PRELIMINARY DRAFT: PLEASE DO NOT QUOTE

An Analysis of the Differential Impacts of Overskilling by Educational Pathway: Is Vocational Education a Safer Route?

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Abstract: We use the Australian HILDA panel survey which is a unique source of panel information on overskilling. We utilise a number of econometric methods including OLS, Propensity Score Matching, RE probit and Dynamic RE Probit with Mundlak corrections and initial conditions to examine overskilling as a form of labour market mismatch and skills underutilization. We estimate the factors driving overskilling and estimate its state dependence and wage effects, first for all education levels and subsequently for each separate education level. We finds evidence of state dependence of overskilling which contradicts the view that labour market mismatches are merely transitory phenomena that should be of little policy concern. When we look at different education pathways we compare post-school educated workers. We find that workers with vocational training are not less likely than university graduates to become severely overskilled, they are less likely to remain overskilled and suffer a lower wage penalty. It is argued that this lower persistence and wage penalties are a consequence of higher levels of specific human capital in vocational training. By contrast, university graduates who are less likely to be overskilled, exhibit much higher persistence and wage penalties. We argue the negative labour market consequences of overskilling among university graduates may be ameliorated by rebalancing provision towards subject areas with more direct links to the labour market. When we examine workers at the bottom of the education and/or wage distributions we conclude that their relative overskilling position could be improved by increasing flows into basic vocations education.

1. Introduction

This paper examines skills underutilization in the workplace as a form of labour market mismatch. Overskilling is adopted as the key measure of mismatch in preference to the more commonly used overeducation variable (see McGuinness 2006 and Sloane 2003 for overviews of this literature). Overskilling is preferred on the grounds that it constitutes a potentially more robust measure of labour market under-utilization (see Mavromaras et al. 2007a and 2007b for a discussion of the relative merits of overeducation and overskilling based measures of mismatch). The paper focuses on a number of key labour market outcomes related to overskilling, namely, its incidence, its over time persistence and its wage effects.

The paper distinguishes employees by their education attainment and considers the extent to which labour market outcomes related to overskilling may differ by education. In particular the paper draws on the distinction of general and specific human capital and examines overskilling differences between individuals who undertook vocational training and those who obtained their qualifications via an academic pathway. It might be reasonably expected that the effects of overskilling may vary by education type on the grounds that vocational training tends to be more focused on equipping individuals with skills that have practical applications in the labour market than academic pathways such as universities. Provided that VET graduates are successful in finding employment that relates to their training, then, other things equal, they should be in a position to apply a larger proportion of their VET skills to their workplace environment. By contrast, it is often claimed that academic courses lead to qualifications that in many fields equip individuals with knowledge and skills of lesser practical application. Assessing the effects of overskilling by education type will allow us to draw some inferences on the relative merits of rebalancing current educational provision in terms of the general and specific skills mix it offers.

With its focus on state dependence, the paper seeks to provide new evidence of the extent to which labour market mismatch represents a permanent or a transitory, phenomenon.

The question of over time persistence of overskilling, is clearly important for policy as the cost of labour market mismatches on individuals depends on both the size of the wage penalty and on how long that penalty persists. A number of theories suggest that labour market mismatches are temporary (see Sloane et al. 1999). In matching theories of job search (Jovanovic 1979), mismatched workers improve job matches through repeated job search. Theories of career mobility (Rosen 1972; Sicherman and Galor 1990) predict that workers may deliberately enter their preferred profession at a level lower than would seem commensurate with their qualifications. This enables them to acquire further skills, through on-the-job training and learning and promotes a more rapid career progression. Both theories can explain overskilling as a temporary phenomenon. Although these theoretical possibilities have been recognized in many instances, the empirical aspects of persistent mismatch have not received adequate attention in the literature, principally due to data constraints.

2. The data

The data for this study comes from the first six waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. HILDA is a nationally representative panel dataset of the Australian population that has been in operation since 2001. The sample used here begins with the unbalanced panel of working-age (15 to 64 years) employees.

