Job Mismatches and Labour Market Outcomes: Panel Evidence on University Graduates

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Abstract:

The interpretation of graduate mismatch manifested either as overeducation or as overskilling remains problematical. This paper analyses the relationship of educational and skills mismatch with pay, job satisfaction and job mobility using unique data from the HILDA survey. We find that overeducation and overskilling are distinct phenomena and that their combination results in the most severe negative labour market outcomes. Using panel methodology reduces strongly the size of many relevant coefficients, questioning previous cross-section results in the literature. The paper shows that the relationship between mismatch and labour market outcomes is strongly influenced by unobserved heterogeneity which varies by gender.

JEL classification: J24, J31

Acknowledgements: The data used is the confidentialised unit record file from the Household Income and Labour Dynamics in Australia (HILDA) survey. The HILDA Survey Project was initiated, and is funded, by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs, and is managed by the Melbourne Institute of Applied Economic and Social Research. Financial support by the ESRC (Award ref. No. RES-000-22-1982), the Australian Research Council and the National Institute of Labour Studies, Flinders University is gratefully acknowledged.

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1. INTRODUCTION

Mismatch in the labour market, in the form of educational or skills mismatch, is known to be associated with negative labour market outcomes. Employees who do not utilize fully their education qualifications or their skills and abilities earn lower wages, have lower job satisfaction and experience higher voluntary and involuntary labour mobility. Despite the extensive evidence on such associations, there is little empirical evidence on whether there is a causal relationship between mismatch and negative labour market outcomes. One of the main reasons for this is that in order to estimate such a causal relationship, appropriate panel data and estimation are needed. This paper adopts a panel estimation methodology which permits us to do this and shows for the first time in the literature the presence of such causal effects. An important aspect of this paper is that it uses a data set that contains independent panel information on both types of mismatch alongside panel information on the core labour market outcomes. Recent advances in the literature show that educational and skills mismatches are distinct empirical phenomena with different labour market outcomes that need to be studied separately. This paper defines mismatch as educational only, skills only and both combined, in order to account for these differences. Distinguishing between the two types of mismatch using panel estimation proves to be empirically important.

The paper deals with a central economic issue for developed economies, namely whether university graduates (who are the employees with the highest skills and earnings in the labour market) may be under-utilised in their workplace. By focusing on university graduates, the paper deals with typically one third (and a rising proportion) of the total labour force in paid employment, who generate more than half the total labour income in advanced economies, and who are generally understood to drive productivity improvements and innovation in the workplace. Although the importance of the problem of appropriate educational and skills utilization is shared by all major developed economies including the US and many EU countries, it is only the Australian HILDA survey used in this paper that contains all the necessary information for estimating the causal effects of different types of mismatch on different labour outcomes.

This paper builds on a growing literature on labour market mismatch, most of it focusing on educational mismatch and a smaller literature on skill mismatch, information on which has only recently become available in a limited range of data-sets. In an early study Sicherman (1991) found two stylised facts. First, overeducated workers were paid less than if they were matched, but more than their matched co-workers. Second, undereducated workers were paid more than if they were matched, but less than their matched co-workers. These results have been confirmed in a large number of subsequent studies, but virtually all of these have been based on cross-section analysis and, therefore, may be biased due to the problem of individual unobserved heterogeneity. Exceptions are papers by Bauer (2002) and Tsai (2010) who found that the overeducation pay penalty can be attributed to unobserved heterogeneity or non-random assignment to jobs respectively. The former uses the German Socio-Economic Panel for the years 1984-1998 and finds that compared to pooled OLS, the estimated wage effects of overeducation become smaller, or in some cases disappear altogether, when controlling for unobserved heterogeneity. Tsai uses the US Panel of Income Dynamics over the period 1979-2005 to show that, when one controls for the non-random assignment of workers to jobs, overeducation does not result in lower earnings. Further, none of the earlier studies analyse both educational and skill mismatch together and are, therefore, subject to potential omitted variable problems. In this paper we show that if one is to draw the correct inferences on the effect of labour market mismatch on labour market outcomes, it is necessary not only to use panel estimation but also to use panel data which incorporate both forms of mismatch.

In this paper we utilize the panel element of the Household Income and Labour Dynamics in Australia (HILDA) survey to establish the effect of labour market mismatch on wages and two other important labour market outcomes, namely job satisfaction and labour turnover for graduates. Importantly, the survey contains an appropriate question on overskilling and, though there is no question on overeducation, we derive estimates using the (so-called) empirical method. The nature of the overskilling question does not enable us to determine the degree of underskilling and because the analysis is limited to graduates undereducation is not possible, as this group has the highest level of education. Hence, the possible categories of worker-job matching are limited to:

(a) *Well-matched*: the individual is matched in both education and skills (i.e. is neither overskilled nor overeducated).
(b) *Only overeducated*: the individual is matched in skills but is overeducated.
(c) *Only overskilled*: the individual is matched in education, but overskilled.
(d) *Overeducated and overskilled*: the individual is mismatched in both education and skills.

The overall research strategy adopted here recognizes that when assessing the impacts of job mismatch it is not sufficient to concentrate exclusively on earnings, as is the case with a good deal of the existing literature does. It is not necessarily the case that all forms of mismatch are involuntary in nature and, therefore, represent a productivity constraint. It is possible that mismatch may also arise out of choice as workers compensate lower wages for other intrinsic aspects of the job that increase satisfaction, for example an enhanced work life balance or increased social responsibility. Mismatch may also represent a short-term strategy aimed at acquiring basic work-related skills in order to enhance future levels of job mobility and earnings. Therefore, in order to come a meaningful assessment of the labour market impacts of job mismatch it is necessary to examine its relationship with respect to earnings, job satisfaction and labour market mobility, applying estimation techniques that are robust to the influences of unobserved individual heterogeneity bias.

This paper is structured as follows. Section 2 provides background information on overeducation and overskilling. Section 3 describes the data and Section 4 provides an overview of the estimation methods we use. Section 5 presents estimation results on the relationship between mismatches and (i) wages, (ii) job mobility, (iii) overall job satisfaction and (iv) job satisfaction facets in three separate subsections. Section 6 concludes. Appendix I contains descriptive statistics. An extended Appendix II, which is available upon request, contains the complete estimation results.

2. BACKGROUND

Skill mismatch has become an issue of particular policy concern. The European Union has increasingly focused on it because it is seen as damaging to competitiveness (see, for example, European Commission, 2009). Since the concept of overeducation among university graduates was first introduced by Richard Freeman in 1976 the literature on overeducation has mushroomed, with up to forty percent of the working population identified as falling into this category and often suffering sizeable wage penalties compared to well matched workers. Much of this research has concentrated on university graduates for a number of reasons. University graduates have been the largest and fastest growing single education group in Western labour markets for at least three decades and the trend is not abating. The presence of overeducation in the long-run is a continuing puzzle, given the fact that rates of return to degrees have also been stable or increasing. Further, investment in higher education continues to be the highest per person amongst all education categories. This makes the decision to become a graduate or not a crucial one for all labour market participants, with efficiency implications arising from the presence of overeducation. [1] Despite the considerable research attention that the overeducation phenomenon has received, its interpretation continues to be far from straightforward. First, there continue to be measurement issues arising from the different ways in which overeducation may be estimated as outlined above. Second, some jobs may merely specify a minimum educational requirement rather than a specific level of

[1] Although the presence of mismatch is not restricted to university graduates, the workings and the outcomes differ strongly by education category. This paper focuses on university graduates as the inclusion of employees without post-school education and with post-school vocational education and training would have created a group too diverse to analyse jointly. Mavromaras et al. 2010 show these differences using both Australian and UK data). Put simply, these groups do different jobs in different occupations and sectors and their earnings belong to a different segment of the wage distribution, which does not allow for fruitful joint analysis.

education, as other aspects of human capital may be just as important as qualifications. Third, in many cases educational requirements may be rising over time as jobs become more complex. Fourth, as noted above, an individual may be overeducated simply because he or she is of low ability for that level of qualifications, but this may be difficult to determine in the absence of data measuring individual ability.

