Assessing the Incidence and Wage Effects of Over-skilling in the Australian Labour Market

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Abstract

This paper examines the incidence and wage effects of over-skilling within the Australian labour market. It finds that approximately 30 percent of employees believed themselves to be *moderately over-skilled* and 11 percent believed themselves to be *severely over-skilled*. The incidence of skills mismatch varied little when the sample was split by education. After controlling for individual and job characteristics as well as the potential bias arising from individual unobserved heterogeneity, *severely over-skilled* workers suffer an average wage penalty of 13.3 percent with the penalty ranging from about 8 percent among vocationally qualified employees to over 20 percent for graduates.

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I. Introduction

This paper investigates skill mismatches in the Australian labour market. In the last decades, Australia has witnessed strong economic development, a large proportion of which has been driven by the continual incorporation of new technologies into production and the acquisition and utilization of new skills in the workforce. The macroeconomic environment has been one of expanding production that utilises new and fast-changing technologies, which are operated by an increasingly skilled and more flexible workforce. The resulting changes in the process of acquisition, maintenance and utilization of education and skills has been profound and is clearly still underway. The divide between traditional blue and white collar skills and jobs in the workplace is less useful and less prominent today than it was twenty years ago. Similarly, the nature of the division between practical and theoretical post-compulsory education in schools, colleges and universities has been changing. At the individual level, the way people plan to acquire and maintain skills throughout their employment lives has been changing dramatically. In this environment of profound change, it comes as no surprise that there are strong indications, both in the scientific literature and in the policy debate surrounding skills utilisation, of skill mis-matches in the labour market. It is argued that within the overeducation literature that the joint outcome of the education process and the labour market sorting may be getting some of the matching between people and jobs wrong. It is these mis-matches between people and jobs that motivate this paper.

The main strand in the literature that deals with the issue of inefficiently matched education levels of workers and their jobs investigates the level of so called over-education in the labour market. The conventional definition of an over-educated person is that of someone who has a level of education that is above that necessary for the job they are hired to do.[1] Over-education studies typically concentrate on assessing the incidence of over-education and the wage penalties associated with varying levels of over-education. Most studies have dealt with the over-education of university (or equivalent level) educated graduates. Whilst these studies provide ample evidence regarding the two manifestations of a labour market mis-match (namely the incidence of over-education and the associated wage differences) they do not lend themselves unequivocally to a clear interpretation of over-education as a labour market mis-match. The reason is that they are typically not able to control for systematic unobserved ability differences. Note that education (fully observed by the employer, the employee and the researcher) can be used during the formation (or maintenance) of a worker-job match as a substitute for ability (well observed by the employee, relatively well observed by the employer and typically unobserved by the researcher). To the degree that unobserved ability has played a role in a match, the criticism levied upon over-education research would be that workers who are observed in the data to be over-educated for their job, may simply be workers who have been using formal qualifications as a compensating differential for lower ability. It should be noted that controlling for unobserved ability has been a long standing empirical issue in studies that try to assess the role of education in the labour market.

Notwithstanding the general criticisms of the over-education literature, a number of attempts have been made to identify the wage penalties associated with over-education in the Australian context. Voon & Miller (2005) used the 1996 Census and, adopting an objective mean (OM) approach, reported that approximately 16 percent of males and 14 percent of females were over-educated with the return to a year of surplus schooling

[1] Battu, Belfield & Sloane (2000) for various empirical implementations of this definition and McGuinness (2006) for a review of the international literature.

typically one third the rate received for required schooling. Kler (2005) used the same data and, adopting both the job analysis (JA) and objective mean (OM) approaches, reported a widely varying rate of graduate over-education of between 21 and 46 percent, and found the returns to surplus schooling to be below those of required schooling.[2] Linsley (2005) used data from the 1997 Negotiating the Life Course Survey to estimate a general over-education rate of 30 percent. Rather uniquely within the international literature, Linsley (2005) presents the finding of zero returns to surplus schooling.

With the exception of the findings by Linsely (2005), the majority of over-education studies support the so called assignment interpretation of the labour market (see Sattinger 1993 for an overview of assignment models), whereby wages are determined within a hedonic wage structure which is influenced simultaneously by human capital and job characteristics. Following this interpretation, it is generally assumed in the literature that any wage penalties associated with over-education arise principally because the specific requirements of jobs impose a productivity ceiling that limits the wages that can be (profitably) paid to those matched to these jobs (see McGuinness 2006 for a review of these studies). As a result, observed over-education wage penalties are taken to be a direct consequence of skill under-utilisation and job inflexibility. However, the evidence that over-education constitutes an accurate proxy for employer-employee mis-matches is far from convincing. For instance, Green & McIntosh (2002) used a relatively broad definition of over-skilling to find that less than half the over-educated employees were also over-skilled.

[2] Kler (2005) produced some non-standard results in that the spread between the two estimates was particularly large with the JA estimated incidence almost twice that generated under the OM approach. Furthermore, the return to surplus schooling was initially reported to be above that of required schooling in the male JA based wage equation. However, despite a failure to outline an identification strategy, all results became standard after a sample selection framework was used.

It is clear that at the heart of the over-education debate lies the inherent inability of over-education measures to control for unobserved ability. Indeed this is another manifestation of the more general problem of unobserved ability contaminating the estimation of the relationship between education and earnings. Unobserved ability limits the researcher from arguing convincingly that over-education and the associated wage penalties are a case of inefficient mis-matches in the labour market, principally due to the possibility that any observed association between over-education and wage penalties may be the outcome of unobserved factors resulting in the generation of compensating wage differentials. This paper overcomes this fundamental problem by using a unique self-reported measure of over-skilling and abilities in the workplace, present in the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The measurement of the degree of skills and abilities utilization in the workplace enables this paper to assess the extent, the drivers and the wage consequences of over-skilling in the Australian labour market. The advantage of looking at skills and abilities directly is that the issue of unobserved ability and the associated empirical identification problems can be overcome, as measures of over-skilling encompass both education and ability.

