319)	(0.535)
Only Over-skilled	-0.0451	-0.109	0.0275	-0.0181	-0.0108	-0.0653	0.0624	0.0330
	(0.296)	(0.372)	(0.309)	(0.390)	(0.291)	(0.375)	(0.303)	(0.392)
Only Under-educated	3.027***	2.755***	3.043***	2.823***	0.795***	1.775***	0.787***	1.839***
	(0.273)	(0.359)	(0.278)	(0.367)	(0.196)	(0.409)	(0.202)	(0.416)
Quit x Over-educated & Over-skilled	/	/	0.812	-0.184	/	/	1.555	0.136
	/	/	(1.060)	(1.240)	/	/	(1.044)	(1.209)
Quit x Only Over-educated	/	/	-0.736	-0.0934	/	/	-0.293	0.143
	/	/	(0.587)	(0.682)	/	/	(0.596)	(0.701)
Quit x Under-educated & Over-skilled	/	/	0.145	-0.600	/	/	0.234	-0.670
	/	/	(0.837)	(0.944)	/	/	(0.814)	(0.951)
Quit x Well-matched	/	/	-0.515	-0.289	/	/	-0.530	-0.280
	/	/	(0.470)	(0.567)	/	/	(0.464)	(0.567)
Quit x Only Over-skilled	/	/	-1.127	-1.002	/	/	-1.106	-1.085
	/	/	(0.927)	(1.054)	/	/	(0.909)	(1.063)
Quit x Only Under-educated	/	/	-0.459	-0.720	/	/	-0.361	-0.747
	/	/	(0.468)	(0.554)	/	/	(0.452)	(0.555)
Actual years of education	0.788***	2.787	0.791***	2.767	/	/	/	/
	(0.0747)	(2.267)	(0.0748)	(2.269)	/	/	/	/
Required years of education	/	/	/	/	0.909***	0.521***	0.918***	0.527***
	/	/	/	/	(0.0741)	(0.108)	(0.0748)	(0.109)
Mundlak correction	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Control for States, time periods and unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Log likelihood	-1302	-1189	-1299	-1188	-1269	-1162	-1266	-1160
Wald chi-squared	233.7	270.0	236.0	270.3	264.0	274.8	265.6	275.1
Number of individuals	1311	1311	1311	1311	1311	1311	1311	1311
Observations	2,905	2905	2905	2905	2,905	2,905	2905	2,905

Notes: Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are: Australian, Not Union member, healthy, Well-matched, year 2008 and QLD.
The models include Immigrant status, Time periods Dummies, States Dummies, Unemployment, Union membership, Health status, Work experience, Current job tenure, Current occupational tenure, On-the-job training and Base year hourly wage rates. Workers with the highest occupational scale at base year are excluded because they cannot move further upward. Source: HILDA-Release 9

Model 4B3: Job mismatch and upward wage mobility

(4B. 4)

$$wagegrowth_{i,t}^{*} = x_{i,t}\,\beta + \sum_{j=1}^{6} \alpha_j MTYP_{it} + \overline{\sum_{j=1}^{6} \alpha_j MTYP_{i,t}} + \overline{X}_i \delta + \eta_i + \varepsilon_{i,t}$$

And

(4B. 5)

$$wagegrowth_{i,t}^{*} = x_{i,t}\,\beta + \sum_{j=1}^{6} \alpha_j MTYP_{it} + \sum_{j=1}^{6} \xi_j \left(quit * \alpha_j MTYP_{it}\right) + \overline{\sum_{j=1}^{6} \alpha_j MTYP_{i,t}} + \overline{\sum_{j=1}^{6} \xi_j \left(quit * \alpha_j MTYP_{it}\right)} + \overline{X}_i \delta + \eta_i + \varepsilon_{i,t}$$

In this study upward wages growth during one-year and five-year periods, are respectively examined. Workers with valid data for occupation variable in two consecutive years and five consecutive years are included in the analysis. It takes time for workers to settle down in new jobs when they quit their current positions voluntarily. The first year is a transitory period for them, and they are more likely to suffer a wage reduction in comparison with remaining in their previous employment. However, after a five-year period, some workers may change their mismatched status to a matched status and thus achieve wage growth.