There are three ways in which educational mismatch has been measured in the literature. The first, a subjective measure, is derived from workers' responses to questions on the level of education required either to obtain or perform their current job, which is then compared to their actual qualifications. The second, an objective measure, derives the required level of education for a particular occupation from job analysis. The third alternative, the so-called empirical method is used when a data-set being used does not contain any direct question on educational mismatch. This compares the actual level of education of an individual worker with either the mean or the modal level of education in that occupation, with mismatch usually being defined by convention as a level of education greater than one standard deviation above or below the mean or the mode. The mode is appropriate where the distribution of over- and under-education is asymmetric. Skill mismatch cannot be derived in this manner as it is generally based on workers' responses to a question on the degree to which they are able to use their current complement of skills and abilities in their present job. To the extent that workers are able to judge their own abilities, this can therefore control for differences in abilities across workers in the sample.

There are a number of hypotheses on why individuals may become mismatched. In the case of educational mismatch it has been suggested that certain individuals may have low ability for their level of education compared to their peers and thus be unable to obtain a job commensurate with their educational level. Such individuals will be overeducated, but not necessarily overskilled, and though their pay will be adversely affected, to the extent that they accept the limited nature of their ability, their job satisfaction may not be affected adversely. Some individuals, on the other hand, may choose to accept a job for which they are overqualified because it offers them compensating advantages, such as less stress or a shorter journey to work for instance. In this case such individuals may be both overeducated and overskilled, but despite the pay penalty their job satisfaction may be high and their propensity to quit low. A third possibility is that employers actually prefer overeducated workers because they are more productive and learn more quickly, thus reducing training costs. In these circumstances there may be little or no pay penalty and the mismatch may be temporary if such workers tend to be promoted relatively quickly. Skill mismatch, or more specifically overskilling, may result from workers being hired when the labour market is slack and jobs are hard to find. Skill mismatch may also imply that workers are being underutilized because employers do not possess well-developed hiring practices or sophisticated employee-development strategies, with possible negative effects on wages and almost certainly negative effects on job satisfaction and a higher propensity to quit in so far as such workers are able to do so. There may also be negative effects on management-worker relations (Belfield, 2010).

Some authors have attempted to make progress by disaggregating the overeducation variable. Chevalier (2003) and Chevalier and Lindley (2009) consider job satisfaction as a possible way of showing the degree of match between workers and jobs. They distinguish between genuine and apparent mismatch. Genuine mismatch represents a situation in which a worker indicates possession of more education than is required to perform the job and also a low level of job satisfaction. Apparent mismatch represents a situation in which a worker has more than the required level of education, but is satisfied with the job. This is consistent either with a recognition that the job requirements are adequate for the level of skills possessed by the worker (ie. the worker has low ability relative to that particular level of education) or alternatively that the worker prefers that level of job because it is less demanding or fits in better with leisure-work choices. They have data on first job and employment seven years later, though with a restricted sample which gives rise to some potential selection bias. They use the residual estimated from the first job wage equation to proxy unobservable fixed effects. Those who are genuinely overeducated are found to possess fewer entrepreneurial, management and leadership skills.

Adopting a slightly different approach, Green and Zhu (2010) distinguish between 'real' and 'formal' overeducation according to whether or not this is accompanied by skills under-utilisation. It is found that those in the real overeducation category suffer from higher wage penalties than those in the formal overeducation group and only the former exhibit significantly lower job satisfaction. An alternative approach is to treat overeducation and overskilling separately. Thus, Allen and van der Velden (2001) examine the relationship between educational mismatches and skill mismatches and find that while the former have a strong negative effect on wages the latter do not. Skill mismatches, in contrast, predict the level of job satisfaction and that of on-the-job search much better than does overeducation. Green and McIntosh (2007) find a correlation between overeducation and overskilling of only 0.2, suggesting that they are measuring different things. In a recent study, Mavromaras, et al. (2010) look at the extent of overskilling in Australia and its impact on wage levels using the HILDA data. They also argue that overskilling is a better measure of under-utilisation of labour than overeducation, since it is less likely to be contaminated by unobserved individual heterogeneity than the latter.

Kler (2006) has already used the first wave of HILDA to examine the impact of overeducation on higher education graduates using bivariate probit models to account for possible unobserved heterogeneity, though she does not consider overskilling. She calculates overeducation by using job analysis to determine the educational requirements of particular occupations using ASCO codes. Kler finds that overeducated graduates suffer from lower levels of satisfaction than their matched peers, with the exception of satisfaction with hours worked and job security. However, this may be the result of excluding the overskilling variable. We extend the analysis by making use of the panel element of HILDA and distinguishing between overskilling and overeducation.[2] Only panel information and estimation are capable of controlling for unobservables and none of the above studies used panel data. A recent attempt to use the panel element of the British Household Panel Survey (BHPS) is that of Lindley and McIntosh (2009). As there are no overeducation or overskilling questions in the BHPS, they use the one standard

[2] Kler (2007) has used the Australian Longitudinal Survey of Immigrants (LSIA) to examine the extent of overeducation (based on the objective definition) among tertiary educated immigrants. English speaking immigrants are found to have similar rates of overeducation compared to the native born, but higher rates are found among non-English speaking Asian immigrants. For immigrants in general, the earnings penalty for overeducation was found to be large relative to that of the native born.

deviation over the mode approach to measure overeducation. There is some evidence that unobserved ability explains some of the overeducation and that, for some, overeducation is a temporary phenomenon, but for a sizeable minority there is evidence of duration dependence and this is particularly so for the more highly educated. However, Lindley and McIntosh (2009) do not have a skill mismatch variable and thus are unable to control for unobserved characteristics.

The paper which comes closest to our own is that of Allen and van der Velden (2001). They use a data-set with a longitudinal element to examine a cohort of Dutch graduates from 1990-91 in their first job after graduation and five years after graduation and also identify wage, job satisfaction and mobility outcomes. Apart from the fact that our data are much more recent we have a richer set of controls, which enables our model to explain twice as much of the variation in wages. We also disaggregate by gender as well as identifying the effects of overeducation and overskilling both separately and jointly.

3. DATA

The data used is the confidentialised unit record file from the Household Income and Labour Dynamics in Australia (HILDA) survey. In this study we make use of data from the first seven waves of the HILDA survey. Modeled on household panel surveys undertaken in other countries, the HILDA survey began in 2001 (wave 1) with a large national probability sample of Australian households and their members.[3] The sample used here is restricted to an unbalanced panel of all working-age employees (16-64 for males and 16-59 for females) holding a university degree or equivalent qualification in

[3] See Watson and Wooden (2004) for a detailed description of the HILDA data.

full-time wage employment and who provide complete information on the variables of interest. Summary statistics of the variables used in this study are provided in Appendix I. The sample size we retain is approximately 1,200 observations per wave.

Overskilling is derived from HILDA by using the response 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 to strongly disagree up to 7 strongly agree. Individuals selecting 1, 2, 3 or 4 on the scale are classified as overskilled and those selecting 5 or higher as skill-matched. There is no scope for utilising this HILDA question to examine the phenomenon of underskilling and so we do not address this further here.[4]

Unlike the case of overskilling, HILDA does not contain any questions on overeducation. To overcome this inadequacy of our data, we utilise the ‘empirical method’ which defines a person to be overeducated if he or she has a higher qualification than the norm for employees in the same occupation. We start by categorizing the whole HILDA sample of employees by their years of education and 2-digit occupational classification. Using the mode of education for each occupation, we define a person to be overeducated if his or her educational achievement is above the mode of that occupational group.[5] We also

[4] This paper differs from previous research where overskilling has been classified as severe or moderate, against the well-matched reference category. In this paper, our reference category for matched in the case of skills are responses 5, 6, and 7 respectively in the HILDA data The rationale for not including 4 in the moderately overskilled category has been based on the weak empirical differences that have been traced by our previous research (Mavromaras et al., 2009 and 2010) between those defined as moderately overskilled and well matched in their skills. This choice regarding skills matching is consistent with the matching case in relation to education as the empirical method ignores those whose overeducation is less than one standard deviation over the mode. Those with more than one standard deviation over the mode are called “substantially overeducated” and are a category akin to the “severely overskilled” in the overskilling literature. However, in this paper we forgo the use of the standard deviation measure as our education levels are discrete.

