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Le Wen
The University of Auckland

Sholeh A. Maani
The University of Auckland and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Job Mismatches and Career Mobility*

Does over-education assist or hinder occupational advancement? Career mobility theory hypothesizes that over-education leads to a higher level of occupational advancement and wage growth over time, with mixed international empirical evidence. This paper re-tests career mobility theory directly using a rich Australian longitudinal data set. A dynamic random effects probit model is employed to examine upward occupational mobility, considering two-digit occupational rank advancement and wage growth over three-year intervals. The 'Household, Income and Labour Dynamics in Australia' data across nine years are employed, and a Mundlak correction model is adopted to adjust for unobserved heterogeneity effects and potential endogeneity, both of which are important to over-education analysis. Contrary to career theory, the results point to job mismatch as an economic concern rather than a passing phase, regardless of whether or not workers are skill-matched. Results further show the importance of adjusting for endogeneity.

JEL Classification: J24, J31, J60

Keywords: labour market, over-education, over-skilling, career mobility, occupational mobility, wage growth

Corresponding author:
Sholeh A. Maani
The University of Auckland
Graduate School of Management
12 Grafton Road
Auckland, 1010
New Zealand

E-mail: s.maani@auckland.ac.nz

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I. Introduction

Education-occupation mismatch, a measure of the deviation between the formal education obtained by workers and the education required to perform a job, is typically referred to as ‘over-education’. Over-education has been shown to impact wages (Groot and Maassen van den Brink 2000). In contrast, skill under-utilization, referred to as ‘over-skilling’, provides a more direct measure of the difference between knowledge and skills accumulated by workers and the actual skill requirements of their jobs. Over-skilling has been shown to impact job satisfaction and mobility (Allen and van der Velden 2001).

Career mobility theory, proposed by Rosen (1972), offers an explanation of sustained skill mismatches in the job market. This theory was extended to occupational mobility by Sicherman and Galor (1990) as an extension of human capital theory. Over-education may be a part of the career mobility process and is part of a phase of insertion and adaptation in the early stages of the working life (Groot and Maassen van den Brink 2003). Specifically, over-educated workers may sacrifice a wage premium in their current employment to gain specific skills, or other types of human capital, that enables 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 an 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 recruiting 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.

Theoretically, following career mobility theory, pay penalty and lower job satisfaction are expected to motivate over-educated workers to move to jobs in higher occupational ranks, resulting in a greater rate of growth in wages than was achieved before that move. Therefore, career mobility theory suggests the temporary existence of over-education from a supply-side perspective. However, a temporary expectation of over-education is in contrast to alternative theoretical possibilities of demand-side market imperfections, where job mismatches and lower pay may persist.

Previous studies that have examined the impact of over-education on career mobility have found conflicting results. In the U.S., 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 compared to workers with otherwise similar characteristics. Using the same data for extended years, Robst (1995) found that, over time, over-educated workers in both groups are more likely to move to better jobs that require a higher level of education. Hersch (1995) supported career mobility theory by suggesting that mismatch seems to be optimal. Both Robst and Hersch’s analyses were based on static models that did not adjust for potential endogeneity of over-education. In addition, earlier tests of career theory have mainly employed U.S. data.

Using the German Socio-Economic Panel (1984-1997) in static models, Büchel and Mertens (2004) found that, contrary to 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 are adequately-educated workers. They explained that the reason is country-specific: the U.S. and Germany have different allocation mechanisms and job mobility is freer in the U.S. than in Germany. Contrary findings from a most recent research by Grunau and Pecoraro (2017), using German administrative data, supported career mobility theory. Applying multinomial logit and Ordinary Least Square (OLS) models, the study found that over-educated workers have a higher likelihood of promotion to managerial positions.

Based on the U.S. Current Population Surveys (1994-2000), Rubb (2006) applied a similar empirical approach as Büchel and Mertens and found that 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, they also extend this theory by supporting the earnings growth aspect. Rubb (2013) further used the Panel Study of Income Dynamics (1999-2001) with OLS estimates and found that over-educated workers are more likely to have external firms' upward occupational mobility.

In Australia, Linsley (2005) hypothesized that over-educated workers may optimally choose lower-level employment to take advantage of future promotion opportunities. The analysis based on the 1997 wave of the Negotiating the Life Course Survey in Australia did not support career mobility theory. 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.

The impact of combined over-education and over-skilling on career mobility is much less studied. This paper contributes to the literature by using dynamic models to examine the impact of both over-education and over-skilling on career mobility based on the Household, Income and Labour Dynamics in Australia (HILDA) Survey[1]. The following questions are addressed:

> *To what extent do mismatches influence workers' upward occupational mobility, and upward wage growth?*
>
> *Does career mobility theory explain the education mismatch and skill mismatch in the Australian labour market?*

Utilizing the framework of career mobility theory, the results are expected to have important implications for labour market analysis and policies.