The overskilling variable is constructed using the 7-point scale response to the following question "I use many of my skills and abilities in my current job". A response of 1 corresponds with strongly disagree and 7 with strongly agree. The question is similar to that used in both the work of Allen and van der Velden (2001) and Green and McIntosh (2002).[1] All respondents in the sample were then classified into one of three groups for

[1] In the data employed by Allen and van der Velden (2001), a measure of skills underutilization is constructed from responses, scored on a 5-point scale, to the statement: "My current job offers me sufficient scope to use my knowledge and skills". In contrast, Green and McIntosh (2002) combine responses to two items, both of which have four possible response options. These items are: "In my current

each yearly observation: (i) the severely overskilled (individuals selecting 1, 2 or 3 on this scale); (ii) the moderately overskilled (those selecting 4 or 5); and (iii) the well matched (individuals selecting 6 or 7). Sensitivity tests confirm that the cut-off points for severe and moderate overskilling are appropriate (Mavromaras et al (2007b). Furthermore, it has been established that, in responding to the overskilling question, employees are not consistently factoring in skills that have no relevance to their current job. McGuinness & Wooden (2007) cross-tabulated the overskilling variable with a measure of job complexity to confirm that the more overskilled the worker, the less difficult they consider their job to be demonstrating that the measure will not be biased by respondents incorporating non labour market relevant skills and abilities into their response.[2]

We group education by the highest education qualification obtained. The educational groupings provided within HILDA are: *below year 11* (no qualifications), *year 11 or 12* (accredited qualifications at compulsory schooling level), *certificates* (Vocational), *diplomas and tertiary*. We sub-divide the vocational education category of Certificates into (a) Certificates I and II and below and (b) Certificates III and IV and Apprenticeships. Table 1 reports the incidence of overskilling for all employees by education level. The data here is pooled across all six waves of HILDA and has been weighted using cross-sectional weights in order to ensure it is representative of the population. Vocationally qualified workers account for just less than one quarter of the total sample, with the vast majority of such workers holding qualifications above certificate level II.[3] The relatively small sample size associated with the certificate I and II grouping will restrict the extent to which this category can be examined separately in any detail. Evidence from multivariate wage regressions suggests that relative to the base

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job I have enough opportunity to use the knowledge and skills that I have"; and "How much of your past experience, skills and abilities can you make use of in your present job?"

[2] Job complexity is assessed using responses to the item "My job is complex or difficult", which is scored on the same 7-point scale used to measure overskilling.

[3] Table A1 in the Appendix presents the occupational distribution across education groupings and gives a clear indication of the strongly vocational orientation certificates III and IV. Individuals holding vocational certificates above level II are more heavily represented in occupations such as mechanics, fabricators, electricians, construction workers, other tradespersons and intermediate clerical and service workers than in other occupations.

case of individuals with no qualifications at all, those holding certificates I or II earn a premium of 6 per cent, those with year 11 or 12 qualifications earn 10 per cent more, those with certificates III or IV earn 15 per cent more and graduates with a degree earn 36 per cent more.[4] There appear to be considerable differences in the returns from certificate levels I or II and certificate levels III or IV.

The HILDA data (waves 1 to 6) shows that approximately 58 per cent of Australian employees consider themselves to be well matched in their present employment, 28 per cent report that they are moderately overskilled and 14 per cent report that they are severely overskilled. These rates are broadly in line with those reported in analysis of the first four waves of HILDA by Mavromaras et al. (2007a). Also consistent with that study, is the finding that the incidence of both moderate and severe overskilling, is more pronounced among lower educational groupings. The data suggests that, within the Australian labour market, 17 to 19 per cent of workers with the lowest levels of educational attainment are employed in jobs that they consider to be highly menial and low skilled.

Table 1: Reported overskilling in Employment

Highest Education Level (Australia)	*Extent of Overskilling (%)*			
	Well Matched	*Moderately Over-skilled*	*Severely Over-skilled*	*%*
All employed				
Year 10 and Below	50.99	30.68	18.32	18.69
Year 11-12	47.39	32.25	20.36	25.79
Certificates I and II and below	45.19	35.88	18.92	1.73
Certificates III and IV and Apprenticeship	62.13	27.88	9.99	21.02
Advanced diploma and tertiary	62.46	26.33	11.21	32.78
All qualifications	56.06	29.16	14.78	100.00
No of observations	23,688	12,322	6,245	42,255

Note: HILDA waves 1 to 6 (years 2001-2006) were used with population weights

When we examine the incidence of overskilling by education level, vocationally trained workers with certificates level I and II report some of the highest rates of both moderate and severe overskilling reinforcing the view that these workers are heavily concentrated

[4] Detailed results are available from the authors.

at the lower end of the labour market. Nevertheless, such workers account for less than 8 per cent of all vocationally qualified persons observed here and less than 2 per cent of the total sample. By contrast, vocationally trained workers with certificates III or IV report overskilling that is more like that of workers with advanced diploma / tertiary education. This suggests that a clear majority of vocationally trained workers perform relatively well in the labour market in terms of their ability to achieve employment that matches well with their skills.