[5] The mean and median could be too dependent on the shape of the distribution, and hence we follow the majority of the recent literature and use the mode.

considered using an “objective method” similar to the one used by Kler (2005) to define overeducation. The Australian and New Zealand Standard Classification of Occupations (ANZSCO) provides a detailed list of minimum required qualifications for each 2-digit occupation, which could be used as an “objective method” for determining the threshold to define overeducation. However, we found that these minimum required qualifications are generally consistent with the modes of education we obtain using the “empirical method” and, where they differ, the ANZSCO measures appear questionable (e.g. degree for farmers). It follows that defining overeducation using either of these two measures will lead to very similar results; hence we simply use the ‘empirical method’ in this paper. As found in other studies, the correlation between overeducation and overskilling in the HILDA data is relatively low at 0.197 for men, 0.243 for women and 0.218 for both genders combined. Within our sample, 14.3% of men are overeducated only, 8.4% overskilled only and 5.7% both overeducated and overskilled. For women the proportions are slightly lower, only 11.9%, 7.0% and 5.4% respectively. All of these are lower than the often cited 40% figure by Freeman (1978), who looked across the entire educational distribution and not only graduates as we do here.

The HILDA survey contains a question in the person self-completion questionnaire on how satisfied or dissatisfied individuals are with different aspects of their job, using a scale between 0 (least satisfied) and 10 (most satisfied). This includes questions on overall satisfaction along with five facets of job satisfaction (total pay, job security, the nature of work itself, hours of work and flexibility). The HILDA data set uniquely provides contemporary panel information on both overskilling and the job satisfaction aspects that are necessary for our analysis of the impact of job-worker mismatch on core labour market outcomes such as wages, job satisfaction and job mobility.

3.1 Wages of Graduates by Match Type

Table 1 reports the unadjusted average gross weekly wage levels for each combination of mismatch by gender. Not surprisingly, earnings were higher for males for each category of mismatch. Irrespective of gender, workers who were either overeducated and/or overskilled earned substantially less than well-matched employees. Within both the male and female sub-samples, average earnings were lowest for graduates who were both *overskilled and overeducated*. The next highest raw differential related to graduates who were *overeducated only*. The wages of *overskilled only* graduates appeared to reflect the lowest wage penalty, being closest to the wages of well-matched graduates.

[Table 1 here]

3.2 Job Satisfaction of Graduates by Match Type

Table 2 looks at the extent to which rates of overall job satisfaction vary according to the type of observed labour market match. The highest rates of job satisfaction were found among *well-matched* workers (a mean of 7.6 for both males and females) and those who were *overeducated only*. The *overskilled only* had average levels of satisfaction which were a full point lower. For men those who were *both overeducated and overskilled* had the lowest level of average job satisfaction among all groups, but for women this state was on average preferable to being *overskilled only*.

Table 2 suggests that overeducation alone, at least as defined here through the empirical method, is clearly not associated with lower levels of job satisfaction. At a level of 6.6 for both males and females, the average job satisfaction levels among workers who were *overskilled only* were well below those of *well-matched* and *overeducated only* workers. In general, the lowest levels of overall job satisfaction were reported by employees who were *both overeducated and overskilled*, (with a mean of 6.3 for males and 6.9 for females). Average job satisfaction and the way it is distributed in Table 2 suggest that the real driver of differences is overskilling and not overeducation.

[Table 2 here]

3.3.Job Mobility of Graduates by Match Type

Table 3 presents the extent of labour market mobility among our sample. HILDA records whether respondents left their job since the last interview and the reasons underlying the job separation. We follow McGuinness and Wooden (2009) by splitting reported job separations into voluntary (quits), involuntary (layoffs) and other categories. [6] Approximately 15 per cent of males and 16 per cent of females per annum were found to have left their jobs. Annual rates of voluntary separation averaged approximately 10 per cent for men and 12 per cent for women, while layoffs were 1 or 2 per cent and separations for other reasons 2 or 3 per cent. These patterns varied considerably when the data was broken down by each category of mismatch. The definition of job mobility

[6] Individuals were classified as having voluntarily separated if they gave any of the following as their main reason for leaving their previous employer: (i) not satisfied with job; (ii) to obtain a better job / just wanted a change / to start a new business; (iii) retired / did not want to work any longer; (iv) to stay at home to look after children, house or someone else; (v) travel / have a holiday; (vi) returned to study / started study / needed more time for study; (vii) too much travel time / too far from public transport; (viii) change of lifestyle; or (ix) immigration.

needs to use data from two consecutive interviews and the relevant matching status is the one reported in the first interview to reflect the way mismatch may induce mobility.

[Table 3 here]

Table 4 reveals that the incidence of voluntary separations was substantially higher among workers who were mismatched for whatever reason than among those who were well-matched. In this paper we are principally concerned with estimating the impact of origin mismatch on job mobility, i.e. does mismatch increase mobility? A related question, which we do not examine here, is the degree to which mobility may either preserve or lead to a mismatch, i.e. does mobility eliminate mismatch?

[Table 4 here]

4. ESTIMATION METHODOLOGY

4.1 Wage Effects of Job Mismatch

To investigate the effect of job mismatch on wage, we estimate the following earnings function:

$$\ln Y_{it} = \alpha_0 + \alpha M_{it} + \beta X_{it} + \varepsilon_{it} \tag{1}$$

where $\ln Y_{it}$ is the log of weekly earnings and M_{it} contains three job mismatch dummy variables as defined earlier, namely *overeducated only*, *over skilled only* and *both overeducated and overskilled* for individual i at time t. X is a matrix of other relevant personal and workplace characteristics that are used as control variables in the estimation, including age, marital status, number of children, socioeconomic background, unemployment history, country of origin, employment and occupational tenure, union membership, firm size and industry.[7] ε is the conventional error term. We estimate equation (1) using a pooled OLS model on a sample of working age full-time graduate employees, separately for male and female. The use of pooled regression is a good starting point and benchmark for the analysis. It provides us with an overview of the relationships we examine in terms of the cross sectional differences in the sample. Although largely informative in a descriptive sense, pooled regression estimates are always subject to biases due to unobserved systematic individual differences in the sample. Thus, we also use panel estimation which controls for time invariant unobserved individual heterogeneity and allows us to come closer to making inferences about causal effects. The first panel estimation uses a fixed effects model (the within estimator), which takes the form below:

$$\ln Y_{it} = \alpha_0 + \alpha M_{it} + \beta X_{it} + a_i + u_{it} \qquad (2)$$

where a_i is not assumed to have a distribution but is instead treated as the individual fixed (and estimable) effect , and u_{it} is an idiosyncratic error. An issue with such a fixed effects estimator, though, is that it is unable to identify time-invariant factors, although this is not a consideration in a random effects model. Mundlak (1978) has also demonstrated that the conventional random effects model can be adjusted to account for the (potential) correlation between unobserved heterogeneity and explanatory variables.

[7] Variables are listed and explained in detail in Appendix I.

Thus, the following random effects model is estimated – with the addition of the Mundlak correction – that also controls for unobserved time-invariant individual heterogeneity:

$$\ln Y_{it} = \alpha_0 + \alpha M_{it} + \beta X_{it} + \xi_1 \overline{M}_i + \xi_2 \overline{X}_i + v_{it} \tag{3}$$

where $\overline{M}_i$ and $\overline{X}_i$ are the time averages of M_{it} and X_{it} for individual *i* respectively, and v_{it} is a composite error term. In principle, the estimates of α and β in equation (3) approximate the fixed effects (within) estimators (see Wooldridge 2009). Unlike the fixed effects model in equation (2), the random effects with Mundlak correction model obtains explicit estimates on the variables with little or no over time variation within the observation period of the data.

4.2 Job Satisfaction and Job Mobility Effects of Job Mismatch

For clarity of interpretation we have converted the ordered job satisfaction variables into binary variables. In the HILDA data job satisfaction is measured as a 0 to 10 (lowest to highest) scale. We use a binary variable which is zero for values between 0 and 6 and is one for values between 7 and 10. Similar data conversions are common in the literature (e.g. Winkelman and Winkelman 1998, Hamermesh 2001). Apart from a loss in estimation precision, this data conversion entails the risk that measurement error may dominate residual variation in a systematic way (Ferrer-i-Carbonell and Frijters 2004). Extensive sensitivity analyses regarding the cut-off points we use were carried out suggesting that first, there is large enough variation in the binary job satisfaction measure (21 percent change status) and second, estimation results are not sensitive to the exact cut-off point selected.[8] The same conversion has been applied to each job satisfaction facet variable. The relationship between job mobility and matching models the incidence of having moved job since the previous wave as a function of the level of mismatch experienced in that previous wave. Thus, the question we ask in the mobility estimations is whether mismatch influences the stability of employment. We initially model all job separations jointly before estimating models for voluntary (quits) and involuntary (layoffs) mobility separately.