This study contributes to the international literature in several ways. First, the study provides new evidence by examining career mobility theory in a dynamic setting. Most previous research has employed static models to evaluate the impact of job mismatch. Static models are special instances of dynamic models, which constrain the coefficients on lags of dependent variables and coefficients on initial status of dependent variables to zero. If both coefficients are significant, then some omitted variable problems exist in static models[2].

Second, the longitudinal data and the econometric modelling address potential biases from individual heterogeneity and unobserved characteristics, which are factors of special significance in educational and job-mismatch analyses.

Third, in addition to occupational rank mobility, the analysis provides parallel analyses on the effect of job mismatches on wage growth.

Fourth, the analysis reveals whether over-education or over-skilling, separately or jointly, can lead to future upward career mobility. The combined variables, incorporating both educational and skill mismatches in this analysis, better control for workers' heterogeneity than would be the case if only an education mismatch or skill mismatch variable were used. This addresses workers' mobility resulting from the under-utilization of either education or skills or both, which has not received much attention in previous studies.

Finally, the methodology examines career mobility outcomes for workers with different job match conditions and compares differences between outcomes for 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). The two selected groups are most closely related to the hypotheses of career mobility theory. For example, a very important matter when studying job mismatches is 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 previous mismatches may be temporary and merely a part of the career development process. In addition, this movement may not involve any actual cost to them. Alternatively, if demand side factors are at work, the impacts of over-education can be negative or positive, and potentially long lasting.

Section 2 describes the data and the variables used in this study. The analytical framework is discussed in Section 3. Empirical results are discussed in Section 4. Section 5 concludes.

II. Data and Variables

Data

The data used in this research are sourced from the first nine waves of the HILDA Survey[3]. This interview-based survey began in 2001 with a nationally representative sample. Following the respondents for nine years since 2001 allows the use of panel features of the data over a significant period of time. The sample is restricted to an unbalanced panel of male full-time employees aged 23-64[4].

A major advantage of the HILDA dataset is that it allows the use of appropriate panel data techniques based on longitudinal information. The rich panel (longitudinal) data and panel estimation methods used in this paper allow controls for potential endogeneity and unobserved individual heterogeneity by observing the same individuals who change into matched or mismatched jobs within the nine-year period of this study. During this time period the individuals in the sample move in and out of jobs and receive wages that change. For example, close to 25 per cent of the sample moved from over-educated to matched or undereducated positions, or vice versa, at least once during the period of the study. This aspect is useful in providing variation across both time and individuals. This feature of the data and the modelling applied are particularly important in the analyses of job mismatches.

A second advantage of the dataset is that it contains rich coverage of relevant variables. For example, the HILDA survey provides information on job separation from wave 2 onwards. Workers who have changed jobs since the last interview were asked to identify the main reason they stopped working in the job that they had held at the time of the previous interview [5]. To test the effect of job mismatch on job separation, this research matches this variable with previous job mismatch status[6]. Educational mismatched information is derived from each survey year (wave) of HILDA, and skill mismatched self-reported variables are available in the data for each job and all years. HILDA also provides information on the reason for all job separations, making it possible to identify quits and other voluntary job separations that are important to career theory hypotheses of job progressions.

Because the focus of this study 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 full-time or part-time students are excluded. Time periods and unemployment are included as explanatory variables.

Variables

The earnings variable is the natural logarithm of hourly wage from main job (in constant year 2009 dollars).

Education and skill mismatch

The over-education measure is based on the conventional Mode method (Kiker, Santos, and Mendes de Oliveira 1997)[7]. The over-education variable is time variant. It is derived by comparing actual years of education of the individual to each year's Mode of education for their current main job, based on a two-digit occupational index. The Mode variable is derived at the two-digit occupational category level for greater accuracy. The Mode reflects the level of required education by computing the amount of education most commonly occurring within an occupational category. Over-skilling is defined by following conventional approaches (Mavromaras et al. 2013b) based on self-reported data[8].

According to the definitions of required education and over-skilling, and considering both education mismatch and skill mismatch, the entire sample is divided into six job-matching groups.

- Well-matched: both education and skills match the job's requirements.
- Only over-educated: over-educated but skill-matched.
- Only over-skilled: over-skilled but not over-educated.
- Over-educated and over-skilled: the individual works in a position where both education and skill level exceed those required.
- Only under-educated: under-educated but skill matched.
- Under-educated and over-skilled: the individual works in a position where he is both under-educated for the job and also over-skilled.