In accordance with the models in Equations (4B.4) and (4B.5), random effects estimations results are given in Tables 4B.4 and 4B.5.

Within a one-year period, only over-educated workers are less likely to experience wage

growth; however, within a five-year period, they will seemingly experience positive wage growth, even though this effect is not significant when compared to the wage growth experienced by well-matched workers across occupations.

Positive and significant wage growth is found among under-educated & over-skilled workers within one year; such growth becomes stronger during a five-year period.

Quitting one's occupation has a significant effect on wage growth among three types of workers.

When compared to workers who remain in the same employment position, but also hold similarly mismatched status, over-educated workers who quit from previous employment do not suffer from any temporary lowering of wage growth within one year of new employment, however, after five years, they have a disadvantage; this is presented by a negative, significant coefficient. This suggests that over-educated workers should stay in their employment positions rather than quitting them.

In contrast, only over-skilled workers have a temporary disadvantage in wage growth over one year of employment; seemingly, for them, there is no long-term loss of wage growth.

Only under-educated workers are less likely to have wage growth from leaving their employment within one year; after five years, they appear to have less likelihood of experiencing wage growth.

Table 4B. 4: Random Effect Estimations of Job Mismatch on One-year Upward Wage Mobility within and across Occupations

	Dependent variable=1 if wage growth > mean plus standard deviation during a one-year period							
	Control educational attainment Across Occupations				Control occupational level Within Occupations			
Explanatory Variables	(1) RE	(2) CRE	(3) RE	(4) CRE	(5) RE	(6) CRE	(7) RE	(8) CRE
Main panel estimation results			*With interaction effects*				*With interaction effects*	
Over-educated & Over-skilled	-0.0317	-0.137	-0.0297	-0.0985	0.128	-0.0403	0.128	-0.00273
	(0.124)	(0.188)	(0.129)	(0.196)	(0.128)	(0.209)	(0.133)	(0.216)
Only Over-educated	-0.00885	-0.239*	0.00256	-0.226*	0.122*	-0.144	0.134*	-0.130
	(0.0720)	(0.132)	(0.0747)	(0.134)	(0.0728)	(0.158)	(0.0753)	(0.160)
Under-educated & Over-skilled	0.105	0.387**	0.133	0.429**	-0.0758	0.303	-0.0517	0.343*
	(0.119)	(0.179)	(0.124)	(0.185)	(0.107)	(0.193)	(0.113)	(0.199)
Only Over-skilled	-0.0366	0.0460	0.0253	0.128	-0.0361	0.0512	0.0257	0.133
	(0.106)	(0.143)	(0.112)	(0.150)	(0.106)	(0.143)	(0.112)	(0.150)
Only Under-educated	0.0558	0.0403	0.0796	0.0835	-0.112*	-0.0379	-0.0904	0.00404
	(0.0850)	(0.136)	(0.0872)	(0.138)	(0.0680)	(0.153)	(0.0709)	(0.155)
Quit x Over-educated & Overskilled	/	/	-0.0332	-0.427	/	/	-0.00732	-0.414
	/	/	(0.416)	(0.496)	/	/	(0.415)	(0.495)
Quit x Only Over-educated	/	/	-0.134	-0.234	/	/	-0.125	-0.233
	/	/	(0.201)	(0.254)	/	/	(0.201)	(0.254)
Quit x Under-educated & Over-skilled	/	/	-0.235	-0.335	/	/	-0.217	-0.333
	/	/	(0.312)	(0.401)	/	/	(0.312)	(0.401)
Quit x Well-matched	/	/	0.0204	-0.0350	/	/	0.0156	-0.0380
	/	/	(0.157)	(0.196)	/	/	(0.157)	(0.196)
Quit x Only Over-skilled	/	/	-0.530*	-0.758**	/	/	-0.533*	-0.757**
	/	/	(0.303)	(0.368)	/	/	(0.303)	(0.368)
Quit x Only Under-educated	/	/	-0.229	-0.504**	/	/	-0.230	-0.503**
	/	/	(0.176)	(0.226)	/	/	(0.176)	(0.226)
Actual years of education	0.0571***	0.326	0.0577***	0.387	/	/	/	/
	(0.0202)	(0.733)	(0.0202)	(0.735)	/	/	/	/
Required years of education	/	/	/	/	0.0674***	0.0393	0.0677***	0.0395
	/	/	/	/	(0.0206)	(0.0356)	(0.0207)	(0.0356)
Mundlak correction	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Control for States, time periods and unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Log likelihood	-4616	-4133	-4613	-4126	-4614	-4132	-4611	-4125
Wald chi-squared	394.1	947.8	398.6	955.6	396.0	949.1	400.4	956.9
Number of individuals	1770	1770	1770	1770	1770	1770	1770	1770
Observations	6990	6990	6990	6990	6990	6990	6990	6990