Having a more general and accurate definition of over-skilling, this paper investigates labour market mis-matches at all education levels. It utilises a direct question which is asked of employees regarding the degree to which they possess more skills and abilities than those required by their current job. Those who are defined to be over-skilled (that is, those who state that they have more skills and abilities than what their job requires) need not necessarily be over-educated, they simply can do more things than their job is requiring. Note that the presence of unobserved ability is not a problem in this context, as skills include both formal and informal education as well as innate ability. Provided that formal and informal human capital is correctly controlled for, any remaining wage penalties associated with over-skilling will be a good measure of under-utilisation of human capital in the labour market. It follows that because the more general measure of over-skilling used in this paper includes an assessment of ability, it lends itself more readily to the interpretation of an employer-employee mis-match and is a better measure for the study of resulting labour market inefficiencies than the conventional measures of over-education.

The remaining paper is structured as follows. Section IIcontains a description of the relevant part of the HILDA data. Section III describes the methods used and presents the econometric results. Section IV contains a discussion and Section V concludes. An Appendix contains more detailed estimation results and sensitivity tests.

II. The HILDA Data

II.1 General description of the data

The data for this study comes from the first five waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Modelled 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. The sample used here is restricted to all working-age employees in full-time employment who provide complete information on the variables of interest in any of the five annual survey waves (2001 to 2005). The effective sample size used in this paper is 5,843 individuals. A detailed description of the HILDA data can be found in Watson and Wooden (2004).

Weekly earnings in main job are used as the wage variable and the analysis includes controls for a wide range of individual and job characteristics. [3]

II.2 Measuring over-skilling

Our measure of over-skilling is derived from the respondents agreement or not with the statement: "I use many of my skills and abilities in my current job", with scores on a 7-point scale available. A response of 1 implies strong disagreement and a response of 7 implies strong agreement with the statement. All respondents in the sample were then classified into one of three groups for each yearly observation: (i) the *severely over-skilled* (individuals selecting 1, 2 or 3 on the scale); (ii) the *moderately over-skilled* (those selecting 4 or 5); and (iii) the *well matched* (individuals selecting 6 or 7).[4] It should be noted that variables similar to the one used here to construct the over-skilling measure can only be found in a few datasets and that there has been limited research in this direction, with researchers having tended to concentrate on various subjective and objective measures of over-education instead. This paper argues that the use of over-skilling variables can provide further and significant understanding in the area of skill under-utilisation and the resulting mis-matches in the labour market.

The paper notes that, as is the case with studies of over-education, researchers need to be wary of overstating the impact of over-skilling by failing to control for informally accumulated human capital and for unobserved heterogeneity related to skills. For instance, it may be the case that apparently *severely over-skilled* workers are less

[3] The Appendix contains a description of the variables used and their summary statistics.
[4] The over-skilling variable was reduced to a three-level ordinal variable rather than the original 7-way one. This was done after experimentation indicated that whilst the estimation of the 2 cut off points (instead of the six cut off points that would be possible) was carried out much more precisely, there were no losses in the overall performance of the estimation by using a three-way dependent variable. Note that, unlike when formal qualifications are used to measure mis-matches and where both over-education and under-education may make sense, there is no analogous concept of under-skilling in this context.

experienced and consequently have had less (off- and/or on-the-job) training relative to their *well-matched* counterparts (i.e. those who agree strongly with the statement that they use many of their skills and abilities in their current job). Wage gaps may therefore reflect such differences in human capital accumulation. However, one would expect biases related to the measurement of over-skilling to be limited because of the presence of both “skills” and “abilities” in the over-skilling question. Notwithstanding these considerations, the estimations include controls for employment and occupational tenure to ensure that experience is well represented in the empirical specification used.[5]

II.3 Over-skilling by education level

The distinction of the incidence of over-skilling by education level (measured by the highest qualification attainment) is important from the policy point of view as it refers to different segments of both the education provision mechanisms and the labour market itself. Descriptive statistics are presented in Table 1. Around 4 percent of Australian full time employees are educated to below year 10, 33 percent are educated to between years10 and 12, 36 percent have reached certificated / diploma level and 27 percent have university education.

[5] There could be an argument with respect to unobserved heterogeneity, following the lines that the over-skilled may be less able than the well matched workers in some unobserved respect. To the degree that this lower ability is perceived by them, it will be reflected in their over-skilling response as they are asked directly about using their abilities. If this lower ability is not perceived by them, the resulting lower ability levels could be reflected in lower earnings and biased estimates. The data at hand does not distinguish the two possibilities and results depend on accurate perceptions of employees of their own abilities.

Table 1: Over-skilling by Education level

Highest Education Level (percentage of the total sample)	Extent of Over-skilling			Total
	Well matched	*Moderately over-skilled*	*Severely over-skilled*	
Below Year 10 (4%)	55.01	26.70	18.30	100.00
Year 10-12 (33%)	52.36	33.41	14.23	100.00
Certificates and diplomas (36%)	58.77	30.89	10.34	100.00
University Level (27%)	63.63	27.49	8.89	100.00
Total sample	57.83	30.62	11.54	100.00

Note: Sample consists of 7,815 working age employees in full-time employment in HILDA waves 4 and 5 (years 2004 and 2005)