Since binary variables are used for job satisfaction and job mobility, the pooled OLS and fixed effects model become unavailable. Instead, we use both a pooled probit model and a random effects probit model with a Mundlak correction to estimate the effect of job mismatch on job satisfaction and job mobility, leaving the explanatory variables to be the same as those used in the wage effects estimation.[9]

In all, this paper uses a number of estimation methods. Each type of estimation contains different information and the comparisons we present are informative. The use of the pooled data serves two purposes. First, it provides a set of estimates that is comparable with the majority of the literature estimates, where panel data methods have not been utilised. Second, it provides a reasonable estimate of the association between labour

[8] Our approach resembles that of Winkelman and Winkelman (1998) and Hamermesh (2001). It sacrifices some of the information in the data for simplicity of estimation and interpretation. Ferrer-i-Carbonell and Frijters (2004) criticize this loss of data on the grounds that too few changes in status may remain in the data after its conversion from a scale to a binary variable, which raises the danger that measurement error may bias estimates. They propose an alternative Fixed Effects Logit estimation which they find to produce coefficients in line with estimations that include individual random effects and Mundlak corrections, which is the approach used in this paper. Our sensitivity analyses show clearly that changing the cut-off point from 6 to 7 to 8 leaves estimation results largely unchanged.

[9] Thus, the estimating equations are now synonymous with those detailed in equations (2) and (3) previously, but where the dependent variable is now a dichotomous indicator.

market outcomes and the mismatch. Pooled estimates will reflect the net association between wages, satisfaction and mobility with mismatch, caused by all observed and unobserved factors. By contrast, panel estimates will be much closer to the causal effects between the dependent and independent variables, as they control for both observed and unobserved individual heterogeneity. It is worth noting that, since the information contained in the data is the same for both estimations, the major difference in the estimates is that the panel estimation controls for unobserved heterogeneity, while the pooled estimation does not. However, the panel estimates also have their limitations as they cannot handle well the cases where there is little variation over time. We discuss these issues below when we contrast and interpret pooled cross section with random and fixed effects panel results.

5. REGRESSION RESULTS

5.1 Wage Effects of Job Mismatch

Possibly the most important and definitely the most well-researched consequence of mismatch is the effect it may have on wages. A common result in the literature, as noted earlier, is that mismatches are associated with lower pay, which reflects the lower productivity of a sub-optimal worker-job match, though it must be noted that overeducated workers do receive higher pay than their educationally appropriately matched co-workers, suggestive of some productivity advantage to being overeducated (see Sicherman, 1991). Table 5 shows that OLS estimation produces highly significant coefficients in all types of mismatch. Not surprisingly, the strongest associations are found for those who are both overeducated and overskilled. The Random Effects (RE) model with Mundlak corrections produces, as expected, almost identical estimates as the Fixed Effects model and in all cases much weaker estimates than the OLS pooled model.

[Table 5 here]

The first main result in Table 5 is that controlling for unobserved heterogeneity removes most of the wage impact for men who are *overeducated only* or *overskilled only*. Graduate men who change status from a *well-matched* job to an *overeducated only* or an *overskilled only* job do not suffer a wage penalty. It is only *well-matched* graduate men who change status to a job where they are *both overeducated and overskilled* that suffer an approximate 5.9 per cent wage penalty.[10]

It is noteworthy that the panel estimates of wage penalties due to mismatch are substantially different from the estimates of overall association produced by the OLS models, suggesting that unobserved systematic differences play a significant role in determining mismatch effects. Women in full-time employment appear to suffer a wage penalty when they change status from a well-matched to a mismatched job for all types of mismatch. This is a significant result as it ties with the literature on discrimination which has found that gender pay differentials are higher at the hiring point.[11] When we compare

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[10] Underlying the estimation of our models is the movement between mismatch states between time t and time t-1. Such figures are set out in Appendix Table A4 and they show that of 5,883 observed pairs, 22% (or 1,289 cases) changed status between waves. While there are a limited number of bi-lateral movements between different forms of mismatch (see Appendix Table A5), the focus of this work is transitions between a well-matched state and various states of mismatch. The number of such movers in the sample certainly allows for meaningful and well-defined estimates to be derived from the longitudinal framework adopted here.

[11] Mavromaras and Rudolph (1997) estimated gender pay differentials at the hiring point using administrative data from the Federal Employment Office in Germany and found that the hiring process is associated with an increase in gender pay differentials. Their sample contains only workers who are hired after an out of work spell and their estimations find a hiring wage penalty for women.

the wage penalties of both men and women we see that women suffer a worse pay deterioration than men when changing status from a well-matched job into a mismatched job, the differential being net of systematic differences in unobserved individual heterogeneity.

However, there is some recent evidence to suggest that Fixed Effects estimators (and by extension Random Effects estimates after the incorporation of Mundlak corrections) may themselves be biased by under-estimating the true impact of some covariates in a model. Buddelmeyer et al. (2010) suggested that fixed effects can absorb a good deal of the explanatory power of those time-varying variables that show little variation within the time period covered by the sample at hand. This is potentially a concern for studies of skill mismatch, given that existing evidence suggests that both overeducation and overskilling are relatively time-persistent states (McGuinness 2006). To investigate this possibility, we estimate a two-stage model whereby we extract the individual level fixed effects from a first-stage Fixed Effects estimation and use them as the dependent variable in a second-stage pooled OLS regression with all the time varying means of each of our original explanatory variables (that is, the Mundlak controls) on the right hand side. The inclusion of the Mundlak means as right-hand-side variables provides an indication of the relative contribution of each variable (including the mismatch indicators on which this paper focuses) to the overall fixed effect.

Table 6 reports the coefficients and t-statistics of the mismatch controls along with the adjusted R^2 of each regression. The time varying averages as right hand side variables explain a high proportion of the overall individual level fixed effects, more so for females as reflected in the adjusted R^2 statistics. The results confirm that the variables indicating *overeducated only*, *overskilled only* and *both overskilled and overeducated* account for a proportion of the fixed effect. The negative signs suggest that the coefficients for the Fixed Effects and the Random Effects with Mundlak corrections models reported in Table 5 may be under-estimating (with the exception of females whose changed status to an *overskilled only* job yields a positive coefficient, thus over-estimating the true impact of the mismatch variables on wages). Table 6 results show some interesting gender differences. The mismatch penalty for males is under-estimated for all types of mismatch, but notably less for *only overskilled* males. This may not be surprising, in that overskilling is the variable that changes most through individual job moves and thus contains most over time variation. Interestingly, the result of under-estimated mismatch wage penalty holds largely unchanged for females in the category of *overeducated only* and *both overskilled and overeducated*, but is reversed for females who are *overskilled only*.

[Table 6 here]

5.2 Overall Job Satisfaction and Mismatch

We treat job satisfaction as an outcome of mismatch by observing the effect that each type of mismatch has on resulting job satisfaction levels after we have controlled for other factors that may also affect job satisfaction. The interpretation of our results is that where a mismatch does not appear to reduce job satisfaction it is more likely that this mismatch reflects voluntary under-utilisation of skills or qualifications (or, at least if not voluntary, not harmful according to the worker). By contrast, a mismatch that reduces job satisfaction is more likely to reflect involuntary under-utilisation. Tables 7a and 7b present the difference(in coefficients and marginal effects respectively) in overall job satisfaction between the *well-matched* and those that belong to one of the three categories of mismatch, estimated using pooled (cross-section) probit and Random Effects (panel) probit with Mundlak corrections. We report results for males and females separately. Estimates on *overeducation only* (Tables 7a and 7b, Column 1) suggest that, once we have controlled for mismatch that is attributable to being overskilled, mismatch attributable to being overeducated only has no discernible effect on the job satisfaction of males and females alike. This result is in agreement with Green and Zhu's (2008) finding that education mismatch in itself does not lower the level of job satisfaction.[12]

[Tables 7a and 7b here]