The focus of this analysis is on the group of over-educated workers who are skill matched (group 2) or over-skilled (group 4) as depicted in career mobility theory.

Nevertheless, compared to earlier studies (Mavromaras et al. 2013b), the sample in this paper is expanded from graduates to the entire range of working-age employees. Thus, information on under-education is also available in this study, which affords new insights.

[Table 1 here]

Table 1 shows the difference between educational and skill mismatch. Overall, 27.6 per cent of workers are employed in positions that require a lower level of education than that which they possess; and 18.6 per cent of workers report that they have not fully used their skills and abilities in their current job. Over-skilled workers are evenly distributed in three education mismatch groups, making up approximately six per cent of workers within each group. Table 1 also shows that over-education and over-skilling are different concepts and conditions. Therefore, a combination of education mismatch and skill mismatch would provide a more comprehensive analysis of the quality and degree of match.

Upward occupational advancement and wage growth

Workers experience upward occupational mobility if they have experienced a higher occupational rank between two time periods (*t-k* and *t*). In the HILDA survey, the Australian Socioeconomic Index 2006 (AUSEI06) provides the occupational status of current main job, which is an index of occupational rank. For example, medical practitioners are at the top of the scale (100), then other health professionals (94), university lecturers and tutors (92) and legal professionals (91). Labourers are placed at the bottom of the scale.

An endogeneity issue arises in the definition of upward occupational mobility and upward wage growth variables. Workers in some occupations experience greater mobility than do workers in others. As a result, average wages, along with occupational scale, experience larger increases in some occupations than in other occupations. Thus, it is ambiguous when workers experience wage growth or occupational upward mobility as to whether that growth or upward mobility is due to their own attributes, or to the worker being employed in an occupation that is characterized by the larger increases described above. To answer this question, this paper examines occupational mobility and wage growth within 2-digit occupations between 2001 and 2009.

This research finds occupational mobility is relatively stable, with the exception of a small upward or downward movement for professionals, operators and labourers during the nine-year period. Thus, dummy variables are used to define upward occupational mobility as 1, in cases where workers move to a higher occupational rank between times *t-k* and *t* (three-year intervals in this case), and 0 otherwise.

In contrast, 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. Farmers and farm managers, arts and media professionals, health and welfare support workers, sales support workers and other groups all experienced, to some extent, a fluctuation in earnings between 2001 and 2009. This evidence suggests that some occupational groups experienced 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 resulting from any individual change.

This issue is relevant to this analysis and the specification of the variable reflecting upward wage growth. Büchel and Mertens (2004), for example, state 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 the 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 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 survey wave (survey year); 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 three-year period.

Further information reveals that chief executives, general managers and legislators, specialist managers and health professionals have higher earnings than those who work in other occupations. Farm, forestry and garden workers, food preparation assistants and other labourers have the lowest wage rate.

To test career mobility theory when job separations are experienced, the focus in this study is on two groups of workers: workers across job-matched and job-mismatched conditions who (a) experience a voluntary separation (quit) and (b) workers who experience 'no changes' (stay). These two groups provide the most relevant groups for testing the validity of the theory. Workers who are laid off or who leave their jobs for other reasons are excluded.

Table 2 provides summary statistics for the variables of interest by job-match or job-mismatch category, and for sub-groups who quit and changed their job, and those who remained in their job. As may be expected, workers who quit, or workers who stay in their jobs, between six different job mismatched groups, have differing job characteristics. Younger workers with less experience, shorter occupational tenure, shorter tenure in their current job and less earnings than their older counterparts, are more likely to leave their employment voluntarily. Excepting over-skilled workers, among the other five types of mismatched workers, eight to 10 per cent fewer workers left their employment in order to have on-the-job training than workers who remained in their employment. 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 groups.

[Table 2 here]

III. Analytical Framework

Due to low job satisfaction in their current employment, over-educated workers or workers whose skills are under-utilized 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 because once workers enhance their experience and equip themselves with specific skills, they are likely to be offered more responsible positions and experience wage growth. Following this analysis, the relationship between job mismatch and upward mobility is tested.

The results address the question of whether or not career mobility theory can be used to explain the over-education phenomenon, with a rich panel dataset that allows adjustment for potential endogeneity and original condition biases in static models. The analyses also reveal whether over-education and over-skilling are merely temporary or are persistent effects.

In order to make better use of the longitudinal features of the data the dynamic standard random effects probit models, with varying specifications, 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.