As a proportion of the entire sample, 58 percent of workers were found to be *well matched*, 31 percent were *moderately over-skilled* and 11 percent were assessed to be *severely over-skilled*. The incidence of moderate over-skilling does not vary by level of education: the incidence of moderate over-skilling among workers with below year 10 educational attainment is approximately equal to that of graduate employees. By contrast, the incidence of severe over-skilling differs by level of education, dropping steadily from 18 percent for workers with the lowest level of educational attainment to just below 9 percent for graduates. Given that individuals with below year 10 attainment are likely to be extensively employed in the lower value added end of the labour market, the relatively high perceived incidence of over-skilling among this group suggests that many of these workers are likely to be employed in what they perceive to be highly menial operations. The observed association between severe over-skilling and education level would appear to be consistent with the "bumping down" hypothesis, whereby a lack of demand for high skilled labour results in lower skilled employees being "bumped down" into lower skilled occupations with the level of aggregate displacement increasing as we move down the skills spectrum.[6]

[6] A further potential consequence of this hypothesis is that workers at the lowest end of the skills distribution are more likely to be forced out of employment altogether. It is not within the scope of this paper, however, to analyse this possibility.

III. Estimation Results

III.1 Over-skilling and wage penalties

A wage regression for the whole sample is reported in Table 2. In an attempt to account for both supply and demand of labour covariates, the regression specification includes controls for educational attainment, country of origin, socio-economic background, age, marital status, number of children, unemployment history, employment and occupational tenure, union membership, firm size and industry. The model appears to be well specified, explaining almost 40 percent of the variation in wages. On average, *severely over-skilled* workers were found to earn 13.3 percent less than their *well matched* counterparts. The corresponding wage penalty associated with moderate over-skilling is much lower at 4.9 percent.

Table 2: Wages and over-skilling – Full sample results

Explanatory variable	*Coefficient*	*Standard error*
Severely over-skilled	-0.135***	(0.016)
Moderately over-skilled	-0.050***	(0.010)
Female	-0.162***	(0.011)
Migrant (English speaking country)	0.011	(0.015)
Migrant (non-English speaking country)	-0.087***	(0.014)
Education – Year 10 to 12	0.143***	(0.023)
Educational – Certificate / diploma	0.208***	(0.023)
Educational – Degree or higher	0.469***	(0.025)
Proportion of past year spent in unemployment	-0.004	(0.002)
Father was a professional	0.052***	(0.014)
Urban	0.034**	(0.016)
Not married (or de facto)	-0.094***	(0.011)
Occupational experience (years)	0.004***	(0.001)
Employment tenure (years)	0.003***	(0.001)
Age – 25 to 39 years	0.202***	(0.017)
Age – 40 to 54 years	0.242***	(0.019)
Age – 55 to 64 years	0.273***	(0.024)
Union Member	0.040***	(0.011)
Have children aged between 5 and 14	0.034***	(0.012)
Have children aged below 5	0.039**	(0.016)
Constant	6.678***	(0.098)
Observations	5843	
Prob > F	0.0000	
R-square	0.4036	

Note: Ordinary Least Squares results. The dependent variable is log weekly wages. The sample consists of full-time employees of working age. Controls for Industry and Firm Size were included in the estimation. Asterisks indicate significance at the 1, 5 and 10 percent levels (***/**/* respectively).

The remaining results largely conform to expectations with earnings being substantially higher for individuals who are: male, better educated, married, with children, older, living in urban areas, of higher social status, with longer occupational tenure and with longer employment tenure.

Table 3 splits the sample by education level in order to assess the extent to which the over-skilling wage penalties may vary by level of educational attainment. The wage penalty to severe over-skilling varies substantially by level of schooling but in a non-linear fashion. There is nothing to suggest that *severely over-skilled* workers with below year 10 education incur any wage penalty relative to well matched workers with similar levels of education. Within the year 10 to 12 education grouping the wage penalty for severe over-skilling is highly significant at 12.9 percent. However, the corresponding wage penalty for severely over-skilled employees with diplomas and certificates is somewhat lower at 8.5 percent. A potential explanation for the weaker wage penalties among workers with diplomas and/or certificates is that this education group will contain the bulk of trade workers who tend to be more heavily unionized, which will in turn result in less variation in the earnings of workers within similar occupations. University educated workers (9 percent of the sample) who are *severely over-skilled* earn 23.8 percent less than their well matched counterparts.

The higher wage penalty associated with severe over-skilling within the graduate workforce is not surprising given that these individuals will have the highest productivity potential and will therefore be most heavily constrained in the presence of any job related productivity ceiling. Finally, there was only limited evidence of wage penalties arising from moderate over-skilling, with a 7.1 percent wage penalty occurring within the certificate and/or diploma grouping and a 5.1 percent wage penalty among university graduates.