Notes: Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are: Australian, Not Union member, healthy, Well-matched, year 2008 and QLD.
The models include Immigrant status, Time periods Dummies, States Dummies, Unemployment, Union membership, Health status, Work experience, Current job tenure, Current occupational tenure, Job scale, On-the-job training and Base year hourly wage.
Source: HILDA-Release 9

Table 4B. 5: Random Effect Estimations of Job Mismatch on Five-year Upward Wage Mobility within and across Occupations

	Dependent variable=1 if wage growth > mean plus standard deviation during a five-year period							
	Control educational attainment Across Occupations				Control occupational level Within Occupations			
	(1)*	(2)*	(3)*	(4)*	(5)*	(6)*	(7)*	(8)*
Explanatory Variables	RE	CRE	RE	CRE	RE	CRE	RE	CRE
Main panel estimation results			***With interaction effects***				***With interaction effects***	
Over-educated & Over-skilled	-0.224	0.242	-0.218	0.284	-0.278	-0.275	-0.264	-0.213
	(0.253)	(0.361)	(0.266)	(0.378)	(0.263)	(0.402)	(0.273)	(0.415)
Only Over-educated	0.175	0.293	0.207	0.356	0.172	-0.199	0.202	-0.136
	(0.151)	(0.242)	(0.156)	(0.249)	(0.153)	(0.294)	(0.158)	(0.300)
Under-educated & Over-skilled	0.136	0.617*	0.0414	0.573*	0.0290	1.095***	-0.0676	1.057***
	(0.244)	(0.326)	(0.254)	(0.338)	(0.225)	(0.363)	(0.235)	(0.375)
Only Over-skilled	-0.0705	0.107	0.0291	0.176	-0.0870	0.0997	0.0137	0.172
	(0.212)	(0.262)	(0.225)	(0.278)	(0.212)	(0.263)	(0.225)	(0.279)
Only Under-educated	-0.224	-0.105	-0.152	0.0151	-0.340**	0.331	-0.267*	0.460
	(0.172)	(0.247)	(0.178)	(0.253)	(0.144)	(0.285)	(0.149)	(0.291)
Quit x Over-educated & Over-skilled	/	/	-0.247	-0.833	/	/	-0.392	-0.991
	/	/	(0.836)	(0.974)	/	/	(0.835)	(0.963)
Quit x Only Over-educated	/	/	-0.636	-1.097**	/	/	-0.643	-1.131**
	/	/	(0.451)	(0.539)	/	/	(0.450)	(0.543)
Quit x Under-educated & Over-skilled	/	/	1.279	0.843	/	/	1.326	0.873
	/	/	(0.820)	(0.923)	/	/	(0.820)	(0.927)
Quit x Well-matched	/	/	-0.156	-0.456	/	/	-0.131	-0.429
	/	/	(0.334)	(0.401)	/	/	(0.334)	(0.403)
Quit x Only Over-skilled	/	/	-1.006*	-0.963	/	/	-1.009*	-0.972
	/	/	(0.590)	(0.683)	/	/	(0.590)	(0.687)
Quit x Only Under-educated	/	/	-0.943***	-1.428***	/	/	-0.930***	-1.432***
	/	/	(0.356)	(0.424)	/	/	(0.356)	(0.426)
Actual years of education	0.0627	-1.673	0.0638	-1.694	/	/	/	/
	(0.0430)	(1.584)	(0.0435)	(1.601)	/	/	/	/
Required years of education	/	/	/	/	-0.0561	-0.221***	-0.0602	-0.224***
	/	/	/	/	(0.0432)	(0.0724)	(0.0437)	(0.0734)
Mundlak correction	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Control for States, time periods and unemployment	YES	YES	YES	YES	YES	YES	YES	YES
Log likelihood	-1853	-1744	-1846	-1733	-1853	-1740	-1846	-1728
Wald chi-squared	221.7	306.8	225.1	311.7	223.6	306.6	227.2	311.3
Number of individuals	1369	1369	1369	1369	1369	1369	1369	1369
Observations	3049	3049	3049	3049	3049	3049	3049	3049

