

Job Mismatches and Labour Market Outcomes:

Panel Evidence on Australian University Graduates

Kostas Mavromaras^{1,4}, Seamus McGuinness², Nigel O’Leary³, Peter Sloane^{1,3,4} and Zhang Wei¹

¹ *National Institute of Labour Studies, Flinders University*

² *Economic and Social Research Institute, Dublin*

³ *WELMERC, Swansea University*

⁴ *IZA, Bonn*

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Abstract:

Interpretation of the phenomenon of graduate mismatch in the form of either overeducation or overskilling remains problematical. In an attempt to resolve at least some of the issues, this paper makes use of the panel element of the HILDA survey, distinguishing between four possible combinations of education/skills mismatch for full time graduate employees and controlling for individual unobserved heterogeneity. For men we find 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. Overeducation has no significant effect on the job satisfaction of either men or women, but overskilling either on its own or jointly with overeducation reduces job satisfaction. There are clear gender differences in these results. Finally, the effect of mismatch on job mobility is greatly reduced when we account for unobserved heterogeneity: overeducation on its own or jointly with overskilling increases quits for men. The paper supports the view that overeducation and overskilling are two distinct mismatch phenomena with different labour market outcomes and that the combination of overeducation and overskilling is the most severe type of mismatch. The use of appropriate panel methodology reduces considerably the size of many of the relevant coefficients, indicating that cross section results should be viewed with caution and also suggesting the presence of considerable unobserved heterogeneity which is shown to vary by gender.

JEL classification: J24, J31

Keywords: Overeducation, Overskilling, Wages, Job Mobility, Job Satisfaction, Gender.

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Corresponding author:

Kostas Mavromaras, National Institute of Labour Studies, Flinders University, GPO Box 2100, Adelaide, South Australia 5001. k.mavromaras@flinders.edu.au

1 INTRODUCTION

There is 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). 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 data which incorporate both forms of mismatch.

This of course implies that education and skill mismatch are measuring different things, but in fact the correlation between the two is not very high as shown below.

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 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 in this way, 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, for instance, less stress or a shorter journey to work. 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).

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

This paper is structured as follows. Section 2 provides background information on overeducation and overskilling. Section 3 describes the data and provides an overview of the estimation methods we use. Section 4 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 5 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.¹ 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

¹See, for instance, European Commission, *New Skills for New Jobs; Anticipating and Matching Labour Market and Skills Needs*, Director-General for Education and Culture, April, 2009.

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. 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 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.

Some authors have attempted to make progress by disaggregating the overeducation variable. Chevalier (2003) considered job satisfaction as a possible way of showing the degree of match between workers and jobs. He distinguished 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. There is, however, no skill mismatch variable in his data set. Adopting a slightly different approach Green and Zhu (2008) distinguished between 'real' and 'formal' overeducation according to whether or not this was accompanied by skills under-utilisation. It was found that those in the real overeducation category suffered from higher wage penalties than those in the formal overeducation group and only the former exhibited significantly lower job satisfaction. An alternative approach is to treat overeducation and overskilling separately. Thus, Allen and van der Velden (2001) examined the relationship between educational mismatches and skill mismatches and found that while the former had a strong negative effect on wages the latter did not. Skill mismatches, in contrast, predicted the level of job satisfaction and that of on-the-job search much better than did overeducation. Green and McIntosh (2007) found a correlation between overeducation and overskilling of only 0.2, suggesting that they were measuring different things. In a recent study, Mavromaras, et al. (2010) looked 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 (2008). As there are no overeducation or overskilling questions in the BHPS, they use the one standard 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. Lindley and McIntosh (2008) do not have a skill mismatch variable and thus are unable to control for unobserved characteristics.

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.

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. The 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 members³. 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 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 See Watson and Wooden (2004) for a detailed description of the HILDA data.

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 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

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.

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.

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.

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.

Table 1: Wages of graduates by type of job match

	<i>Male</i>	<i>Female</i>
<i>Well-matched</i>	1537.4	1102.8
<i>Overeducated Only</i>	1161.0	883.0
<i>Overskilled Only</i>	1322.9	1011.7
<i>Overskilled & Overeducated</i>	910.9	711.3

Note: 1. The sample is working age full time employees from HILDA 2001-2007.
2. Wages are measured by current weekly gross wages & salary from the main job (wscme) in Australian dollars without inflation adjustment.