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. These added components $\overline{X_\iota}\delta$ in the model, based on average values in the model across individuals and years of panel data, address endogeneity (such that the coefficients approximate unbiased fixed effects estimates (e.g. as shown by Wooldridge 2010)).

In the latent model (equation 1), β is unbiased if explanatory variables x_{it} and individual specific effects μ_i are independent, that is

$$y_{it}^* = x_{it}\,\beta + \mu_i + \varepsilon_{it}\ , \tag{1}$$

where $E[\mu_i|X_i] = 0,$ and $\varepsilon_i|\ X_i \sim$ 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 $\mu_i = \overline{X_\iota}\delta + \eta_i$, where $\eta_i|\ X_i \sim$ N$(0,\sigma_\eta^2)$. It assumes zero correlation between $\overline{X_\iota}$ and η_i. Mundlak's approach is used to control for endogeneity effects due to unobserved individual effects.

Combining Wooldridge's approach and the Mundlak 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.

$$\mu_i = \Upsilon_0 y_{i0} + \overline{X_\iota}\delta + \eta_i \tag{2}$$

where $\eta_i|X_i, y_{i0} \sim$N$\left(0, \sigma_\eta^2\right)$.

Thus, the dynamic model is written as:

$$y_{it}^* = \Upsilon y_{it-1} + x_{it}\,\beta + \Upsilon_0 y_{i0} + \overline{X_\iota}\delta + \eta_i + \varepsilon_{it} \tag{3}$$

Importantly, these added components $\overline{X_\iota}\delta$ in the model, based on average values in the model across individuals and years of panel data, address endogeneity, such that the coefficients β approximate unbiased fixed effects estimates (e.g. Wooldridge 2010). The estimates of Υ examine the state dependence of the dependent variable.

IV. Models and Results

Two models applied to panel data, and summarized in this section, examine the impact of education and skill mismatches on occupational mobility and wage growth. The modelling approach adopted aims to provide enhanced precision in the analysis of job mismatch outcomes, through the estimation methods adopted, and by using the longitudinal nature of the data.

Upward occupational advancement and mismatch

Upward career mobility predicts that over-educated workers experience higher upward occupational mobility than their counterparts.

Model 1: Upward occupational mobility and mismatch

$$OC^*_{i,(t,t+k)} = \gamma OC_{i,(t-1,t+k-1)} + \gamma_0 OC_{i,0} + \sum_{j=1}^{5} \alpha_j MTYP_{j,i,t} + \sum_{j=1}^{6} \xi_j (quit * MTYP_{j,i,t}) + \sum_{j=1}^{5} \pi_j \overline{MTYP_{j,i}} + \sum_{j=1}^{6} \psi_J \, \overline{(quit * MTYP_{j,i})} + x_{i,t}\, \beta + \overline{X_i}\delta + \eta_i + \varepsilon_{i,t} \tag{4}$$

The dummy variable $OC^*_{i,(t,t+k)}$ indicates whether worker *i* has moved into a higher-ranked occupation between time t and $t+k$, and takes the value 1 if he has moved to a more highly-ranked occupation than the positions held in previous years[9]. $OC_{i,0}$ represents the initial upward occupation movement status. $x_{i,t}$ is a vector of personal and job characteristics for worker *i* at year *t*. Variable $MTYP_{j,i,t}$ denotes the various types of mismatch occurring. Each type of mismatch is a dummy variable. In Equation (4), ξ_j reveals the effects of job quitting associated with workers' original job mismatch status, of the job held at time *t*, on future upward occupational mobility when compared to workers who have the 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-and-over-skilled and only-over-educated individuals. Variable η_i is an individual specific effect and is not correlated with the covariates. The variable $\varepsilon_{i,t}$ is the error term.

Estimation results are given in Table 3. Columns 2 and 4 report results from the CRE probit models, which control for endogeneity. The RE results in Columns 1 and 3 are presented as benchmarks only, since these conventional estimations do not address endogeneity. The results from these two models are significantly different. Auxiliary statistical tests confirm the choice of the Mundlak correction (in CRE estimation) over conventional estimations without the correction (RE models). In addition, statistical tests confirm the greater explanatory power of our dynamic models compared to alternative static specifications.

The results, in Tables 3 and 4, are given by marginal effects, which are calculated for the average person who has all characteristics at mean values, for a one unit change in the explanatory variables.