Notes: Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.
Base-categories are Australian, Not Union member, healthy, Well-matched, year 2008 and QLD.
The models include Immigrant status, Time periods Dummies, States Dummies, Unemployment, Union membership, Healthy status, Work experience, Current job tenure, Current occupational tenure, Job scale, On-the-job training and Base year hourly wage. Source: HILDA-Release 9

Appendix 4C: Definition of Variables

Personal Characteristics	
(1) General	
Age	Continuous age variable, expressed in years.
Married	Dummy variable, 1 if married (or de facto), zero otherwise.
Not healthy	Dummy variable, 1 if has Long term health condition, disability or impairment, zero otherwise.
(2) Qualifications	
Years of actual education	Continuous educational attainment variable, expressed in years.
Graduate	Dummy variable, 1 if highest qualification is Doctorate, Masters, grad diploma, grad certificate and Bachelor, zero otherwise.
Diploma	Dummy variable, 1 if highest qualification is Advanced diploma or diploma, zero otherwise.
Certificate	Dummy variable, 1 if highest qualification is certificate I II III or IV, zero otherwise.
Without Qualification	Dummy variable, 1 if highest qualification is year12 or below, zero otherwise.
(3)Country of birth	
Australian	Dummy variable, 1 if born in Australia, zero otherwise.
ESB immigrant	Dummy variable, 1 if born in an English speaking country, zero otherwise.
NESB immigrant	Dummy variable, 1 if born in a non-English speaking country, zero otherwise.
Job characteristics	
(1) General	
Job occupational scale (Jbmo6s)	AUSEI06 occupational status scale, current main job
Unemployment rate	Unemployment rate annually, refer to 6202.0 - Labour Force, Australia, Australian Bureau of Statistics
EXP	Continuous variable, expressed in potential years of work experience, calculated by hgage-edhighy-5.
EXP^2	Continuous variable, experience square
Job Tenure	Continuous variable, expressed in year's tenure in the current job.
Job Tenure squared	Continuous variable, expressed in year's tenure square in the current job.
Hourly wage	Continuous variable, expressed in current weekly gross wages and salary from main job divided by combined hours per week usually worked in main job 2009$
Log hourly wage	Continuous variable, expressed in the natural logarithm of hourly wages from main job
Union member	Dummy variable,1 if union member, zero otherwise
Training	Dummy variable, 1 if taking part in any work related training in the past 12 months, zero otherwise
Overall job satisfaction	Dummy variable,1 if a respondent has responses of 7, 8, 9 or 10 on the scale of question "When all things are considered, how satisfied you with your job are?", zero otherwise
Quit	Dummy variable, 1 if worker leaves job voluntarily, zero otherwise.
(2) Job mobility variables	
Occupational mobility during a one-year period (PDUS1)	Dummy variable, 1 if worker moves to a higher occupational rank between t and t+1, and 0, if otherwise.
Occupational mobility during a three-year period (PDUS3)	Dummy variable, 1 if worker moves to a higher occupational rank between t and t+3, and 0, if otherwise.
Occupational mobility during a five-year period (PDUS5)	Dummy variable, 1 if worker moves to a higher occupational rank between t and t+5, and 0, if otherwise.
Wage growth during a one-year period (DUWG1)	Dummy variable, 1 if wage growth during a one year exceeds the mean plus one standard deviation of wage growth in the same occupation group during that period.
Wage growth during a three-year period (DUWG3)	Dummy variable, 1 if wage growth during a three-year period exceeds the mean plus one standard deviation of wage growth in the same occupation group during that period.
Wage growth during a five-year period (DUWG5)	Dummy variable, 1 if wage growth during a five-year period exceeds the mean plus one standard deviation of wage growth in the same occupation group during that period.
Mismatched status (Cross -wave Mode measure)	
Over-educated	Dummy variable, takes the value 1 if being over-educated, zero otherwise.
Under-educated	Dummy variable, takes the value 1 if being under-educated, zero otherwise.
Education matched	Dummy variable, takes the value 1 if being adequately educated, zero otherwise.
Years of over-education	Continuous variable, the years of over-education.
Years of under-education	Continuous variable, the years of under-education.
Years of required-education	Continuous variable, the years of adequate education.
Over-educated & Over-skilled	Dummy variable, takes the value 1 if over-educated and skill under-utilised, zero otherwise.
Only Over-educated	Dummy variable, takes the value 1 if over-educated but skill matched, zero otherwise.
Under-educated & Over-skilled	Dummy variable, takes the value 1 if under-educated and skill under-utilised, zero otherwise.
Well-matched	Dummy variable, takes the value 1 if adequately educated and skill matched, zero otherwise.
Only Over-skilled	Dummy variable, takes the value 1 if adequately educated but skill under-utilised, zero otherwise.
Only Under-educated	Dummy variable, takes the value 1 if under-educated but skill matched, zero otherwise.