Irrespective of gender, workers who were either overeducated and/or overskilled earned substantially less than well-matched employees. Within both the male and female subsamples, average earnings were lowest for graduates who were both overeducated and overskilled. 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.

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).

Table 2: Overall job satisfaction of graduates by type of job match

<i>Job satisfaction</i>	<i>Well matched</i>		<i>Overeducated only</i>		<i>Overskilled only</i>		<i>Overskilled and overeducated</i>	
	M	F	M	F	M	F	M	F
0	0%	0%	0%	0%	1%	1%	0%	1%
1	0%	0%	0%	0%	1%	1%	1%	1%
2	0%	0%	1%	1%	2%	1%	4%	0%
3	1%	2%	2%	1%	4%	5%	2%	4%
4	2%	1%	2%	2%	4%	5%	8%	1%
5	4%	5%	3%	5%	10%	12%	12%	12%
6	8%	9%	8%	12%	15%	15%	17%	12%
7	24%	22%	22%	20%	30%	27%	28%	29%
8	36%	33%	35%	35%	23%	22%	18%	25%
9	20%	21%	19%	19%	8%	8%	7%	13%
10	4%	6%	8%	7%	2%	3%	2%	2%
Total	100%	100%	100%	100%	100%	100%	100%	100%
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: The sample is working age full time employees from HILDA 2001-2007.

Job Mobility of graduates by match type

Table 3 presents the extent of labour market mobility among our sample. HILDA records the degree to which respondents left their job since the last interview and the reasons underlying the job separation.

Table 3: Job mobility of graduates

	<i>Graduates</i>	
	<i>Male %</i>	<i>Female %</i>
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%
Number of cases	3,831	3,291

Note: 1. Figures relate to job movement from main job between two consecutive interviews. 2. The sample is working age full time employees in both of the interviews from HILDA 2001-2007.

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 lay-offs 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 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.⁷

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.

⁷ One could investigate how mismatch may be eliminated or not through mobility, in which case one would wish to work on the mismatch associated with both origin and destination jobs. This would be an interesting question but it lies beyond the scope of this paper.

Table 4: Job mobility of graduates by type of job match in the first interview

	<i>Males</i>			
	<i>Matched</i>	<i>Overeducated</i>	<i>Overskilled</i>	<i>Both</i>
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%
	<i>Females</i>			
	<i>Matched</i>	<i>Overeducated</i>	<i>Overskilled</i>	<i>Both</i>
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%

See notes to Table 3. Job mobility is defined by changed jobs between consecutive interviews. Matching status as reported in the first of the two interviews.

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.

4. Estimation and Results

This paper reports results based on a number of estimation methods. Each type of estimation contains different information and the comparisons we present are informative. We begin with the simplest pooled estimates generated using the HILDA data as if it were derived from a simple cross section data set. For wages we use Ordinary Least Squares (OLS), and for job satisfaction and job mobility a probit estimation. 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. For wages we use both Fixed Effects estimation and Random Effects with Mundlak

corrections, the latter providing more information on the variables that contain little or no over time variation within the observation period allowed by the data length.⁸

For clarity of interpretation we have converted the ordered job satisfaction variables into binary variables (the dependent job satisfaction variable takes the value 1 if the respondent reports a job satisfaction level of 7 or above and zero otherwise), but only after carrying out considerable sensitivity analyses regarding the cut-off points we use and finding that results are not sensitive on the exact cut-off point we use. The same conversion has been applied to the estimation of each job satisfaction facet. 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 is whether mismatch influences the stability of employment of employees. We initially model all job separations jointly before estimating models for voluntary (quits) and involuntary (layoffs) mobility separately.

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 methods have not been utilised. Second, it provides a reasonable estimate of the association between labour 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, 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

⁸ We have also estimated but not reported here for space reasons a random effects (RE) model with and without Mundlak corrections to demonstrate that this approach approximates to that of a standard fixed effects model, a factor that becomes relevant later when we attempt to estimate binary choice panel models for which no fixed effects procedure is available.

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 with random effects panel results.

Wage Effects of Job Mismatch

Probably 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). To assess the impact of the various forms of job mismatch on wages we begin with an OLS model before moving to panel estimation, using both fixed and random effects specification on a sample of working age full-time graduate employees, controlling for both supply of and demand for labour covariates. Results are presented in Table 5. The regression specification included controls for gender, age, marital status, number of children, socioeconomic background, unemployment history, country of origin, employment and occupational tenure, union membership, firm size and industry⁹. Table 5 shows that OLS estimation generates highly significant coefficients in all types of mismatch. Not surprisingly, the strongest associations found for those who are both overeducated and overskilled. The Random Effects 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.