[Table 3 here]

It is worth noting that in the over-education literature, a reference group is required and assigned for comparing over-educated workers to otherwise similar workers. For example, if the model compares over-educated workers with adequately educated workers (controlling for the same level of actual schooling), over-educated worker must work in positions that require a lower occupational rank than adequately educated worker. These workers are in different occupations (‘across occupations’ comparison (e.g. Sicherman 1991; Büchel and Mertens 2004)). Alternatively, if the model compares over-educated workers with adequately educated workers (controlling for the same level of ‘required education’), over-educated worker and adequately educated worker must have jobs that require the same level of schooling. But over-educated workers must have a higher level of schooling than adequately educated worker (a ‘within occupations’ comparison (e.g. Robst 1995)). For completeness, Tables 3 and 4 provide results based on both alternatives (across occupations (Columns 1 and 2), and within occupations (Columns 3 and 4)). These results reveal some differences with the choice of the base group applied in the literature.

As can be seen from Columns 2 and 4 of Table 3, we find that over-education has negative impacts on occupational advancement in subsequent time periods, with dynamic modelling specifications that also control for potential endogeneity of over-education. Workers with average characteristics who experienced upward occupational mobility in the previous three-year period are more likely to move upwards in occupational rank in the current three-year period, than are other workers. Position from which a worker starts has a significant and positive impact on future upward occupational mobility. 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 educational attainment is larger than those found when accounting for the required amount of education to perform jobs. This 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-and-over-skilled and only-over-educated workers are less likely to move upwards in a three-year period. In particular, otherwise ‘average’ over-educated-and-over-skilled workers have a 26 per cent lower probability of moving 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. By contrast, average under-educated-and-over-skilled workers and average only-under-educated workers enjoy around a 34 per cent higher probability of moving to a higher occupational rank than average well-matched workers.

Within occupations, otherwise average only-under-educated workers experience a 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, it is evident from Columns 2 and 4 of Table 3 that job quitting plays a small role in upward occupational mobility. Workers in 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. Auxiliary tests confirm that with equivalent static model specifications some important coefficients change. Notably, the results based on static models that are equivalent to those reported suggest that the impact of over-education on upward career mobility is smaller or insignificant. In addition, the results in Table 3 show that when endogeneity is not addressed (e.g. in RE models), the negative effect of job mismatches on career mobility is underestimated. This combined evidence further supports the importance of dynamic models that account for heterogeneity and endogeneity in this setting where endogeneity can play an important role[10].

Upward wage growth and mismatch

Upward career mobility is accompanied by wage growth. To test this prediction, a binary wage growth model was constructed, based on a three-year period. The approach of Büchel and Mertens (2004) is extended in this study.

Workers experience upward career mobility if their wage growth from year t to $t+k$ is higher than the mean wage growth plus one standard deviation during that period in their status group (g) in the time periods 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. Variable $w_{g,y}$ is log hourly wage for the group of workers who have the same mismatch status as worker *i*.

Model 2: Upward wage growth and mismatch

$$
\begin{aligned}
WG^{*}_{i,(t,t+k)} &= \gamma WG_{i,(t-1,t+k-1)} + \gamma_0 WG_{i,0} + \sum_{j=1}^{5} \alpha_j MTYP_{j,i,t} + \sum_{j=1}^{6} \xi_j (quit * MTYP_{j,i,t}) \\
&+ \sum_{j=1}^{5} \pi_j \overline{MTYP_{j,i}} + \sum_{j=1}^{6} \psi_J \overline{(quit * MTYP_{j,i})} + x_{i,t}\, \beta + \overline{X_i} \delta + \eta_i \\
&+ \varepsilon_{i,t}
\end{aligned}
\tag{5}
$$

where $WG^{*}_{i,(t,t+k)}$ is a dummy variable and takes the value 1 if worker *i* has experienced average wage growth during k years. Coefficients ξ_j examine the effects on upward wage growth caused by job leaving in varying types of job mismatch. If career mobility theory holds, then the coefficients are expected to be positive among the over-educated-and-over-skilled and the only-over-educated workers.

Upward wage growth is examined during a three-year period. Workers with valid data for the occupation variable in three consecutive years are included in the analysis. It takes time for workers to settle into their new jobs if they leave voluntarily from their current positions. The first year is a transitory period in which 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 achieve wage growth.

The results of the dynamic random effects models with Mundlak corrections that adjust for potential endogeneity are given in Columns 2 and 4 of Table 4. Workers with more years of education are more likely to experience wage growth.

[Table 4 here]

The coefficients of the lagged dependent variables are positive and significant. This implies that ‘average’ workers who have experienced wage growth in the previous three-year period would enjoy a 14 per cent higher likelihood of wage growth in the following three-year period relative to average workers who had not experienced such previous wage growth. Additional models we estimated show that 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 in the previous three-year period, 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.