Table 3: Wage Regression by Education Level

	Weekly Wages			
Explanatory variable	Below Year 10	Year 10-12	Certificates and diplomas	University level
Severely over-skilled	-0.040	-0.130***	-0.085***	-0.241***
	(0.092)	(0.024)	(0.027)	(0.035)
Moderately over-skilled	0.019	-0.024	-0.071***	-0.053**
	(0.075)	(0.017)	(0.017)	(0.021)
Female	-0.124	-0.189***	-0.146***	-0.157***
	(0.082)	(0.018)	(0.020)	(0.019)
Migrant from English speaking country	-0.128	-0.010	0.065**	0.005
	(0.114)	(0.026)	(0.026)	(0.028)
Migrant from non-English speaking country	-0.224*	-0.037	-0.071***	-0.128***
	(0.123)	(0.025)	(0.026)	(0.024)
Proportion of past year spent in unemployment	0.002	-0.003	-0.001	-0.004
	(0.008)	(0.005)	(0.004)	(0.006)
Father was a professional	0.329	0.019	0.115***	0.001
	(0.252)	(0.028)	(0.025)	(0.021)
Urban	-0.028	0.033	0.022	0.051
	(0.088)	(0.026)	(0.025)	(0.034)
Not married (or de facto)	-0.076	-0.112***	-0.114***	-0.047**
	(0.077)	(0.019)	(0.018)	(0.021)
Occupational experience (years)	0.002	0.002*	0.003***	0.005***
	(0.004)	(0.001)	(0.001)	(0.001)
Employment tenure (years)	0.002	0.003**	0.004***	0.002
	(0.005)	(0.001)	(0.001)	(0.001)
Age between 25 and 39 years	0.319**	0.238***	0.152***	0.216***
	(0.152)	(0.025)	(0.030)	(0.043)
Age between 40 and 54 years	0.358**	0.255***	0.168***	0.316***
	(0.145)	(0.027)	(0.032)	(0.047)
Age between 55 and 64 years	0.502***	0.317***	0.192***	0.301***
	(0.154)	(0.038)	(0.040)	(0.055)
A Union Member	0.197***	0.030	0.075***	-0.026
	(0.073)	(0.019)	(0.017)	(0.022)
Have children aged between 5 and 14	0.090	-0.031	0.061***	0.057**
	(0.099)	(0.021)	(0.019)	(0.022)
Have children aged below 5	0.071	0.005	0.057**	0.031
	(0.154)	(0.030)	(0.027)	(0.029)
Constant	6.197***	6.573***	6.643***	6.856***
	(0.177)	(0.039)	(0.043)	(0.062)
Observations	217	1748	2075	1798
Prob > F	0.0001	0.0000	0.0000	0.0000
R square	0.3246	0.3839	0.3444	0.2880

Note: OLS regression results with log weekly wages as the dependent variable. Firm size and industry dummies were included in the regression but are not presented here. Standard errors in brackets.

Looked at in their entirety, the OLS results in Tables 2 and 3 suggest that severe over-skilling is associated with considerable wage penalties. To the degree that these wage penalties reflect the presence of sub-optimal labour market matches in the data (that is, matches that under-utilise the employee's skills and act as earnings constraints) they can be thought of as the manifestation of the resulting productivity and output losses for the whole economy due to skill mis-matches in the workplace. However, one must be cautious about reaching this conclusion, as the OLS models used here implicitly assume that over-skilled and well matched employees all belong to the same (unobserved) ability distribution. This may, in fact, not be the case. For instance, it could be argued that the expansion of educational participation that has taken place in Australia in recent decades (a trend especially present at the university level and shared with the majority of developed economies), has led to increased heterogeneity of graduates and diploma holders etc. through higher numbers of lower ability students accessing each level of education. If this is the case then, even in instances where the sample has been split according to education attainment level, our results could be biased as we may not have been comparing like with like. For example, it may be that over-skilled graduates are the less able in some other unobserved way and that such differences are the principal drivers behind any wage gap. Note, however, that the over-skilling variable that this paper uses makes it unlikely that this would be the case, as the measure of mismatch effectively encompasses work-related ability as well. Nevertheless, in order to ensure that the estimates presented are as free, as the data would permit, from unobserved factors such as ability, the paper extends its modeling strategy accordingly.

III.2 Unobserved heterogeneity biases

In order to check for the possible presence of biases arising from unobserved heterogeneity the paper adopts an estimation approach based on the principles of Propensity Score Matching (PSM). Whilst such matching estimators are built to reduce substantially biases generated by unobserved confounding factors, they cannot be guaranteed to eliminate the impact of unobserved factors. Consequently, further post-estimation sensitivity analysis has been carried out in order to ensure the robustness of the estimates. Effective PSM estimation implies that we can satisfactorily describe the factors that determine the incidence of over-skilling and then balance our data set on this set of key characteristics. We estimate a PSM model based on the covariates presented in Tables 2 and 3, with the intention to generate statistically significant probit models from which to derive propensity scores. The pseudo R^2 values obtained cast doubts on the reliability of this estimation in the present context. To overcome this problem we used the longitudinal nature of the HILDA dataset to construct a key labour market history variable based on whether the individual was over-skilled or not in any of the previous 3 waves. For this variable to be accurate we used two balanced panel data sub-sets consisting of waves 1 to 4 and 2 to 5. In each of the sub-sets, the new variable "*previously over-skilled*" takes the value one for all those who were over-skilled (moderately or severely) in at least one wave in the past and zero otherwise.[7]

Before results are presented, it is useful to give a brief intuitive account in five steps of the way in which PSM estimation is utilised in this paper. In Step 1 we identify those who are severely over-skilled as the "treatment" group. In Step 2 we identify those who are well matched as the "control" group. In Step 3 we match the treatment and control group individuals on all their observed characteristics. It is most crucial at this stage to note that the matching characteristics include past over-skilling status, which can be derived using the panel nature of the HILDA survey. Hence, at the end of Step three we have pairs of matched individuals who, provided that the matching has been done correctly, are very similar in terms of (i) their personal and job characteristics and (ii)

[7] For individuals in wave 4 this involved restricting the sample to those who were previously present in all waves 1, 2 and 3, while for those in wave 5 the sample was restricted to individuals present in all waves 2, 3 and 4.

their past over-skilling, but are different in terms of (iii) their present over-skilling.[8] In Step 4 we compare the differences in the wages for each of these matched pairs. If there is an over-skilling wage penalty over and above what would be caused by the observed variables used in matching and by any unobserved ability (and related) variables, we would expect to find wage differences between the matched treatment and control pairs. If there is no over-skilling wage penalty, we would expect to find no wage differences between the treatment and control groups. Step 5 compares the results from Step 4 with those of OLS estimation which does not control for unobserved ability differences and provides us with a measure of the bias caused by unobserved ability. This process is carried out twice: once comparing the severely over-skilled with the well matched and once comparing the moderately over-skilled with the well matched. The results of Step 5 show that there is no evidence of unobserved individual heterogeneity bias in the severely over-skilled category, but there may be evidence of unobserved individual heterogeneity bias in the moderately over-skilled category.