⁹ Variables are listed and explained in detail in Appendix I.

Table 5: Graduate Wage Effects of Job Mismatch (overedu: edu>mode)
View bachelors the same as other graduates (16 years of education)

	<i>Relative to Well-Matched:</i>		
	<i>Overeducated only</i>	<i>Overskilled only</i>	<i>Overskilled and overeducated</i>
<u><i>Full-time males</i></u>			
OLS	-0.215*** (-11.38)	-0.094*** (-4.07)	-0.309*** (-10.54)
RE with Mundlak corrections	-0.003 (-0.12)	-0.011 (-0.68)	-0.059** (-2.22)
Fixed Effects	-0.003 (-0.15)	-0.012 (-0.66)	-0.059** (-2.12)
Mismatch incidence	625	367	250
Observations		4,361	
<u><i>Full-time females</i></u>			
OLS	-0.212*** (-11.25)	-0.034 (-1.56)	-0.317*** (-11.80)
RE with Mundlak corrections	-0.057*** (-2.60)	-0.053*** (-3.36)	-0.088*** (-3.70)
Fixed Effects	-0.055** (-2.43)	-0.053*** (-3.14)	-0.086*** (-3.45)
Mismatch incidence	457	267	206
Observations		3,837	

Note: t-statistics in brackets; * ** *** denotes significance at the 10%/5%/1% level. Mismatch incidence RE/FE denotes Random/Fixed Effects estimation. Log-Wage is the dependent variable.

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 a 5.9 percent wage penalty.

It is noteworthy that the estimates of wage penalties due to mismatch are nowhere near the estimates of overall associations produced by the OLS models, suggesting that unobserved systematic differences play a substantial role in the way mismatch effects are determined. 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 upon re-employment.¹⁰ When we compare 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, also the 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 soak up 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.

¹⁰ Mavromaras and Rudolph (1997) estimated gender pay differentials upon re-employment using administrative data from the Federal Employment Office in Germany and found that the re-employment process is associated with an increase in gender pay differentials.

Table 6: Impact of Job Mismatch on Individual Fixed Effects

	<i>Relative to Well-Matched:</i>		
	<i>Overeducated Only</i>	<i>Overskilled only</i>	<i>Overskilled and overeducated</i>
<i>Full-time male</i>			
Fixed Effect – OLS	-0.316*** (-15.83)	-.117*** (-4.13)	-.324*** (-10.23)
Adjusted R ²	0.79	0.79	0.79
<i>Full-time female</i>			
Fixed Effect – OLS	-0.241*** (-11.86)	.066** (2.51)	-.323*** (-11.86)
Adjusted R ²	0.83	0.83	0.83

Notes: Marginal effects with t-stats in brackets; * ** *** denotes significance at the 10%/5%/1% level; Random Effects regression with Mundlak correction.

Table 6 reports the coefficients and t statistics of the mismatch controls along with the adjusted R² 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 R² 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*.

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.

Table 7 presents the difference in overall job satisfaction between the *well-matched* (i.e. those that are neither overeducated nor overskilled) 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* (Table 7, 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.¹¹

¹¹ There is a hint in the overeducated only results that, when we shift from cross-section to panel results (i.e. after controlling for unobserved individual heterogeneity, using the RE panel model with Mundlak corrections) a small dissatisfaction effect arises, both 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, and found no such pattern in the overskilling job satisfaction relationship.

Table 7. Overall Job Satisfaction for Graduates by Gender:
Marginal Effects from Alternative Estimation Strategies

	<i>Relative to Well-Matched:</i>		
	<i>Column 1.</i> <i>Overeducated</i> <i>only</i>	<i>Column 2.</i> <i>Overskilled only</i>	<i>Column 3.</i> <i>Overskilled and</i> <i>overeducated</i>
<i>Full-time male</i>			
Pooled probit	0.027 (0.36)	-0.685*** (-8.81)	-0.877*** (-8.96)
RE probit (with Mundlak corrections)	-0.077 (-0.57)	-0.328*** (-2.76)	-0.621*** (-3.49)
<i>Full-time female</i>			
Pooled probit	-0.024 (-0.28)	-0.661*** (-7.58)	-0.380*** (-3.38)
RE probit (with Mundlak corrections)	-0.225 (-1.44)	-0.625*** (-4.58)	-0.622*** (-2.84)

Notes: t-ratio in brackets; Job satisfaction cut-off point at 7; / / / denotes significance at the 10%/5%/1% level.