Estimates on *overskilled only* (Tables 7a and 7b, Column 2) suggest that overskilling can be a prime cause of lower job satisfaction, with some gender differences present. For males, controlling for unobserved heterogeneity in the estimation leads to considerable reduction in the job satisfaction negative effect, more than halving the marginal effect (from -0.222 to -0.069). This difference between the two estimates implies that unobserved heterogeneity introduces a negative bias on the effect of mismatch on job satisfaction, which would suggest that male employees of a generally unhappy disposition towards work are more likely to end up in jobs that under-utilise their skills,

[12] There is a suggestion in the overeducated only results that, when we shift from cross-section to panel results (i.e. after controlling for unobserved individual heterogeneity with the RE model with Mundlak corrections) a small dissatisfaction effect arises, as the magnitude of estimates rise, especially for females. However, their statistical significance remains well below acceptable levels. One possible explanation would have been that a sub-group among females would respond differently to overskilling. We examined a number of sample splits, including one between married and single females, but could find no such pattern in the relationship between overskilling and job satisfaction.

for reasons that are not explained by our data. This pattern is repeated for males who are both overeducated and overskilled. For females, controlling for unobserved heterogeneity has a statistically less discernible effect (from -0.222 to -0.174), which suggests that females with a generally unhappy disposition towards work may be as likely to end up in an *overskilled only* job as their happier counterparts. Females end up with the same reduction in job satisfaction as males when they move from a well-matched job to a job where they are both overeducated and overskilled (panel marginal effect is -0.152 for males and -0.173 for females). Note the different direction in the change in estimates of dissatisfaction after controlling for unobserved heterogeneity: For males we see a clear decrease in the dissatisfaction marginal effect from -0.298 to -0.152, while for females we see an increase from -0.120 to -0.173, indicating that unobserved heterogeneity bias works in the opposite direction for males and females. This implies that, although we find that the generally happier females are more likely to end up in the *both overeducated and overskilled* category than their male counterparts, the dissatisfaction caused by ending up in such a job is equally strong for both males and females (-0.152 for males and -0.173 for females). In conclusion, estimates of the comparison between those who are well-matched with those who happen to be *both overskilled and overeducated* (Tables 7a and 7b, Column 3) clearly suggest that even after we have controlled for all available observable attributes and all time invariant unobservable attributes, job satisfaction can be still shown to be seriously damaged by this type of severe mismatch. Our results clearly do not contradict those of Green and Zhu regarding the importance of combined overskilling and overeducation.

5.3 Facets of Job Satisfaction and Job Mismatch

The data contain detailed information about the degree of satisfaction regarding several facets of employment, namely, pay, job security, work, hours and flexibility. Estimation results by gender for all job satisfaction facets are in Table 8. The first row reported for each gender in Table 8 is the estimate of overall job satisfaction (already reported in Table 7) and the rows that follow report the facets of job satisfaction. A similar picture arises to the one for overall job satisfaction in that being *overeducated only* does not have an impact on satisfaction (with the exception of hours dissatisfaction by overeducated males). Table 8 suggests that for the *overskilled only* the only facet that is consistently statistically significant is that of work satisfaction, which is bound to be a closely related to the overall satisfaction variable. It is possible that, empirically, these two variables are not as clearly distinguishable from one another as we would like them to be. It is worth noting, however, that for both males and females the work satisfaction estimates are stronger than the overall job satisfaction ones. The marginal effects of being overskilled only in the pay satisfaction estimation have a statistical significance close to the 10 percent level, positive for males (with a t-ratio of 1.64) and negative for females (with a t-ratio of -1.57, very near the margin of the 10% significance level). The implication here is that men who change status from *well-matched* to *overskilled only* jobs tend to be more satisfied with their pay. Note that this conclusion is in agreement with the estimated wage penalties where we find no wage penalty for *overskilled only* males and a small penalty for females. Moving to workers that are *both overskilled and overeducated,* we note that dissatisfaction with work is clearly present and that there is clear hours dissatisfaction for males and job security dissatisfaction for females.

[Table 8 here]

5.4 Job Mobility and Job Mismatch

Job separations have been argued to be a consequence of inadequate matches (McGuinness and Wooden, 2009). It is useful to distinguish between voluntary separations (quits initiated by the employee) from involuntary separations (layoffs initiated by the employer), although we should bear in mind that, in practice, there will be occasions where this decision will be endogenous. Thus, voluntary mobility is more likely to reflect dissatisfaction expressed by the employee, while involuntary mobility is more likely to reflect dissatisfaction expressed by the employer. We estimate the probability of an individual changing jobs between two consecutive interviews depending on their level of mismatch in the job that they left (denoted as “in origin job” in Table 9), in order to examine if employees who are mismatched in their job are more or less likely to quit or be laid off than their well-matched counterparts. We maintain the same estimation methodology and specification and compare a pooled (cross section) probit with a Random Effects probit model with Mundlak corrections, separating our sample by gender.

Table 9 contains estimation results on job mobility by type of mobility and gender. The first clear message is that, after we have controlled for individual unobserved heterogeneity, neither of the three categories of mismatch has any significant effect on involuntary job mobility and it is just overeducation on its own or jointly with overskilling that increases voluntary mobility, and then only for males. The general lack of a significant direct effect of mismatch on mobility appears to be in contrast to other published work which has typically been either based on cross section estimation or short panel data. It is worth noting that the pooled probit models in Table 9, which contain many statistically significant estimates of mismatch (especially male layoffs), lose their significance when we use panel estimation. This suggests that some of that significance was caused by unobserved heterogeneity bias. Note that we reached a similar conclusion in the wage estimations after controlling for unobserved heterogeneity. Notwithstanding this evidence, we think the issue of job mobility and mismatch remains unclear, principally because we fail to control for employer-specific unobserved heterogeneity, which we would expect to be pertinent in the case of layoffs.

[Table 9 here]

The comparison between the pooled probit and the Random Effects probit with Mundlak corrections has an important interpretation in this context: given that the pooled results do not control for unobserved individual heterogeneity, while the random effects estimates do, the differences between the two sets of estimates contain information about the association between unobserved heterogeneity and the dependent variable. Following a similar line of argument as with the wage penalties and using the case of *overeducated only* males as an example, we see a very different pattern between quits and layoffs. Removing the effect of unobserved individual characteristics reduces the marginal effect from 0.112 to -0.029 for layoffs and increases it from -0.063 to 0.438 for quits, which means that using pooled regression over-estimates the effect of overeducation on layoffs and under-estimates its effect on quits for males. Put simply, our mobility regressions suggest that overeducated only males possess some unobserved characteristics which increase their probability of being laid off and decrease their probability of quitting. Similar comparisons can be made for the remaining estimates in Table 9 and they show no clear pattern by type of mismatch or by gender.

6. CONCLUSIONS

Much of the earlier literature on graduate mismatch found that there were both pay and job satisfaction penalties to being overqualified, but most of this literature was constrained by the unavailability of data on overskilling and also by the absence of panel data which would have allowed for controls on unobserved individual heterogeneity, such as variations in innate ability or employability. Our data relate to only one country, namely Australia, but the use of the panel element of HILDA and the presence of a question on overskilling enables us to put a new perspective on earlier results from a variety of countries.

In this paper we have introduced a more detailed definition of worker-job mismatch than contained in the earlier literature with a mismatched worker being analysed according to whether he or she is either overeducated, overskilled or a combination of the two. We present two types of estimations: pooled cross-section regression and random effects probit with Mundlak corrections. Pooled regressions can be informative about the overall association between labour market outcomes and mismatch, while random effects estimates give us a measure of the possible causal effect of mismatch on labour market outcomes. We have estimated a large number of models to establish the repercussions of labour market mismatch in terms of individual wages, job satisfaction and job mobility. We also carried out the analysis separately for males and females. In general, the data support the view that overeducation and overskilling are distinct phenomena, that they work differently by gender, that they have a different effect on different labour market outcomes and that the negative effects of being both overeducated and overskilled are more severe.

Our results differ from the earlier literature in a number of respects. First, for men we find there to be a significant pay penalty only for those who are both overskilled and overeducated, while for women there is a significant pay penalty in all cases of mismatch. Secondly, job satisfaction for men is not influenced by overeducation, but it is clearly reduced by overskilling either on its own or jointly with overeducation. Meanwhile for women, the same correlation between overskilling and job satisfaction is again apparent, but the magnitude of the estimated coefficient on overeducation in the job satisfaction analysis is substantial and negative, even if it is not significant at a conventionally accepted level of significance. Thus, while overskilling unambiguously appears to be more welfare reducing than overeducation, there is evidence to suggest that the influence that overskilling has for women's job satisfaction cannot be discounted. We obtain little further insight when we estimate the facets of job satisfaction instead of a measure of overall job satisfaction. Thirdly, in the case of quits, with the exception of overeducation on its own and jointly with overskilling for males, mismatch has no significant effect on the job mobility of either gender. Finally, a core result of this paper is that it shows the very important role played by properly controlling for unobserved heterogeneity when estimating the labour market outcomes of mismatch: past results based on cross section and short panel data sets are shown to contain considerable biases.