The initial status of the dependent variables is negative and significant. Average only-over-educated workers are found to have 8.6 to 12.5 per cent less probability of experiencing wage growth than average well-matched workers across occupations and within occupations. Average over-educated-and-over-skilled workers who leave their current employment have a 34 to 35 per cent lower probability of having wage growth compared with the same types of workers who do not leave their current employment. Once they leave their current job, their future jobs do not provide them with an increase in financial remuneration.

Under-educated-and-over-skilled workers are the other group of workers who suffer a loss from quit action in a three-year period. Average under-educated-and-over-skilled workers who leave their employment have a 34 per cent lower probability of experiencing wage growth than workers who remain in the same employment.

Among workers who do not change jobs, only-over-educated workers have a lower probability of experiencing wage growth over three years when compared 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 compared to well-matched workers.

For only-over-skilled workers, departure lowers the probability of experiencing occupational advancement by 23 per cent within three years. For over-educated-and-over-skilled and under-educated-and-over-skilled workers, departure lowers the probability of experiencing wage growth by 34 to 35 per cent within three years.

An improved performance is found for only-under-educated workers; this includes workers whose skills are under-utilized in the labour market. Only this group experiences upward occupational mobility. Previous research has ignored this group when testing career mobility theory.

Tables 3 and 4 further show that when endogeneity is accounted for, educational and skill mismatched variables have larger negative impact on upward occupational mobility and wage growth. This suggests that without endogeneity adjustment, estimates from RE models underestimate the negative impacts of job mismatches on career advancement, indicating a positive bias due to the correlation of unobserved variables with over-education.

In summary, in an explanation of over-education, evidence from the dynamic random effect probit estimation of job mismatch and upward wage growth during a three-year period reveals that over-education is not a temporary career pathway phenomenon, and that career mobility theory is not applicable to the Australian labour market. Resignation from employment has significant negative impacts on wage growth among over-educated and over-skilled workers within a three-year period[11].

V. Conclusions

This paper examines the effect of job mismatch on upward occupational mobility and upward wage growth during a three-year period in a dynamic setting. The analysis incorporates longitudinal data with controls for potential endogeneity of over-education and analyses of consequences of over-education.

The analysis leads to the several findings that are contrary to earlier tests of career mobility theory without these adjustments. First, and in contrast to results based on earlier static models, a lower likelihood of upward occupational mobility is found among over-educated-and-over-skilled workers and also among workers who are over-educated but skill-matched. These findings do not support career mobility theory's explanation of over-education. Second, a lower likelihood of wage growth is found among over-educated workers. Over-educated-and-over-skilled workers who leave their current jobs are shown to suffer a great disadvantage with respect to wage growth, compared to similarly over-educated-and-over-skilled workers who do not leave their employment during a three-year period.

Overall, the analyses show no evidence that over-educated workers experience upward wage growth throughout their career path. Even when they resign from their current employment, they suffer considerable disadvantage in wage payment in their new employment. This is in contrast with most previous analyses of the theory with non-panel data, static models and models that do not control for individual-related endogeneity.

In addition, upward occupational growth is found only among the group of only-under-educated workers, regardless of whether or not they are skill-matched. This group has been generally overlooked in previous analyses of career mobility.

Education and skill mismatches in employment have important impacts on policy design. The evidence provided in this paper indicates that persistent education-occupation mismatch leads to a significant occupational and wage growth disadvantage for individuals. In addition, to the extent that wages reflect labour productivity, the results indicate a link between job mismatches and lower labour productivity over time. Finally, the results point to the usefulness of further research that examines the consequences of job mismatches within dynamic models.

Notes

1. 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 HILDA data sets are made available to academics through Melbourne Institute. The findings and views reported in this paper are those of the authors and should not be attributed to either FaHCSIA or the Melbourne Institute.

2. Exceptions with dynamic analyses relating to other related questions for graduates are Mavromaras et al. (2013a), Mavromaras and McGuinness (2012) and Mavromaras, Sloane, and Wei (2012). None of these studies examine career mobility theory within a static or dynamic setting.

3. The choice of data years is guided by some major changes in HILDA data in 2011. The period selected provides a period of continuous data and group inclusion in the data.

4. The HILDA dataset has a remarkably high response rate throughout the period. Re-interview rates are high (e.g., 96.3% in wave 9). The potential impact of selection into both employment and full-time employment was examined using a Heckman (1979) selection adjustment. Results are not sensitive to the sample selection.

5. 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 - if workers still work in the same job, and quit (voluntary leaving due to various reasons). The approach to defining job separation variables follows McGuinness and Wooden (2009).

6. For example, wave 9 job change data are transferred to job separation of wave 8.

7. Kiker, Santos, and Mendes de Oliveira (1997) and Verhaest and Omey (2006) show that the Mode method is preferred to Verdugo and Verdugo’s (1989) mean criterion. They found mean criterion changed 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.