Estimates on *overskilled only* (Table 7, 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 -0.685 to -0.328). 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, 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 hardly discernible effect (from -0.661 to -0.625), which suggests that females with a generally unhappy disposition towards work are equally 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 estimate is -0.621 for males and -0.622 for females), but unlike males, controlling for unobserved heterogeneity increases their dis-satisfaction (from -0.380 to -0.622) 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 dis-satisfaction caused by ending up in such a job is equally strong for both males and females (-0.621 for males and -0.622 for females). In conclusion, estimates of the comparison between those who are well-matched with those who happen to be *both overskilled and overeducated* (Table 7,

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.

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.

Table 8: Job Satisfaction Facets for Graduates

	<i>Relative to Well-Matched:</i>		
	<i>Column 1: Overeducated only</i>	<i>Column 2: Overskilled only</i>	<i>Column 3: Overskilled and overeducated</i>
<i>Full-time male</i>			
Overall job satisfaction	-0.077 (-0.57)	-0.328*** (-2.76)	-0.621*** (-3.49)
Pay satisfaction	0.041 (0.32)	0.200 (1.64)	-0.078 (-0.45)
Job security satisfaction	0.183 (1.33)	-0.077 (-0.57)	0.066 (0.35)
Work satisfaction	0.053 (0.39)	-0.533*** (-4.53)	-0.604*** (-3.49)
Hours satisfaction	-0.206* (-1.66)	-0.167 (-1.40)	-0.442** (-2.44)
Flexibility satisfaction	0.077 (0.59)	-0.033 (-0.27)	-0.147 (-0.82)
<i>Full-time female</i>			
Overall job satisfaction	-0.225 (-1.44)	-0.625*** (-4.58)	-0.622*** (-2.84)
Pay satisfaction	-0.090 (-0.64)	-0.210 (-1.57)	-0.103 (-0.49)
Job security satisfaction	-0.194 (-1.17)	-0.147 (-0.89)	-0.415* (-1.72)
Work satisfaction	-0.079 (-0.49)	-0.870*** (-6.31)	-1.17*** (-5.34)
Hours satisfaction	0.089 (0.58)	0.152 (1.08)	-0.304 (-1.36)
Flexibility satisfaction	0.036 (0.25)	-0.036 (-0.26)	-0.062 (-0.29)

Notes: Marginal effects with t-statistics in brackets; */**/** denotes significance at the 10%/5%/1% level; Satisfaction cut-off point at 7 for all facets. Estimation is by Random Effects Probit with Mundlak correction using the same specification as in Table 7. For reasons of space we do not report the cross section results.

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 dis-satisfaction 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 dis-satisfaction with work is clearly present and that there is clear hours dis-satisfaction for males and job security dis-satisfaction for females.

4.3 Job mobility and Job Mismatch

Another possible adverse effect of a job mismatch is the degree to which it may influence job mobility. 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.

Table 9b: Effects of Job Mismatch on Graduate Job Mobility - Marginal Effects

Type of Job Loss	<i>relative to Well-Matched:</i>		
	<i>Column 1</i> <i>Overeducated</i> <i>Only (Lagged)</i>	<i>Column 2</i> <i>Overskilled</i> <i>Only (Lagged)</i>	<i>Column 3</i> <i>Both Overskilled and</i> <i>overeducated (Lagged)</i>
<i>Full-time male</i>			
<u><i>Job Loss (All causes)</i></u>			
<i>Pooled probit</i>	-0.054 (-0.41)	0.098 (0.63)	0.445** (2.55)
<i>Random Effects probit (with Mundlak corrections)</i>	0.216 (1.03)	0.044 (0.21)	0.497* (1.83)
<u><i>Lay offs (Involuntary Job Loss)</i></u>			
<i>Pooled probit</i>	0.112 (0.54)	0.610*** (2.65)	0.553* (1.93)
<i>Random Effects probit (with Mundlak corrections)</i>	-0.029 (-0.08)	0.377 (1.03)	0.359 (0.70)
<u><i>Quits (Voluntary Job Loss)</i></u>			
<i>Pooled probit</i>	-0.063 (-0.44)	-0.125 (-0.72)	0.271 (1.47)
<i>Random Effects probit (with Mundlak corrections)</i>	0.438* (1.85)	-0.066 (-0.28)	0.593** (1.98)
<i>Full-time female</i>			
<u><i>Job Loss (All causes)</i></u>			
<i>Pooled probit</i>	-0.253* (-1.77)	0.234 (1.51)	-0.323 (-1.54)
<i>Random Effects probit (with Mundlak corrections)</i>	-0.245 (-1.06)	0.364* (1.66)	-0.179 (-0.47)
<u><i>Lay offs (Involuntary Job Loss)</i></u>			
<i>Pooled probit</i>	-0.878 (-1.18)	-0.021 (-0.03)	-
<i>Random Effects probit (with Mundlak corrections)</i>	-	-	-
<u><i>Quits (Voluntary Job Loss)</i></u>			
<i>Pooled probit</i>	-0.164 (-1.16)	0.102 (0.68)	-0.277 (-1.36)
<i>Random Effects probit (with Mundlak corrections)</i>	-0.276 (-1.19)	0.102 (0.47)	-0.271 (-0.72)