A key finding is that when we control for unobserved individual heterogeneity (including ability) and for skill mismatch in the overeducation equations, there are no negative wage effects or job satisfaction effects for men. This overturns much of the existing literature on overeducation and is consistent with male preferences (or choice) being in accord with the outcome that there is a non-pecuniary compensating differential for overeducated men. For women, however, there is a negative wage effect and a negative (though not statistically significant – t = -1.42) job satisfaction effect. This finding may shed light on the nature of women's mismatch in the labour market which could be manifested through constrained choice outcomes, such as the tied stayer and tied mover hypotheses for married women, discrimination against women in general, or career interruptions for family reasons.

The results suggest that it is on overskilling and particularly its combination with overeducation that policy attention should be focussed. Overskilling, whether on its own or jointly with overeducation, clearly has a negative effect on the welfare of men and women and its eradication may have benefits for employers and employees alike. It is particularly interesting that the wage penalty of mismatch is higher for females and so is their reported dissatisfaction caused by mismatch, especially so by overskilling. Mismatch appears to be more damaging for females.

REFERENCES

Allen, J. and van der Velden, R. (2001). “Education Mismatches Versus Skill Mismatches: Effects on Wages, Job Satisfaction, and On-the-Job Search,” *Oxford Economic Papers*, 53, 434-452.

Bauer T. (2002), “Educational Mismatch and Wages: A Panel Analysis”, *Economics of Education Review*, 21, 221-229.

Belfield C. (2010), “Over-education: What Influence Does the Workplace Have?”, *Economics of Education Review*, 29, 236-245.

Buddelmeyer H., Lee W-S. and Wooden M. (2010), “Low-Paid Employment and Unemployment Dynamics in Australia”, *Economic Record*, 86(272), 28-48.

Chevalier A. (2003), “Measuring Overeducation”, *Economica*, 70(209), 509-531.

Chevalier A. and Lindley J. (2009) “Over-education and the Skills of UK Graduates”, *Journal of the Royal Statistical Society,* Series A, 172(2), 287-337.

European Commission (2009), *New Skills for New Jobs; Anticipating and Matching Labour Market and Skill Needs,* Luxembourg.

Ferrer-i-Carbonell A. and Frijters P. (2004), “How Important is Methodology for the Estimates of the Determinants of Happiness?”, *The Economic Journal,* 114, 641-659.

Freeman R.B. (1978), *The Overeducated American*, Academic Press.

Green F. and McIntosh S. (2007), “Is There a Genuine Under-utilization of Skills amongst the Over-qualified?”, *Applied Economics*, 39(4), 427-439.

Green F. and Zhu Y.(2010), “Overqualification, Job Dissatisfaction, and Increasing Dispersion in the Returns to Graduate Education”, *Oxford Economic Papers*, 62(4), 740-763.

Kler, P. (2005), “Graduate Overeducation in Australia: A Comparison of the Mean and Objective Methods”, *Education Economics*, 13, 47-72.

Kler P. (2006), “The Impact of Overeducation on Job Satisfaction Among Tertiary Educated Australians”, unpublished manuscript, University of Queensland.

Kler P. (2007), “A Panel Data Investigation into Over-education among Tertiary Educated Australian Immigrants”, *Journal of Economic Studies*, 34(3), 179-193.

Lindley J. and McIntosh S.(2009),”A Panel Data Analysis of the Incidence and Impact of Overeducation”, Department of Economics, University of Sheffield, Working Paper, May, ISNN 1749-8368.

Mavromaras, K., McGuinness, S. and Fok Y.K. (2009). “Assessing the Incidence and Wage Effects of Overskilling in the Australian Labour Market”, *Economic Record*, 85(268), 60-72.

Mavromaras, K., McGuinness, S., O’Leary, N., Sloane, P. and Y. K. Fok (2010) “The Problem of Overskilling in Australia and Britain.” *The Manchester School*, 40(3), 219-241.

Mavromaras, K., and Rudolph, H. (1997), "Wage Discrimination in the Reemployment Process." *Journal of Human Resources* 32(4), 812-860.

McGuinness S. (2006) “Overeducation in the Labour Market”. *Journal of Economic Surveys* 20, 387–418.

McGuinness, S. and Wooden, M.(2009), “Overskilling, Job Insecurity and Career Mobility”, *Industrial Relations*, Vol. 48(2), 265-286.

Mundlak Y.(1978), “On the Pooling of Time Series and Cross Section Data”, *Econometrica*, 46(1), 69-85.

Sicherman N. (1991), “Overeducation in the Labor Market,” *Journal of Labor Economics*, 9(2), 101-122.

Tsai Y .(2010), “Returns to Overeducation: A Longitudinal Analysis of the U.S. Labor Market, *Economics of Education Review*, 29(4), 606-617.

Watson, N. and Wooden, M. (2004), “The HILDA Survey Four Years On”, *Australian Economic Review*, 37(3), 343-349.

Wooldridge, J. (2009), “Correlated Random Effects Models with Unbalanced Panels”, Manuscript (version July 2009), Michigan State University.

Table 1: Wages of graduates by type of job match

	Males	*Females*
Well-matched	1537.4	1102.8
Overeducated only	1161.0	883.0
Overskilled only	1322.9	1011.7
Overskilled and overeducated	910.9	711.3

Note: The sample consists of all working age full-time employees in the HILDA 2001-2007 survey; wages are measured as "nominal gross weekly wages and salary from main job in Australian dollars".

Table 2: Overall job satisfaction (percentage) of graduates by type of job match and gender

Job satisfaction	*Well-matched*		*Overeducated only*		*Overskilled only*		*Overskilled and overeducated*	
	M	F	M	F	M	F	M	F
0	0.1	0.1	0.0	0.0	0.5	1.1	0.4	1.0
1	0.2	0.3	0.3	0.4	0.5	0.7	1.2	1.5
2	0.5	0.5	1.1	0.7	2.5	0.7	4.4	0.0
3	1.2	1.5	1.6	0.7	4.1	5.2	2.4	3.9
4	1.8	1.4	1.8	1.8	4.1	4.9	8.4	1.0
5	4.2	5.4	2.7	5.0	10.4	12.4	12.0	12.1
6	7.7	8.8	8.5	11.6	15.3	14.6	17.2	11.7
7	23.9	22.1	21.8	19.7	30.0	27.3	27.6	29.1
8	36.2	33.0	34.7	34.6	23.2	22.1	18.0	24.8
9	20.1	21.2	19.0	18.8	7.6	8.2	6.8	13.1
10	4.0	5.5	8.5	6.8	1.9	2.6	1.6	1.9
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mean job satisfaction	7.6	7.6	7.7	7.6	6.6	6.6	6.3	6.9
Cases	3,119	2,906	625	457	367	267	250	206

Note: Working age full-time employees (HILDA 2001-2007). The unit of analysis is person-wave.

Table 3: Job mobility of graduates (percentages)

	Males	*Females*
Did not change job	85.1	83.8
Layoff (involuntary)	2.3	1.2
Quits (voluntary)	10.4	11.8
Other	2.2	3.2
Cases (person-wave)	3,831	3,291

Note: Working age full-time employees (HILDA 2001-2007); percentages of job movements from main job between two consecutive interviews.

Table 4: Job mobility of graduates (percentages) by type of job match in the first interview and by gender

	Males			
	Well-matched	*Overeducated only*	*Overskilled only*	*Overskilled and overeducated*
Did not change job	89.6	84.6	83.0	74.5
Layoff (involuntary)	1.4	3.2	4.5	4.6
Quits (voluntary)	7.5	10.8	11.1	16.8
Other	1.5	1.3	1.4	4.1
	Females			
	Well-matched	*Overeducated only*	*Overskilled only*	*Overskilled and overeducated*
Did not change job	88.3	87.7	76.0	81.7
Layoff (involuntary)	1.2	0.6	2.6	0.0
Quits (voluntary)	8.8	10.7	15.1	13.7
Other	1.7	1.0	6.3	4.6

Note: Working age full-time employees from HILDA 2001-2007;
percentages of job movements from main job between two consecutive interviews;
job mobility is defined as a change in jobs between consecutive interviews;
matching status defined as that reported in the first of the two interviews.