3 Estimation method

The estimation approaches employed within the paper differ considerably depending on the question at hand. In order to modeling the incidence of overskilling we use a pooled probit estimation and a Random Effects (RE) probit estimation. We note that the RE framework is not without problems in that the individual-specific component of the error term ε_i is assumed to be independent of the observed individual characteristics X_{it}. This is not a sustainable assumption as it flies in the face of empirical evidence in most occasions. The problem has been shown to be alleviated by incorporating in the estimation what is referred to in the literature as the Mundlak (1978) correction. This amounts to assuming that the relationship between X_{it} and ε_i can be written as $\varepsilon_i = \overline{X}_i^{'}\varepsilon + v_i$, where $v_i \sim iid$ follows the normal distribution and is independent of X_{it} and u_{it} for all i and t. In practice this correction amounts to including in the RHS of a regression the individual over time means for each of the time-varying explanatory variables.

When modeling the wage effects of overskilling, concerns relating to unobserved heterogeneity bias are also of concern. In particular, if mismatch is associated with lower ability levels then pay penalties will reflect in part the reduced return to ability and in part the effects of mismatch. Mavromaras et al. 2007a analyzed and discussed this issue in the context of overskilling in great detail and showed that, while a small amount of bias was evident with respect to the wage impacts of moderate overskilling, the estimates on severe overskilling were generally robust and free of bias. Nevertheless, on the grounds that we cannot totally rule out the influence of bias from our wage estimates we follow

Mavromaras 2007a et al. and present estimates of overskilling wage penalties based on both Ordinary Least Squares and Propensity Score Matching (PSM) estimation, the latter utilizing the panel information in the data for improving the matching.

A novel aspect of this paper is that it exploits the dynamic panel nature of the data to estimate the persistence of overskilling. We estimate the following equation:

$$(1) \qquad OS_{it} = X'_{it}\beta + \gamma OS_{it-1} + \varepsilon_i + u_{it}$$

for $i=1,\ldots,N$, individuals observed over $t=2,\ldots,T$ periods. OS_{it} is the overskilling variable which takes the value 1 for those who are overskilled and zero for those who are well matched, X_{it} contains all observed explanatory variables and ε_i and u_{it} are components of the error term with u_{it} assumed to be *iid*. However, two subtle but nonetheless serious estimation problems would arise if Equation 1 were to be estimated using a standard random effects framework. First, the unrealistic assumption of independence between the covariates and the error term must again be dealt with through the application of the Mundlak correction. We do this. Second, the time-invariance of the individual specific error term ε_i. implies that even after we have corrected for its possible correlation with observed contemporaneous factors (the X_{it}), ε_I will still be correlated with the lagged dependent variable. One can work this problem backwards until it can be shown that assuming the independence between OS_{it-1} and ε_I amounts to assuming that the first observation of OS_{i1} is independent of the individual-specific error term ε_i. This assumption is very difficult to justify on empirical or theoretical grounds. The problem was first identified in the econometrics literature by Heckman (1981) and has been named the problem of initial conditions. Ignoring initial conditions that are correlated with the individual-specific error term ε_i results in overestimating state dependence. That is, the estimated coefficient of OS_{it-1} in Equation 1 will be larger than the true value of state dependence. Heckman proposed that initial conditions can be modelled by using the values of the first wave of a panel data set in order to approximate the true values of the initial conditions. It is desirable when this method is applied that some data that stems from periods that precede the first observed period in the data are included as a means of identification. This method is widely accepted in econometrics for its proven robustness and relative simplicity in estimation. In the estimations we present below we have incorporated both Mundlak corrections and Heckman's method of accounting for the initial conditions. Equation can be now re-written as

(2) $$OS_{it} = X_{it}^{'}\beta + \gamma OS_{it-1} + \overline{X}_{i}^{'}\alpha + \varepsilon_i + u_{it}$$

which is estimated simultaneously with the initial condition equation written as

(3) $$OS_{i1} = Z_{i1}^{'}\beta + \theta\alpha_i + u_{i1}$$

Note that Equation 2 utilises data starting from period 2, while Equation 3 utilises data exclusively from period 1. Further, Z_{i1}, the list of RHS variables in Equation 3, contains all of the X_{it} and $\overline{X}_i$ plus some additional instruments that are chosen to contain pre-period 1 information.[5] We have used for estimation the STATA procedure ***redprob*** developed by Mark Stewart.[6]