The results of two over-skilling probit estimations (one where the dependent variable is "being presently moderately over-skilled" and one where it is "being presently severely over-skilled") are presented in Table 4.

[8] A point that has to be made regarding this step and in anticipation of the sensitivity tests that are carried out in a later section of the paper, is that the way we use PSM here reduces unobserved bias, but it cannot be argued that it eliminates it automatically. This is the reason why we carry out the sensitivity tests. Later on in the paper it is argued that unobserved heterogeneity at the level of the individual is not a problem with these estimates. The encouraging results from the sensitivity tests are crucial as they support this argument.

Table 4: Probit estimation for present over-skilling

Explanatory variable	*Severely over-skilled*		*Moderately over-skilled*	
Previously over-skilled	1.249***	0.094	0.927***	0.051
Female	0.013	0.086	-0.013	0.059
Migrant from English speaking country	-0.097	0.119	-0.140*	0.080
Migrant from non-English speaking country	0.253**	0.123	0.164**	0.083
Proportion of past year in unemployment	(dropped)	(dropped)	0.088	0.076
Educational attainment – Year 10 to 12	0.156	0.192	0.218	0.145
Education – Certificate / diploma	-0.015	0.191	0.206	0.143
Education – Degree or higher	-0.134	0.201	0.143	0.150
Father was a professional	-0.050	0.119	0.009	0.075
Urban	0.035	0.113	0.186**	0.077
Not married (or de facto)	0.134	0.086	0.077	0.059
Occupational experience (years)	-0.015***	0.005	0.000	0.003
Employment tenure (years)	-0.004	0.006	0.002	0.004
Age – 25 to 39 years	-0.088	0.153	-0.084	0.121
Age – 40 to 54 years	-0.126	0.161	-0.161	0.124
Age – 55 to 64 years	-0.409	0.202	-0.376**	0.145
A Union Member	-0.106	0.084	-0.067	0.056
Have children aged between 5 and 14	-0.117	0.090	0.053	0.058
Have children aged below 5	-0.134	0.128	-0.005	0.081
Constant	-1.299***	0.306	-1.068***	0.223
Observations	2586		3333	
Prob > F	0.0000		0.0000	
Pseudo R square	0.2070		0.1158	

Note: The dependent variable is 'presently over-skilled'. Standard errors are in brackets. Firm and size and industry dummies are included in the estimation but not reported here.

It is encouraging that the main finding in Table 4 is that having been previously over-skilled within the context of either current or previous employment, was the most important determining factor in current moderate and severe over-skilling. In addition to the previously over-skilled variable some additional factors are important in explaining the presence of over-skilling. The probability of being *severely over-skilled* was higher for workers with lower occupational tenure, those aged under 25, for migrants from non-English speaking backgrounds and for workers without children. Although the coefficients are not reported here, severe over-skilling was less prominent in the property and finance industries and in the public sector. With respect to moderate over-skilling, the incidence was higher again for younger workers as well as for those living in urban locations. In addition, workers in firms employing less than 5 workers are more likely to be *moderately over-skilled* relative to those employed in firms with 50 or more workers. Nevertheless, the variable of over-riding importance remains that of having been previously over-skilled. Note that our modeling strategy (i.e. using the PSM estimation) enables us to compare the wages of over-skilled workers with the wages of workers with like characteristics who, while previously over-skilled, were successful in exiting the over-skilled state. As such the estimations compare like individuals when assessing the wage consequences of labour market mismatch. The results of the data balancing procedure for the *severely over-skilled* are reported in Table 5.

Table 5: Balances for PSM (for the severely over-skilled group)

Characteristic differences: All working age full-time employees		*1. Treated (Over-skilled)*	*2. Control (Well-matched)*	*3. t- statistic*
Previously over-skilled	*Unmatched*	0.922	0.442	17.270***
	PSMatched	0.922	0.911	0.490
Female	*Unmatched*	0.318	0.343	-0.890
	PSMatched	0.318	0.324	-0.150
Migrant (English speaking country	*Unmatched*	0.105	0.120	-0.780
	PSMatched	0.105	0.100	0.200
Migrant (non-English speaking country)	*Unmatched*	0.120	0.088	1.870*
	PSMatched	0.120	0.120	0.020
Past year % spent in unemployment	*Unmatched*	0.000	0.000	Dropped
	PSMatched	0.000	0.000	
Education – Year 10 to 12	*Unmatched*	0.411	0.252	6.140***
	PSMatched	0.411	0.395	0.420
Education – Certificate / diploma	*Unmatched*	0.357	0.368	-0.360
	PSMatched	0.357	0.366	-0.230
Educational attainment – Degree or higher	*Unmatched*	0.195	0.347	-5.530***
	PSMatched	0.195	0.197	-0.060
Father was a professional	*Unmatched*	0.102	0.130	-1.410
	PSMatched	0.102	0.101	0.030
Urban	*Unmatched*	0.886	0.862	1.190
	PSMatched	0.886	0.878	0.310
Single	*Unmatched*	0.345	0.253	3.550***
	PSMatched	0.345	0.342	0.090
Occupational tenure (years)	*Unmatched*	9.087	12.658	-6.270***
	PSMatched	9.087	9.413	-0.520
Employment tenure (years)	*Unmatched*	7.829	10.447	-5.260***
	PSMatched	7.829	7.958	-0.230
Age – 25 to 39 years	*Unmatched*	0.396	0.325	2.570**
	PSMatched	0.396	0.394	0.070
Age – 40 to 54 years	*Unmatched*	0.438	0.499	-2.060**
	PSMatched	0.438	0.448	-0.240
Age – 55 to 64 years	*Unmatched*	0.069	0.136	-3.420***
	PSMatched	0.069	0.067	0.130
A Union Member	*Unmatched*	1.625	1.566	2.040**
	PSMatched	1.625	1.616	0.240
Have children aged between 5 and 14	*Unmatched*	0.228	0.280	-1.980**
	PSMatched	0.228	0.244	-0.470
Have children aged below 5	*Unmatched*	0.093	0.114	-1.110
	PSMatched	0.093	0.092	0.030