Table 5: Graduate wage effects of job mismatch by type of job match and gender

	Relative to well-matched:		
	Overeducated only	*Overskilled only*	*Overskilled and overeducated*
Males			
OLS	-0.215***	-0.094***	-0.309***
	(-11.38)	(-4.07)	(-10.54)
RE with Mundlak corrections	-0.003	-0.011	-0.059**
	(-0.12)	(-0.68)	(-2.22)
Fixed Effects	-0.003	-0.012	-0.059**
	(-0.15)	(-0.66)	(-2.12)
Mismatch incidence	625	367	250
Cases		4,361	
Females			
OLS	-0.212***	-0.034	-0.317***
	(-11.25)	(-1.56)	(-11.80)
RE with Mundlak corrections	-0.057***	-0.053***	-0.088***
	(-2.60)	(-3.36)	(-3.70)
Fixed Effects	-0.055**	-0.053***	-0.086***
	(-2.43)	(-3.14)	(-3.45)
Mismatch incidence	457	267	206
Cases		3,837	

Note: Estimated coefficients with t-statistics in brackets; */**/*** denotes significance at the 10%/5%/1% level; dependent variable is the log of gross weekly wages; the unit of analysis is person-wave.

Table 6: Impact of job mismatch on individual fixed effects by type of job match and gender

	Relative to well-matched:		
	Overeducated only	*Overskilled only*	*Overskilled and overeducated*
Males			
Fixed Effect – OLS	-0.316***	-0.117***	-0.324***
	(-15.83)	(-4.13)	(-10.23)
Adjusted R^2	0.79	0.79	0.79
Female s			
Fixed Effect – OLS	-0.241***	0.066**	-0.323***
	(-11.86)	(2.51)	(-11.86)
Adjusted R^2	0.83	0.83	0.83

Note: Estimated coefficients with t-statistics in brackets;
*/**/*** denotes significance at the 10%/5%/1% level;
the unit of analysis is person-wave.

Table 7a: Overall job satisfaction for graduates by type of job match and gender (coefficients)

	Relative to well-matched:		
	Overeducated only	*Overskilled only*	*Overskilled and overeducated*
Males			
Pooled probit	0.027	-0.685***	-0.877***
	(0.36)	(-8.81)	(-8.96)
RE probit (with Mundlak corrections)	-0.077	-0.328***	-0.621***
	(-0.57)	(-2.76)	(-3.49)
Females			
Pooled probit	-0.024	-0.661***	-0.380***
	(-0.28)	(-7.58)	(-3.38)
RE probit (with Mundlak corrections)	-0.221	-0.627***	-0.618***
	(-1.42)	(-4.59)	(-2.82)

Note: Estimated coefficients with t-statistics in brackets;
The sector dummy variable *construction* is dropped in the estimations for females due to insufficient observations.
*/**/*** denotes significance at the 10%/5%/1% level.

Table 7b: Overall job satisfaction for graduates by type of job match and gender (marginal effects)

	Relative to well-matched:		
	Overeducated only	*Overskilled only*	*Overskilled and overeducated*
Males			
Pooled probit	0.007	-0.222***	-0.298***
	(0.37)	(-7.69)	(-7.83)
RE probit (with Mundlak corrections)	-0.014	-0.069**	-0.152***
	(-0.55)	(-2.37)	(-2.75)
Females			
Pooled probit	-0.007	-0.222***	-0.120***
	(-0.28)	(-6.73)	(-3.06)
RE probit (with Mundlak corrections)	-0.052	-0.174***	-0.173**
	(-1.30)	(-3.79)	(-2.32)

Notes: estimates refer to marginal effects at the sample means of the independent variables with t-statistics in brackets;
*/**/*** denotes significance at the 10%/5%/1% level.

Table 8: Job satisfaction facets for graduates by type of job match and gender

	Relative to well-matched:		
	Overeducated only	*Overskilled only*	*Overskilled and overeducated*
Males			
Overall job satisfaction	-0.077	-0.328***	-0.621***
	(-0.57)	(-2.76)	(-3.49)
Pay satisfaction	0.041	0.200	-0.078
	(0.32)	(1.64)	(-0.45)
Job security satisfaction	0.183	-0.077	0.066
	(1.33)	(-0.57)	(0.35)
Work satisfaction	0.053	-0.533***	-0.604***
	(0.39)	(-4.53)	(-3.49)
Hours satisfaction	-0.206*	-0.167	-0.442**
	(-1.66)	(-1.40)	(-2.44)
Flexibility satisfaction	0.077	-0.033	-0.147
	(0.59)	(-0.27)	(-0.82)
Females			
Overall job satisfaction	-0.225	-0.625***	-0.622***
	(-1.44)	(-4.58)	(-2.84)
Pay satisfaction	-0.090	-0.210	-0.103
	(-0.64)	(-1.57)	(-0.49)
Job security satisfaction	-0.194	-0.147	-0.415*
	(-1.17)	(-0.89)	(-1.72)
Work satisfaction	-0.079	-0.870***	-1.17***
	(-0.49)	(-6.31)	(-5.34)
Hours satisfaction	0.089	0.152	-0.304
	(0.58)	(1.08)	(-1.36)
Flexibility satisfaction	0.036	-0.036	-0.062
	(0.25)	(-0.26)	(-0.29)

Notes: Estimated coefficients with t-statistics in brackets;
*/**/*** denotes significance at the 10%/5%/1% level;
estimation is by Random Effects orobit with Mundlak correction using the same specification as in Table 7;
for reasons of space cross section results are not reported.

Table 9: Effects of job mismatch on graduate job mobility by type of job match and gender

Type of job loss	*Relative to well-matched:* *Overeducated only (lagged)*	*Overskilled only (lagged)*	*Overskilled and overeducated (lagged)*
<u>*Males*</u>			
Job change (all causes)			
Pooled probit	-0.054	0.098	0.445**
	(-0.41)	(0.63)	(2.55)
RE probit (with Mundlak corrections)	0.216	0.044	0.497*
	(1.03)	(0.21)	(1.83)
Layoffs (involuntary)			
Pooled probit	0.112	0.610***	0.553*
	(0.54)	(2.65)	(1.93)
RE probit (with Mundlak corrections)	-0.029	0.377	0.359
	(-0.08)	(1.03)	(0.70)
Quits (voluntary)			
Pooled probit	-0.063	-0.125	0.271
	(-0.44)	(-0.72)	(1.47)
RE probit (with Mundlak corrections)	0.438*	-0.066	0.593**
	(1.85)	(-0.28)	(1.98)
<u>*Females*</u>			
Job change (all causes)			
Pooled probit	-0.253*	0.234	-0.323
	(-1.77)	(1.51)	(-1.54)
RE probit (with Mundlak corrections)	-0.245	0.364*	-0.179
	(-1.06)	(1.66)	(-0.47)
Layoffs (involuntary)			
Pooled probit	-0.878	-0.021	
	(-1.18)	(-0.03)	-
RE probit (with Mundlak corrections)	-	-	-
Quits (voluntary)			
Pooled probit	-0.164	0.102	-0.277
	(-1.16)	(0.68)	(-1.36)
RE probit (with Mundlak corrections)	-0.276	0.102	-0.271
	(-1.19)	(0.47)	(-0.72)

Notes: Estimated coefficients with t-statistics in brackets;
*/**/*** denotes significance at the 10%/5%/1% level;
- denotes insufficient observations to support estimation.

APPENDIX I

Table A1 presents the incidence of the various categories of mismatch across each of the seven waves of HILDA. There is little evidence of any consistent pattern in the data in terms of rising or falling rates of mismatch. Table A2 presents the distribution of the job satisfaction by gender and wave. Table A3 presents sample descriptives. Tables A4 and A5 present the number of transitions between mismatch states.