4. Estimation results and discussion

3.1 Factors determining the incidence of overskilling

We begin our empirical analysis by estimating the factors determining the incidence of severe and moderate overskilling. We begin with a pooled model using binary probit estimation presented in Table 2. Depending on the overskilling level, we use two

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[5] We have chosen a number of historical variables asked at the first interview. These are (i) a set of dummies which indicate the country of birth (Australia, Not Australia but English speaking, not Australia and not English speaking) of the individual, which can be safely presumed to have been determined before overskilling status and (ii) two further dummies indicating parental employment status (one for a professional father and one for a professional mother) the values of which were also in all probability determined before the overskilling status in the first period.

[6] The STATA ado files and a number of useful related papers can be found by visiting Mark Stewart's website at http://www2.warwick.ac.uk/fac/soc/economics/staff/faculty/stewart/publications. These are well explained and are an excellent starting point for the practitioner who wishes to use these estimation methods. The precise algebra of the likelihood function we estimate is presented by Mark Stewart, so we do not replicate this here.

different sub-samples in order to have the same reference category. In the first case of severe overskilling the dependent variable takes the value of 1 if the individual is severely overskilled and zero if they are well matched, with the moderately overskilled excluded from the estimation. In the second case of moderate overskilling the dependent variable takes the value of 1 if the individual is moderately overskilled and zero if they are well matched, with the severely overskilled excluded from the estimation[7]. It should be noted that although estimation that uses a pooled sample of all observations has a number of limitations, which will be addressed in the subsequent analysis, it is a useful starting point and benchmark for further analysis.

Both severe and moderate overskilling vary by the level of education. Certificates I and II appear to be more likely to be moderately overskilled (relative to those with education below year 11) although the small cell size for this category should be borne in mind when looking at this result. Education above certificate II or above year 12 is associated with lower levels of overskilling and better job matches. Most of the other covariates in Table 2 suggest that the determinants of both severe and moderate overskilling are very similar, a somewhat unexpected result given that the wage effects of both types of mismatch tend to be very different[8]. Overskilling is negatively correlated with occupational experience, hours worked and employment in smaller firms. Furthermore, both moderate and severe overskilling are unevenly distributed amongst industries, with construction, finance, property, education, defense, health, cultural and personal services associated with lower overskilling.

[7] We split the samples in this way in order to retain comparability of results with the literature where overskilling is divided between moderate and severe. A simple way to check if this matters is by estimating an ordered probit with the ordered overskilling variable in the left hand side. We did this (results are reported in the Appendix) and we conclude that we cannot trace any major differences between the results based on the separate estimation of the two sub-samples reported in Table 3 and those based on the complete sample reported in the Appendix. Intuitively put, and as one would expect in the presence of a statistically robust model, the ordered probit result look very much like an average of the results from the two separate estimations.

[8] The literature is consistently reporting that the pay penalty associated with severe overskilling tends to be more precisely estimated and of a higher magnitude than that of moderate overskilling.

Table 2: Probit Estimations of Severe and Moderate Overskilling (Pooled)