Note: Marginal effects with t-ratio in brackets; / / / denotes significance at the 10%/5%/1% level. For Full Specification see Appendix.- Insufficient observations to support estimation.

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.¹² It is worth noting that the pooled probit models in Table 9, which contain

¹² Some of the mobility associations have been shown to be statistically too weak. This is usually interpreted as lack of evidence of the relationship in question. Note that in the case of past work that used short panels this could also be because of low levels of change recorded in the data, indicating the need for further work when more waves of the HILDA survey and a larger sample become available. Our estimates are based on 7 waves of data, which may still be a small number with insufficient mobility in the data. This could be a reasonable argument for the both overeducated and overskilled category of mismatch, where, indeed we had to drop the variable due to insufficient information for women. It would not however, be a reasonable argument regarding the other two mismatch variables.

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. It should be noted that this conclusion is similar to the one reached about the reduced level of significance of overskilling wage penalties in the wage estimations after controlling for unobserved heterogeneity. Notwithstanding this evidence, we think the issue 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.

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 quitting and decrease their probability of being laid off. 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.

5. Conclusions

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 and that they have a different effect on different labour market outcomes. In general 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. Second, for both genders job satisfaction is not influenced by overeducation, but it is clearly reduced by overskilling either on its own or jointly with overeducation. Thus overskilling appears to be more welfare reducing than overeducation. For many overeducation is a matter of choice or necessity, whereas overskilling is a matter of regret. We obtain little further insight when we estimate the facets of job satisfaction instead of a measure of overall job satisfaction. Third, 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.

The results suggest that it is on overskilling and particularly its' combination with overeducation that policy attention should be focused. Since overeducation has no clearly negative effect on the welfare of either men or women, its occurrence should not be a matter of major policy concern. However, overskilling whether on its own or jointly with overeducation does so and its eradication may have benefits for employers as well as employees. 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.

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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 A1: Graduate overeducation and overskilling by wave and gender

	<i>Wave 1</i>		<i>Wave 2</i>		<i>Wave 3</i>		<i>Wave 4</i>		<i>Wave 5</i>		<i>Wave 6</i>		<i>Wave 7</i>	
	<i>M</i>	<i>F</i>												
<i>Well matched</i>														
Percent	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
<i>Only Overeducated</i>														
Percent	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
<i>Only Overskilled</i>														
Percent	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
<i>Overskilled and Overeducated</i>														
Percent	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
<i>Complete sample</i>														
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: The sample is working age full time employees from HILDA 2001-2007.

Table A2 presents the distribution of the job satisfaction, by gender and wave.

Table A2: Job satisfaction of graduates by wave and gender

	<i>Wave 1</i>		<i>Wave 2</i>		<i>Wave 3</i>		<i>Wave 4</i>		<i>Wave 5</i>		<i>Wave 6</i>		<i>Wave 7</i>	
<i>JS (job satisfaction)</i>	<i>M</i>	<i>F</i>												
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%
<i>Total</i>	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
<i>Mean JS</i>	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
<i>Cases</i>	688	572	674	562	658	567	669	559	711	609	701	643	695	692

Note: The 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

<i>Explanatory variable</i>	<i>mean (sd)</i>	
	<i>Male</i>	<i>Female</i>
Age	39.517 (10.067)	37.514 (10.510)
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	45.784 (8.669)	42.876 (8.056)
Tenure in the current occupation	9.486 (9.172)	8.786 (9.215)
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	0.8166 (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: The sample is working age full time graduate employees from HILDA 2001-2007, including 4361 males and 3837 females.