5. Conclusion

Education-occupation mismatch and skill under-utilisation have been contentious issues in the labour market literature. Significant earnings losses due to mismatch were found by Sicherman (1991) in the U.S. and summarised by Groot and Maassen Van den Brink (2000), and Rubb (2003) across countries based on cross-sectional data. However, these results are under challenge due to the existence of unobserved heterogeneity.

Longitudinal analyses of the impacts of over-education on earnings address this 'omitted variable' (unobserved heterogeneity) problem, and they have been applied in Germany (Bauer, 2000) and in the U.S. (Tsai, 2010) labour markets. This study extends the literature by applying these methods to the Australian labour market.

The thesis has addressed a number of questions concerning mismatch in the Australian labour market. The questions relate to the over-education earnings effects, the over-education earnings effects for specific sub-groups, and the dynamic mobility effects of education and skill mismatch. The panel approach is applied to examine these questions based on nine years of longitudinal data. The study addresses individual heterogeneity effects that are important for mismatch analysis, and thereby extends the international literature.

In the main body of analyses, I have examined the impacts of over-education over the period 2001-2007, i.e. without the global financial crisis (GFC) years 2008 and 2009. The global financial crisis (GFC) is covered in this empirical study in an augmented version of the model which includes years 2008 and 2009. The estimation results when GFC years are included are similar to the main results. This implies that relative wage growth between over-educated workers and adequately educated workers is not sensitive to the global financial crises.

Essay one:

The analyses began with identifying the appropriated measure to define the required years of over-education from four alternative measures of over-education. I provide evidence on and compare the four conventional methods to measure over-education. The incidence of over-education is influenced by which method is used. This analysis shows that in HILDA how belonging to the over-educated category is related to the choice of measurement variable. Each of the four methods discussed earlier has advantages and disadvantages. The Mode measure is used in the analyses in this thesis incorporating over-education and under-education due to its several advantages. These are: objective and statistically based; the most common method used across studies for comparison; readily available in data sets; it allows frequent change in the measure as technology and markets change.

Without controlling for unobserved heterogeneity, pooled OLS results are consistent with the stylised facts specified by Sicherman (1991). Over-educated workers earn less and under-educated workers earn more than adequately educated workers who have the same years of education but work in jobs that demand the level of education they have acquired. The returns to years of required education, over-education and under-education are 5.2 per cent, 4.3 per cent and -3.7 per cent, respectively. After accounting for the unobserved heterogeneity (ability, motivation, etc.), the effects of required education, over-education and under-education decrease in magnitude and become statistically insignificant. Therefore, the results indicated that educational mismatch does not have a significant effect on earnings after accounting for the unobserved heterogeneity. These longitudinal results are in line with longitudinal studies of Bauer (2002) and Tsai (2010).