Table 5 shows that prior to matching there were substantial characteristic differences between the treated (over-skilled) and the control (well-matched) individuals. This is made clear by comparing Column 1 (Treated) with Column 2 (Control) for the Rows marked *Unmatched*. After the data was matched on the basis of propensity scores, any such differences were eliminated. This can be sen by comparing Column 1 (Treated) with

Column 2 (Control) for the Rows marked *PSMatched*. This result confirms that the procedure was effective in matching individuals on key characteristics, in particular with regards to their over-skilling history. Similar results are found when the data on *moderately over-skilled* workers is balanced. Having established the trustworthiness of the matched data, we compare the PSM results with the earlier OLS results in Table 6.

Table 6: The effect of over-skilling on wages (comparing OLS with PSM estimates)

Dependent variable: Log (weekly wage)	**OLS**	**PSM (neighbors matching)**	**PSM (radius matching)**	**PSM (kernel matching)**
All working age full-time employees				
Severely over-skilled	-0.133***	-0.138***	-0.140***	-0.134***
	(0.015)	(0.030)	(0.024)	(0.024)
Moderately over-skilled	-0.050***	-0.022	-0.033**	-0.030*
	(0.010)	(0.020)	(0.017)	(0.017)
Graduates				
Severely over-skilled	-0.238***	-0.263***	-0.233***	-0.232***
	(0.035)	(0.076)	(0.054)	(0.054)
Moderately over-skilled	-0.051**	-0.049	-0.032	-0.032
	(0.021)	(0.037)	(0.031)	(0.032)
Certificates and diplomas				
Severely over-skilled	-0.085***	-0.182***	-0.099**	-0.110**
	(0.027)	(0.057)	(0.043)	(0.046)
Moderately over-skilled	-0.071***	-0.016	-0.029	-0.018
	(0.017)	(0.030)	(0.024)	(0.025)
Year 10-12				
Severely over-skilled	-0.129***	-0.110***	-0.150***	-0.142***
	(0.024)	(0.041)	(0.037)	(0.037)
Moderately over-skilled	-0.023	-0.037	-0.020	-0.025
	(0.017)	(0.034)	(0.029)	(0.029)

Results obtained using the total data set in the first column of Table 6, indicate that the PSM wage penalty estimates are closely in line with the OLS estimates for the *severely over-skilled*, but not so for the *moderately over-skilled* workers. Looking at the PSM *versus* OLS comparison by education levels, suggests that, for the university graduates, the OLS estimates for the *severely over-skilled* are in agreement with the PSM estimates, but the size of the estimates for the *moderately over-skilled* graduates is somewhat lower and statistically not significant. Results for those with certificates and/or diplomas suggest that the OLS results are, if nothing else, under-estimating the wage penalty of this group for the *severely over-skilled* and as with the graduates, they over-estimate the wage penalty for the *moderately over-skilled.* Results for those with education between years 10 and 12 suggest no differences between OLS and PSM.[9]

In conclusion, results in Table 6 suggest that the PSM estimates largely confirm the OLS estimates regarding the wage penalty of the severely over-skilled, with the possible exception of the Education group Certificates and/or Diplomas. By contrast, PSM results suggest that OLS results over-estimate (under-estimate/correctly estimate) the wage penalty of the *moderately over-skilled* graduates (certificate and or diplomas/Year 10-12), indicating the presence of various types of biases in that part of the sample.

IV. Discussion

Estimation results suggested that severe over-skilling is associated with a wage penalty that ranges between 8 and 20 percent, depending on the education category the employee belongs to.[10] To the degree that this wage penalty is the result of a labour market mis-match, one could make projections about the overall cost to the economy of employee-job mis-matches. A very rough example follows for illustrative purposes. First, we consider that about one in ten employees in Australia fall into the over-skilled category. Second, we disaggregate the Full Time employees according to the HILDA based distribution of educational attainment. We then use the estimated wage penalties by educational attainment for severely over-skilled employees to derive the following

[9] The PSM results in Table 6 may still be subject to hidden biases due to the underlying assumptions of PSM estimation. The results of robustness tests that were carried out follow Rosenbaum (2002) and suggest that the PSM estimates can be considered reliable and robust to potential bias arising from unobserved heterogeneity (see Appendix).
[10] These are averages of the OLS and PSM based estimates for vocationally qualified and graduates respectively.

average per annum losses of $3,979 for vocationally qualified employees, $6,257 for those educated to between years 10 and 12 and $13,723 for graduates. Third we multiply the estimated number of severely over-skilled workers at each education level by their average estimated pay penalty. Putting all severely over-skilled employees together the average becomes $7,140 of wage penalty per employee per year and adds up to a total of AUD5.94bn for 2005. It should be borne in mind that this is only a very broad brush calculation for illustration purposes, which when compared with the 2005 Australian GDP of just over AUD230bn, suggests the order of magnitude of the mis-match problem revealed by the estimations in this paper. There is also some evidence that the estimated wage penalty may be an underestimate of total productivity losses due to skill mis-matches. Dearden, Reed & van Reenan (2006) use panel data and methodology to suggest that when looking at the relationship between training, productivity and wages in the UK, wage effects tend to be around half as large as the total productivity impacts. This is another indication that the economy-wide effects of over-skilling presented in this paper should be treated with some caution as they may be under-estimating the true penalties of mis-matches to the economy.