Table A1: Graduate overeducation and overskilling (percentage) by wave and gender

	Wave 1		*Wave 2*		*Wave 3*		*Wave 4*		*Wave 5*		*Wave 6*		*Wave 7*	
	M	*F*	*M*	*F*	*M*	*F*	*M*	*F*	*M*	*F*	*M*	*F*	*M*	*F*
Well matched														
Per cent	73	79	68	77	72	73	72	74	71	76	73	75	71	76
Cases	462	429	415	379	437	384	450	382	457	423	464	442	434	468
Overeducated only														
Per cent	13	10	14	11	13	14	13	13	15	13	14	11	18	12
Cases	83	55	82	56	80	71	83	65	98	71	89	67	110	72
Overskilled only														
Per cent	8	6	11	6	8	8	8	8	9	6	8	7	7	7
Cases	51	35	67	31	48	41	53	41	56	32	49	43	43	44
Overskilled and overeducated														
Per cent	6	4	7	6	7	6	6	5	5	5	5	7	5	5
Cases	35	23	42	29	40	29	39	28	32	28	34	39	28	30
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Cases	631	542	606	495	605	525	625	516	643	554	636	591	615	614

Note: Sample is working age full-time employees from HILDA 2001-2007.

Table A2: Job satisfaction (percentage) of graduates by wave and gender

	Wave 1		*Wave 2*		*Wave 3*		*Wave 4*		*Wave 5*		*Wave 6*		*Wave 7*	
JS (job satisfaction)	M	F	M	F	M	F	M	F	M	F	M	F	M	F
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
1	0	1	0	1	1	0	0	1	0	0	1	1	0	0
2	1	1	1	1	1	1	1	1	1	1	0	0	1	1
3	3	2	1	2	2	2	2	2	1	2	1	1	1	2
4	2	2	3	2	3	2	3	2	3	2	2	1	2	2
5	5	8	6	7	6	6	6	6	4	5	4	5	4	6
6	10	9	10	10	9	9	7	9	9	10	10	10	7	11
7	25	20	27	23	23	25	23	24	24	25	25	23	24	22
8	30	29	28	30	33	30	38	30	36	34	35	35	37	32
9	18	21	18	18	18	20	16	20	17	17	19	18	19	20
10	6	7	4	7	4	4	4	5	5	4	3	6	4	4
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Mean JS	7.4	7.4	7.3	7.4	7.3	7.4	7.4	7.4	7.5	7.4	7.5	7.5	7.6	7.4
Cases	688	572	674	562	658	567	669	559	711	609	701	643	695	692

Note: Sample is working age full-time employees from HILDA 2001-2007.

Definition of Variables:

Wage: Log of current weekly gross wages & salary from the main job.

Overall job satisfaction: Dummy variable, takes the value 1 if overall job satisfaction is 7 or above, zero if 0 to 6.

Facets of job satisfaction: Pay satisfaction, job security satisfaction, work satisfaction, hours satisfaction and flexibility satisfaction are defined in the same way as overall job satisfaction.

Job mobility:

Job loss: Dummy variable, takes the value 1 if an individual has job loss between two consecutive interviews, zero otherwise.

Lay offs (Involuntary job loss): Dummy variable, takes the value 1 if an individual has involuntary job loss between two consecutive interviews, zero otherwise.

Quits (voluntary job loss): Dummy variable, takes the value 1 if an individual has voluntary job loss between two consecutive interviews, zero otherwise.

Mismatch variables:

Overeducated Only: Dummy variable, takes the value 1 if an individual is overeducated only, zero otherwise.

Overskilled Only: Dummy variable, takes the value 1 if an individual is overskilled only, zero otherwise.

Overskilled and overeducated: Dummy variable, takes the value 1 if an individual is overskilled and overeducated, zero otherwise.

Well matched is the reference category.

Age: Continuous variable, expressed in years.

Age Square: Continuous variable, expressed in years.

Married: Dummy variable, takes the value 1 if an individual is married (or de facto), zero otherwise.

Urban: Dummy variable, takes the value 1 if an individual domiciled within a major city, zero otherwise.

Father was a professional: Dummy variable, takes the value 1 if father belonged to a professional occupation, zero otherwise.

Country of birth:

Migrant (English speaking country): Dummy variable, takes the value 1 if migrant from an English speaking country, zero otherwise.

Migrant (non-English speaking country): Dummy variable, takes the value 1 if migrant from a non English speaking country, zero otherwise.

Australian born is the reference category.

Hours per week usually worked in main job: Continuous variable, expressed in hours.

Tenure in the current occupation: Continuous variable, expressed in years.

Firm size:

Less than 5 employees: Dummy variable, takes the value 1 if working in a firm which has less than 5 employees, zero otherwise.

5 to 9 employees: Dummy variable, takes the value 1 if working in a firm which has 5 to 9 employees, zero otherwise.

10 to 19 employees: Dummy variable, takes the value 1 if working in a firm which has 10 to 19 employees, zero otherwise.

20 to 49 employees: Dummy variable, takes the value 1 if working in a firm which has 20 to 49 employees, zero otherwise.

More than 49 employees is the reference category.

Children aged between 5 and 14: Dummy variable, takes the value 1 if an individual has children between the ages of 5 and 14, zero otherwise.

Children aged under 5: Dummy variable, takes the value 1 if an individual has children aged under 5, zero otherwise.

Percent time spent unemployed in last financial year: Continuous variable, value of which lies between 0 and 100.

Union member: Dummy variable, takes the value 1 if an individual is a member of a trade union, zero otherwise.

Sector:

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.

Electricity, gas, water and waste services: 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 warehousing: 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 services: 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.

Health care 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.

Manufacturing is the reference category.

Table A3: Descriptive statistics

Explanatory variable	*Males*	*Females*
Age	39.5 (10.1)	37.5 (10.5)
Age Square	1662.9 (818.2)	1517.7 (817.9)
Married	0.785	0.641
Urban	0.935	0.917
Father was a professional	0.276	0.265
Migrant (English speaking country)	0.131	0.105
Migrant (non-English speaking country)	0.146	0.139
Hours per week usually worked in main job	45.8 (8.7)	42.9 (8.1)
Tenure in the current occupation	9.5 (9.2)	8.8 (9.2)
Tenure with current employer	7.615 (8.416)	6.682 (7.602)
Firm has less than 5 employees	0.044	0.038
Firm has 5 to 9 employees	0.061	0.066
Firm has 10 to 19 employees	0.098	0.089
Firm has 20 to 49 employees	0.177	0.193
Have children aged between 5 and 14	0.284	0.188
Have children aged under 5	0.175	0.052
Percent time spent unemployed in last financial year	0.816 (5.411)	1.243 (7.428)
Union member	0.316	0.458
Agriculture, forestry and fishing	0.015	0.006
Mining	0.023	0.003
Electricity, gas, water and waste services	0.015	0.005
Construction	0.031	0.004
Wholesale trade	0.028	0.014
Retail trade	0.037	0.024
Accommodation and food services	0.006	0.006
Transport, postal and warehousing	0.024	0.009
Information media and telecommunications	0.038	0.040
Financial and insurance services	0.074	0.041
Rental, hiring and real estate services	0.014	0.004
Professional, scientific and technical services	0.160	0.102
Administrative and support services	0.011	0.017
Public administration and safety	0.134	0.102
Education and training	0.195	0.327
Health care and social assistance	0.064	0.238
Arts and recreation services	0.017	0.015
Other services	0.020	0.013

Note: Mean (standard deviation). The sample consists of all working age full-time graduate employees from HILDA 2001-2007, and includes 4361 person-wave males and 3837 person-wave females.

Table A4: Mismatch transitions

	Status at t				
Status at t-1	Well matched	Overskilled only	Overeducated only	Overskilled and overeducated	Total
Well matched	3,873	235	228	37	4,373
Overskilled only	246	157	21	32	456
Overeducated only	223	21	425	77	746
Overskilled and overeducated	57	29	83	139	308
Total	4,399	442	757	285	5,883

Note: Working age full-time employees (HILDA 2001-2007). The unit of analysis is person-wave.

Table A5: Summary mismatch transitions

Transitions between	Number	Percentage
Well matched and overskilled only	481	37
Well matched and overeducated only	451	35
Well matched and both overskilled and overeducated	94	7
Overskilled only and overeducated only	42	3
Overskilled only and both overskilled and overeducated	61	5
Overeducated only and both overskilled and overeducated	160	12
Total transitions	1289	100

Note: Working age full-time employees (HILDA 2001-2007). The unit of analysis is person-wave.