In addition, no significant effects were found among interaction terms between educational mismatches and qualification categories. Likewise, the substitution relationship between over-education and potential work experience no longer exists. However, a positive relationship is still found between over-education and current job tenure, though with smaller effects than those found in the pooled OLS estimations. This implies that over-educated workers may benefit from staying in their current employment.

With respect to effects of over-education on earnings across occupations, the panel fixed effects results are in contrast with the results drawn from the pooled OLS regressions. Technicians do not suffer a wage penalty from educational mismatch. Within occupations, over-educated Sales Workers and over-educated Clerical and Administrative Workers earn 10 per cent and 4 per cent less, respectively, than other workers who work in jobs for which required education is equal to their educational attainments. In contrast, an over-educated manager earns 4 per cent more than a matched manager with other similar characteristics. This evidence indicates that educational mismatch is serious among workers with lower levels of qualification who have been allocated to a lower-level occupation. This result is worthy of further investigation.

The evidence provided in this thesis indicates that unobserved heterogeneity is very important to the study of 'over-education' for immigrants. Even though there is no substantial earnings loss found from education occupation mismatch for average full-time male workers aged 23 to 64, there is a large earnings penalty for mismatched NESB immigrants compared to native born workers.

Essay two:

In the case of immigrant studies, education occupation mismatch is serious among immigrants in comparison to those who are native born. To further investigate heterogeneity effects, the entire sample has been decomposed into: native-born, English speaking background (ESB) immigrants and Non-English speaking background (NESB) immigrants. Flows of skilled immigrants to Australia are increasing based on recent Australian immigration policy, in which endorsed skill helps immigrants to become more employable with the goal of increasing Australia's productive capacity. However, if immigrants tend to work in positions that under-utilise their educational attainment, do they still contribute to the host country economy's development as envisaged? The study has provided evidence on the above question. Based on nine years of HILDA and longitudinal analyses, results show that, in Australia, NESB immigrants suffer a large earnings penalty from over-education.

By using over-education as an indicator, the effect on immigrants' assimilation is examined in the Australian market, and a number of estimation methods and findings are established. On the question of the extent of educational mismatches among immigrants; firstly, 42 per cent of NESB immigrants have been found to work in employment positions which require a lower level of education than the one they possess. Then the determinants of over-education were examined by a correlated random effects logit model with Mundlak correction. After controlling for endogeneity, immigrants have much higher rates of over-education than the native-born. Further analysis showed that this is partly due to imperfect transferability of human capital in the host country. In addition, as time passes, despite gaining local experience or investing in local education, the over-education rates of immigrants do not converge to the rates of natives. The education-occupation mismatch situation for immigrants does not change with increased years since migration. Among NESB immigrants who have migrated at a younger age (less than 12 years old), and earlier arrivals (who arrived before 1979) have lower probability of over-education than older entrants and later arrivals.

The impacts of education-occupation mismatch on earnings among immigrants are examined by both pooled OLS and longitudinal analyses, from the perspectives of both years since migration and transferability of human capital. After controlling for unobserved heterogeneity, such as motivation, luck, or ability, years since migration have a significant impact on earnings for both ESB and NESB immigrants. ESB immigrants have a faster earnings growth rate than those who are native born. Pre-migration education is highly valued and transferable for ESB immigrants, although it has an insignificant impact on earnings for NESB immigrants. ESB immigrants have significantly larger returns to years of domestic experience than those who are Australian born. In contrast, NESB immigrants have lower return to both years of education and years of domestic experience than those who are Australian born. Educational mismatches worsen the NESB situation. With panel fixed effects estimation, NESB immigrants suffer a 9 per cent lower return to each additional year of over-education and a 9 per cent lower return to required years of education when compared to those who are Australian born. This evidence indicates that the earning penalty among NESB immigrants is due, not only to skill under-utilisation, but perhaps also to an earnings disadvantage that cannot be

accounted for by the extensive human capital variables that are included in the models in this study.