V. Conclusion

This paper examined the extent and the impact of over-skilling within the Australian labour market. Over 11 percent of employees were found to be *severely over-skilled,* a further 30 percent were found to be *moderately over-skilled* with the rest *well matched.* These proportions are almost constant across all levels of educational attainment for the *moderately over-skilled* but they vary by education for the other two groups. The probability of being *severely over-skilled* appears to be inversely related to the education level. The probability of being *well matched* appears to be somewhat higher for university graduates.

A number of methods were used to estimate the wage penalty associated with over-skilling. After controlling for a range of personal and job characteristics, the average wage penalty for the *severely over-skilled* employees was estimated at 13.3 percent. Estimated wage penalties were found to vary considerably by education level. The wage penalty of the *severely over-skilled* is at its highest for university graduates. Graduates appear to be least likely to report being *severely over-skilled*, but those who do so, suffer a considerable wage penalty, around the 24 percent level. There is no evidence that *moderately over-skilled* graduates suffer a wage penalty. The similarity between the OLS and PSM estimates and subsequent sensitivity analyses indicate the absence of biases caused by unobserved heterogeneity. The wage penalty for the *severely over-skilled* in the other two education groups (Certificates and/or diplomas and years 10-12) is around the 10-15 percent level and the comparison between PSM and OLS results suggests little evidence of bias. By contrast, the statistical significance of the estimated wage penalty for the *moderately over-skilled* in the other two education groups (Certificates and/or diplomas and years 10-12) appears to be dependent on the estimation method (only OLS estimates show some significance), suggesting that there are biases present in these two groups for the *moderately over-skilled*.

The main conclusion from this paper is that we find substantial evidence that there are many employees who feel underutilized in their jobs. These feelings vary in intensity in a systematic way. We find evidence that although there are some 30 percent of employees who report to be moderately over-skilled, this does not translate into any evidence of disadvantage against them in terms of pay. There is some weak evidence that they may be different in ways that the data does not capture. We find some strong evidence that the 11.5 percent of employees who state that they are severely over-skilled are a mixed bag that varies by education group. The 8 percent of university graduates who report to be severely over-skilled are found to be also severely penalised in their remuneration.

From a methodological perspective, the evidence of mis-match in the graduate labour market arising from the results of this paper is strong and robust for a number of reasons. First, the estimations have controlled for a large number of factors. Second, the over-skilling question used for this study requires individuals to assess their current skills and their ability against what their jobs require. It is worth recalling that the over-skilling question is a general question which refers to both formally and informally acquired skills as well as innate ability. Therefore, the resulting over-skilling measure is likely to be more accurate relative to the measures used in over-education studies, which benchmark education level (as a proxy for skills) against job entry requirements (as a proxy for job requirements). Finally, the use of the PSM framework combined with the sensitivity analysis that follows it ensures that the estimates presented in this paper are unaffected by biases that may arise from individual unobserved heterogeneity. This last point is important as it facilitates the interpretation of the results as the reflection of differences at the employer level.

Having eliminated, as many potential sources of bias as possible, our results suggest that over-skilling is imposing real wage costs on those concerned. The results in this paper are consistent with an assignment interpretation of labour market (mis-)matches whereby the workers can be constrained by job requirements. Our results seem to suggest that in instances where over-skilling occurs, employers are either unable or unwilling to allow workers sufficient discretion in their employment so as to enable them to utilise fully their skills within the workplace. This paper does not provide sufficiently precise estimates in order to derive the overall effect of this type of mis-match for the economy in terms of lost productivity. It is nonetheless worth noting that the wage penalty estimates presented here will only form one part of the total productivity losses from the under-utilisation of these employees and, as such, they can be considered as a lower bound of a productivity loss estimate.

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Appendix

Definition of variables

Female: Dummy variable, takes the value 1 if female, zero otherwise.

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 an non English speaking country, zero otherwise.

Education – year 10 to 12: Dummy variable, takes the value 1 if highest qualification is between years 10 and 12, zero otherwise.

Education – Certificate / Diploma: Dummy variable, takes the value 1 if highest qualification is a certificate or diploma, zero otherwise.

Education – Degree or higher: Dummy variable, takes the value 1 if highest qualification is university, zero otherwise.

Proportion of last year spent in Unemployment: Continuous variable, value of which lies between 0 and 1.

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

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

Not married (or de facto): Dummy variable, takes the value 1 if individual is single, zero otherwise.

Occupational tenure: Continuous variable, expressed in years.

Employment tenure: Continuous variable, expressed in years.

Age between 25 and 39 years: Dummy variable, takes the value 1 if individual aged between 25 and 39, zero otherwise.

Age between 40 and 54 years: Dummy variable, takes the value 1 if individual aged between 40 and 54, zero otherwise.

Age between 55 and 64 years: Dummy variable, takes value 1 if individual aged between 55 and 64, zero otherwise.