8. 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 test confirms that the cut-off points for over-skilled and skill-matched are appropriate.

9. There are 9 time periods in the panel data employed. The dependent variables on upward occupational rank and wage growth are constructed on upward movements at period 4 since period 1, at period 5, since period 2, etc. (over three-year intervals). The lagged dependent variables are accordingly created by the value of the dependent variables in period *t-1* (lagged by one period). The lagged variable measures the effect of a three-year upward occupational rank or wage growth, in the previous year, on current three-year upward mobility.

10. The results from static models are available on request.

11. We also examined upward mobility during a one-year and a five-year period. 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 the current year, as confirmed by the data. The results for the five-year period lead to similar conclusions as the three-year period results reported. The results are available upon request.

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Table 1. Types of Educational and Skill Mismatch (percentage)

VARIABLES	Over-educated & Over-skilled	Only Over-educated	Under-educated & Over-skilled	Well-matched	Only Over-skilled	Only Under-educated
All mismatch	5.40	22.23	6.86	32.04	6.39	27.08
Over-educated	19.55	80.45	/	/	/	/
Under-educated	/	/	20.21	/	/	79.79
Education matched	/	/	/	83.37	16.63	/
Observations	682	2807	866	4045	807	3419

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

Table 2. Types of Educational and Skill Mismatch (percentage): Means of Main Variables Used in the Analysis by Quit Status

	Over-educated & Over-skilled		Only Over-educated		Under-educated & Over-skilled		Well-matched		Only Over-skilled		Only Under-educated	
	Job no change	*Quit*	*Job no change*	*Quit*	*Job no change*	*Quit*	*Job no change*	*Quit*	*Job no change*	*Quit*	*Job no change*	*Quit*
VARIABLES	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	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 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
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
Observations	515	58	2,227	171	659	72	3,190	283	599	86	2,700	238

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

Table 3. Job Mismatch and Occupational Advancement
(Model 1)
Marginal effects (standard errors)

Dependent variable=1 if moved to a higher-ranked occupation during a three-year period ($t \rightarrow t+3$)

	Across Occupations		Within Occupations		
	RE	**CRE**	RE	**CRE**	
	(1)	(2)	(3)	(4)	
VARIABLES	OC3[1]	OC3	OC3	OC3	**Pr(OC3=1|u_i=0)=49%**
Main panel estimation results					Mean of X
Lagged dependent variable					
Upward Occupation Mobility	0.300***	0.316***	0.307***	0.322***	0.496
$OC3_{t-1}$	(0.032)	(0.032)	(0.031)	(0.032)	
Initial condition					
Upward Occupation Mobility	0.289***	0.285***	0.281***	0.282***	0.507
$OC3_0$	(0.039)	(0.039)	(0.038)	(0.038)	
Mismatched status					
Over-educated & Over-skilled $_t$	-0.169***	-0.264***	-0.038	-0.158*	0.044
	(0.059)	(0.071)	(0.064)	(0.091)	
Only Over-educated $_t$	-0.104***	-0.168***	0.018	-0.048	0.246
	(0.036)	(0.055)	(0.035)	(0.068)	
Under-educated & Over-skilled $_t$	0.169***	0.213***	0.005	0.107	0.058
	(0.058)	(0.073)	(0.058)	(0.086)	
Only Over-skilled $_t$	-0.010	0.050	-0.011	0.053	0.062
	(0.054)	(0.066)	(0.054)	(0.065)	
Only Under-educated $_t$	0.253***	0.339***	0.097***	0.245***	0.253
	(0.037)	(0.050)	(0.035)	(0.061)	
Quit and mismatch status					
Quit $_t$ x Over-educated & Over-skilled $_t$	0.087	0.138	0.103	0.169	0.003
	(0.202)	(0.219)	(0.197)	(0.212)	
Quit $_t$ x Only Over-educated $_t$	0.026	-0.014	0.036	-0.015	0.013
	(0.099)	(0.113)	(0.100)	(0.113)	
Quit $_t$ x Under-educated & Over-skilled $_t$	0.017	-0.032	0.038	-0.023	0.007
	(0.141)	(0.166)	(0.140)	(0.167)	
Quit $_t$ x Well-matched $_t$	-0.065	-0.063	-0.069	-0.070	0.024
	(0.078)	(0.096)	(0.077)	(0.096)	
Quit $_t$ x Only Over-skilled $_t$	-0.108	-0.232*	-0.105	-0.229*	0.007
	(0.137)	(0.135)	(0.137)	(0.135)	
Quit $_t$ x Only Under-educated $_t$	-0.169**	-0.147	-0.158**	-0.139	0.019
	(0.077)	(0.094)	(0.077)	(0.094)	
Actual years of education $_t$	0.057***	0.033***	/	/	13.953
	(0.009)	(0.011)	/	/	
Required years of education $_t$	/	/	0.056***	0.049***	14.273
	/	/	(0.008)	(0.016)	
Log likelihood	-1693	-1664	-1690	-1659	
Wald chi-squared	543.6	603.6	560.2	617.7	
Individuals	1,152	1,152	1,152	1,152	
Observations	3,142	3,142	3142	3,142	