Results from specific sub-groups effects offer some implications for immigration policy. There are significant assimilation effects among younger arrivals if arriving in childhood. Immigrants who migrated after 1990 are of a higher skill 'quality' than the earlier cohorts; this is demonstrated by their better labour market performance when compared to the group who migrated between 1980 and 1989. However, if they are over-educated, then they have lower earnings than those who are Australian born. Stronger assimilation effects are found for ESB immigrants with overseas qualifications. Overseas qualifications are transferrable and valued for ESB immigrants in Australia, but not for NESB immigrants. Assimilation effects are found only for NESB immigrants with Australian qualifications. Over-education status reduces earnings for NESB immigrants with overseas qualifications. In summary, empirical results are in line with the recent immigration policy, which is designed to attract highly educated immigrants to migrate to Australia aged between 23 and 34 years. However, it is very important to allocate education occupation efficiently for NESB with overseas qualifications.

The results further show that there is a persistent earning gap between native born and NESB immigrants even when NESB immigrants have achieved all their years of education in Australia. For NESB immigrants with foreign or mixed qualifications, it is important to obtain a job with a good match. Otherwise, immigrants suffer a significant earnings loss from education-occupation mismatches. These findings have implications for immigration policy making, which focus not only on attracting skilled immigrants, but also the likelihood and facilitation of employment into matched positions.

Essay three:

On the question of the effects of over-education and over-skilling on job mobility, the analyses in this essay incorporate the effects of mismatch on a worker's decision to quit, upward occupation mobility and upward wage growth during one-year and three-year periods in a dynamic setting.

The analysis leads to the following findings. First, skill under-utilisation motivates workers to move out of their current employment positions; whereas, education mismatches do not. Second, when controlling for the actual years of education, during one-year and three-year time periods, upward occupational growth is found among under-educated and over-skilled workers and also among the under-educated but skilled-matched workers. By contrast, downward occupational growth is found among over-educated and over-skilled workers and also among the over-educated but skill-matched workers. These findings do not support career mobility theory's explanation for over-education. Further evidence found that both over-education and over-skill are self-perpetuating and persistent. In addition, when accounting for actual years of education, upward wage growth is found among under-educated and over-skilled workers during a one-year period. Downward wage growth is found among over-educated workers during both a one-year period and a three-year period. Over-educated and over-skilled workers who quit their current jobs seemingly suffer a disadvantage with respect to wage growth when compared to those similarly over-educated workers who have stayed in the same employment over a three-year period.

The empirical results for state dependence tests are not in line with career mobility theory. There is no evidence that over-educated workers experience upward wage growth throughout their career path. Even when they resign from their current employment, they appear to suffer considerable disadvantage in wage payment in their new employment. This is in line with findings of Linsley (2005a), based on a different data set in Australia. Skill under-utilisation affects job satisfaction and quitting current job behaviour. Education mismatch explains wage effects. These results are consistent with the previous findings in Mavromaras et al. (2010b), and Allen and Van der Velden (2001).

In Australia, this has been the first use of longitudinal data to examine career mobility theory from a dynamic upward occupational mobility and upward wage growth perspective. A Mundlak (1978) correction model is used to adjust for unobserved heterogeneity.

The evidence provided in this thesis indicates that, after controlling for unobserved

heterogeneity, over-education is a serious problem for NESB immigrants, in particular, older arrival NESB immigrants with overseas qualifications. In addition, the analyses of dynamic mobility indicate that over-education is not a temporary phenomenon, and over-education cannot be explained by career mobility theory in the Australian market. This persistent education occupation mismatch leads to a significant disadvantage for individuals. It is an inefficient use of the economy's labour resources, warranting consideration of policies than can lead to an effective education and occupation match for workers.

The analyses of education occupation mismatch in this thesis suggest a number of lines of future research. A possible extension to the analysis presented in Essay one is to examine the incidence of over-education and its impact on earnings for women. There are differing characteristic between men and women. The outcome of over-education for women is of interest. Much research also remains to be done on immigrants' assimilation. It would be useful in future research to examine effects of mismatch on earnings in a dynamic setting by country of origin. In particular, it seems plausible that the performance of immigrants from New Zealand may be closer to the performance of the Australian born due to a similar culture and education system perhaps leading to a greater transferability of human capital. If this is the case, then including the New Zealand immigrants in with the other immigrants from English speaking backgrounds may have caused the differences in performance between the rest of this group and the performance of the Australian born to be underestimated.

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