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

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

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

Table A1: Descriptive statistics

Explanatory variable	*Mean (sd)*
Female	0.347
Migrant (English speaking country)	0.104
Migrant (non-English speaking country)	0.131
Education – Year 10 to 12	0.319
Educational – Certificate / diploma	0.361
Educational – Degree or higher	0.275
Proportion of past year spent in unemployment	0.162 (2.032)
Father was a professional	0.129
Urban	0.896
Not married (or de facto)	0.318
Occupational experience (years)	10.294 (9.243)
Employment tenure (years)	8.283 (7.851)
Age between 25 and 39 years	0.385
Age between 40 and 54 years	0.408
Age between 55 and 64 years	0.100
Union Member	0.372
Have children aged between 5 and 14	0.224
Have children aged below 5	0.105

Standard deviations are in brackets

Propensity score matching and unobserved heterogeneity

In terms of controlling for unobserved heterogeneity, we follow McGuinness (2007 forthcoming) and use propensity score matching (PSM). The PSM methodology would appear particularly apt as it will allow us to assess the impacts of the treatment group (over-skilled) relative to a group of well-matched individuals who were equally likely to be over-skilled based on a set of observable characteristics. Provided that the estimation conditions for the technique are met, then observations with the same propensity score must have the same distribution of characteristics (both observable and unobservable) independent of the treatment status (see Becker & Ichino, 2002) therefore ensuring that any estimated over-skilling impacts are free from unobserved heterogeneity bias. Nevertheless, we do apply additional checks to ensure that the propensity score estimates themselves are free from any systematic biases.

Propensity score matching (PSM) is a non-parametric technique that allows us to control for the non-random assignment to control and treatment groups and as such it ensures that levels of estimation bias are greatly reduced by comparing the outcomes of individuals in the treatment and control groups who hold very similar characteristics. The propensity score is defined in a seminal work by Rosenbaum and Rubin (1983) as the conditional probability of receiving a treatment given certain determining characteristics:

$$p(X) = \Pr\{D = 1/X\} = E\{D/X\} \qquad (1)$$

Where D is a binary term indicating exposure to the treatment T and X is a vector of determining characteristics. Rosenbaum and Rubin (1983) demonstrate that if exposure to the treatment is random with respect to the determining characteristics then it is also random with respect to a the single dimensional variable p(X). For any individual in a given population denoted by i, if the propensity score $p(X_i)$ is known the Average effect of Treatment on the Treated (ATT) can be estimated as follows:

$$T = E\{Y1_i - Y0_i / D_i = 1\} \qquad (2)$$

$$T = E\{E\{Y1_i - Y0_i / D_i = 1, p(X_i)\}\} \qquad (3)$$

$$T = E\{E\{Y1_i / D_i = 1, p(X_i)\} - E\{Y0_i / D_i = 0, p(X_i)\} / D_i = 1\} \qquad (4)$$

Where the outer expectation is over the distribution of (p(Xi)|Di = 1) and Y1i and Y0i are the potential outcomes in the two counterfactual situations of the treatment and non-treatment, respectively. Effective PSM estimation requires a rich data set that contains sufficient control variables that allow the propensity score to be efficiently modelled and matching to be performed, specifically, for the assumption of homogeneity to hold the determining variables must be balanced given the propensity score. Tests on the PSM estimates generated using the current dataset show that this balancing property is satisfied. It should also be noted that there are a number of available PSM estimation techniques and that each PSM method has certain advantages and drawbacks, however, no one method can be considered superior to any other (Becker & Ichino, 2002). In this study we report the results of Nearest Neighbour with replacement, Radius and Kernel matching.

With respect to the HILDA data we pool waves 4 and 5 and use them as a single cross-section by applying the relevant weights. We also, however, exploit the longitudinal aspect of the data to allow us to derive certain historical variables which allow us to substantially improve our model specifications.

Robustness test for PSM estimates

This section outlines a robustness test for the PSM estimates used in the main text.

Table A2: Rosenbaum bounds for 'treatment' effects

e^{γ} values	p critical	Hodges-Lehmann point estimate			
		t_{max}	t_{min}	CI_{max}	CI_{min}
1.0	0.000000	-0.143326	-0.143326	-0.177457	-0.107608
1.1	0.000000	-0.156260	-0.129898	-0.191040	-0.094593
1.2	0.000000	-0.168232	-0.117025	-0.202398	-0.081882
1.3	0.000000	-0.179318	-0.105840	-0.213187	-0.069419
1.4	0.000001	-0.189702	-0.095868	-0.223169	-0.058398
1.5	0.000011	-0.198611	-0.086276	-0.233034	-0.048274
1.6	0.000081	-0.206764	-0.076404	-0.241928	-0.038555
1.7	0.000429	-0.214867	-0.067667	-0.249529	-0.029197
1.8	0.001733	-0.222228	-0.059397	-0.256923	-0.020450
1.9	0.005590	-0.229926	-0.051645	-0.264081	-0.012796
2.0	0.014911	-0.236671	-0.044399	-0.271224	-0.004940

Note: Rosenbaum bounds calculated using rbounds Sample: Full-time employees of working age

Table A2 provides a further robustness check on the PSM estimate of -14.3 percent derived buy applying nearest neighbour matching on the entire sample. As previously stated, the PSM estimators allow us to compare like individuals in order to derive the wage impact of over-skilling. However, the PSM estimates are based on the very strong assumption of unconfoundess whereby we observe all variables simultaneously influencing both the outcome and participation variables. Given that such an extreme condition is unlikely to have been met there is still scope for hidden bias whereby some unobserved variables could simultaneously and systematically impact both the treatment and outcome variables leading to biased estimates. Consequently, we carry out a sensitivity analysis using Rosenbaum bounds for unobserved heterogeneity at various levels of e^{γ}. The bounds allow us to assess the extent to which an unobserved variable must influence the selection process in order to render the matching estimates unreliable.

The results suggest are results are likely to be robust to such effects, for instance, at $e^{\gamma} = 2$ our estimate of -14.3 percent is still reliable at a 95 percent level of confidence. The basic intuition here is that even in the event of an unobserved factor increasing the likelihood of over-skilling by a factor of 100 percent, our estimate of -14.3 percent remains reliable. The results seem particularly strong given that sensitivity analysis on the Card & Kruger minimum wage study found that results become unreliable between e^{γ} values of between 1.34 and 1.5 (Rosenbaum, 2002).