Notes: [1] OC3 is a dummy variable; takes value of 1 if worker 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, states fixed effects, unemployment, immigrant status, married status, union membership, health status, work experience, current job tenure, current occupational tenure, on-the-job training and base year hourly wage rates.
Source: HILDA-Release 9 (Wave 1-Wave 9).

Table 4. Job Mismatch and Wage Growth
(Model 2)
Marginal effects (standard errors)

Dependent variable=1 if wage growth > mean plus one standard deviation during a three-year period ($t \rightarrow t+3$)

	Across Occupations		Within Occupations		
	RE	**CRE**	RE	**CRE**	
	(1)	(2)	(3)	(4)	
VARIABLES	WG3ˇ	WG3	WG3	WG3	**Pr(WG3=1|u_i=0)=54%**
Main panel estimation results					Mean of X
Lagged dependent variable					
Upward wage growth	0.137***	0.136***	0.137***	0.137***	0.554
$WG3_{t-1}$	(0.019)	(0.019)	(0.019)	(0.019)	
Initial condition					
Upward wage growth	-0.060***	-0.058***	-0.059***	-0.059***	0.559
$WG3_0$	(0.019)	(0.020)	(0.019)	(0.020)	
Mismatch status					
Over-educated & Over-skilled $_t$	-0.093*	-0.049	-0.079	-0.089	0.044
	(0.048)	(0.075)	(0.049)	(0.082)	
Only Over-educated $_t$	-0.034	-0.086*	-0.018	-0.125**	0.246
	(0.027)	(0.049)	(0.027)	(0.059)	
Under-educated & Over-skilled $_t$	0.043	0.033	0.005	0.071	0.058
	(0.047)	(0.069)	(0.044)	(0.073)	
Only Over-skilled $_t$	-0.074*	-0.047	-0.078*	-0.049	0.062
	(0.042)	(0.054)	(0.042)	(0.054)	
Only Under-educated $_t$	-0.003	-0.065	-0.041	-0.030	0.253
	(0.032)	(0.050)	(0.026)	(0.057)	
Quit and mismatch status					
Quit $_t$ x Over-educated & Over-skilled $_t$	-0.244	-0.335**	-0.254*	-0.347**	0.003
	(0.154)	(0.149)	(0.151)	(0.144)	
Quit $_t$ x Only Over-educated $_t$	0.026	0.013	0.031	0.008	0.013
	(0.082)	(0.099)	(0.081)	(0.099)	
Quit $_t$ x Under-educated & Over-skilled $_t$	-0.196*	-0.344***	-0.191*	-0.344***	0.007
	(0.110)	(0.106)	(0.111)	(0.107)	
Quit $_t$ x Well-matched $_t$	0.042	0.034	0.045	0.037	0.024
	(0.061)	(0.079)	(0.061)	(0.079)	
Quit $_t$ x Only Over-skilled $_t$	-0.124	-0.111	-0.124	-0.113	0.006
	(0.118)	(0.141)	(0.118)	(0.142)	
Quit $_t$ x Only Under-educated $_t$	-0.068	-0.117	-0.065	-0.117	0.019
	(0.069)	(0.085)	(0.069)	(0.085)	
Actual years of education $_t$	0.015**	0.023**	/	/	13.953
	(0.008)	(0.010)	/	/	
Required years of education $_t$	/	/	0.001	-0.017	14.273
	/	/	(0.008)	(0.014)	
Log likelihood	-2095	-2078	-2096	-2080	
Wald chi-squared	141.6	170.9	137.9	167.9	
Individuals	1,152	1,152	1,152	1,152	
Observations	3,140	3,140	3,140	3,140	

Notes: ˇWG3 is a dummy variable; takes value of 1 if wage growth > mean plus one 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 similar to those in Table 3.
The models include time periods, state fixed effects, unemployment, immigrant status, married status, union membership, health status, work experience, current job tenure, current occupational tenure, on-the-job training and current job occupational scale.
Source: HILDA-Release 9 (Wave 1-Wave 9)