Explanatory variable	*Severely over-skilled*		*Moderately over-skilled*	
	M.E	Std. Error	M.E	Std. Error
Female	-0.006	0.007	-0.003	0.008
Migrant from English speaking country	-0.017*	0.010	-0.002	0.012
Migrant from non-English speaking country	0.038***	0.011	0.025**	0.012
Education: Year 11 to 12	-0.004	0.009	0.005	0.011
Education: Certificate I and II	-0.003	0.024	0.053**	0.026
Education: Cert. III/IV, Apprenticeships	-0.054***	0.008	-0.044***	0.010
Education – Adv. Dipl., Degree or higher	-0.036***	0.009	-0.043***	0.010
Proportion of past year in unemployment	0.001***	0.000	0.0003	0.0003
Urban	0.010	0.009	0.018*	0.010
Occupational experience (years)	-0.004***	0.000	-0.003***	0.000
Employment tenure (years)	-0.001	0.001	0.001*	0.001
Weekly hours worked	-0.005***	0.000	-0.004***	0.000
Age – 25 to 39 years	-0.003	0.008	-0.007	0.010
Age – 40 to 54 years	0.001	0.009	-0.022**	0.010
Age – 55 to 64 years	-0.015	0.012	-0.058***	0.013
A Union Member	-0.002	0.007	-0.004	0.008
Have children aged between 5 and 14	-0.012*	0.007	0.013	0.008
Have children aged below 5	-0.018*	0.009	-0.015	0.010
Firm size- less than 5 people	-0.034***	0.008	-0.032***	0.009
Firm size- between 5-9 people	-0.042***	0.008	-0.030***	0.010
Firm size- between 10-19 people	-0.031***	0.008	-0.023**	0.010
Firm size- between 20-49 people	-0.020***	0.008	-0.013	0.009
Industry- Agric., forestry and fishery	0.013	0.018	-0.008	0.020
Industry- Mining	-0.042*	0.023	-0.027	0.027
Industry- Electricity, gas and water	-0.034	0.035	-0.026	0.036
Industry- Construction	-0.059***	0.010	-0.044***	0.015
Industry- Wholesale	0.019	0.016	0.008	0.018
Industry- Retail	0.012	0.012	-0.004	0.013
Industry- Accom. Cafes and Restaurants	0.017	0.015	-0.012	0.017
Industry- Transport	0.016	0.017	0.013	0.019
Industry- Communication	0.031	0.026	0.011	0.027
Industry- Finance	-0.071***	0.012	-0.056***	0.018
Industry- Property& Business Services	-0.066***	0.009	-0.041***	0.013
Industry- Defence	-0.098***	0.009	-0.053***	0.016
Industry- Education	-0.138***	0.007	-0.155***	0.012
Industry- Health	-0.117***	0.007	-0.127***	0.012
Industry- Cultural & recr. Services	-0.076***	0.012	-0.098***	0.018
Industry- Personal & other services	-0.061***	0.011	-0.086***	0.017
Observations	29978		36198	
Pseudo R square	0.1435		0.0357	
Restricted Log Likelihood	-14504.94		-22900.13	
Unrestricted Log Likelihood	-12423.55		-22082.37	

There are few estimates that differ by level of overskilling. For instance, relative to Australian natives, migrants from English speaking (non English speaking countries) are less (more) likely to be severely overskilled. There is some evidence that moderate overskilling is lower among the 40 plus age group. The main limitation of the pooled results reported in Table 2 is that all observations are treated as independent of one another so that changes that happen to specific individuals over time cannot be identified. In addition, it is also possible that the estimates presented in Table 2 are biased because some variables may be picking up unobserved individual differences, such as innate ability or motivation, which may be driving the likelihood of overskilling, thus causing unobserved heterogeneity bias. This is a very common problem in the empirical estimation of data relating to educational achievement, largely because education tends to be treated as an investment and is non-randomly obtained at higher levels by those with higher levels of ability. As a result, when positive returns to education are estimated without taking into account non-randomly distributed ability levels, these returns are biased upwards reflecting in part returns to education and in part returns to (unobserved) ability. In the following analysis we control for those unobservables that are constant over time, by utilizing the panel aspect of our data and adopting a modeling approach that "differences out" these constant unobservables.

We estimate a random effects (RE) probit model with a Mundlak correction and report results in Table 3. Noting that the RE probit results are broadly similar to those of the pooled estimation we concentrate on some important differences, presumably arising from the main difference in the two estimation methods, namely from controlling (the RE case) or not controlling (the pooled case) for unobserved individual heterogeneity. Obtaining a tertiary qualification significantly reduces the probability of severe overskilling, however, tertiary education is no longer shown to reduce the likelihood of moderate overskilling. Certificates III and IV no longer have an impact on either level of overskilling.

Table 3: Random Effects Probit Estimations of Severe and Moderate Overskilling

Explanatory variable	*Severely over-skilled*		*Moderately over-skilled*	
	M.E.	Std. Error	M.E.	Std. Error
Female	-0.007*	0.004	-0.005	0.010
Migrant from English speaking country	-0.006	0.006	0.0004	0.014
Migrant from non-English speaking country	0.025***	0.008	0.035**	0.015
Educational attainment – Year 11 to 12	0.013	0.013	-0.002	0.032
Education – Certificate I and II	-0.025*	0.013	0.131*	0.079
Education – Certificate III and IV and apprenticeship	-0.009	0.012	-0.002	0.037
Education – Advanced diploma or Degree or higher	-0.036***	0.013	-0.038	0.043
Proportion of past year in unemployment	0.000	0.000	-0.0001	0.0004
Urban	-0.015	0.011	-0.030	0.023
Occupational experience (years)	0.000	0.000	0.0001	0.001
Employment tenure (years)	0.001	0.000	0.002**	0.001
Weekly hours worked	-0.002***	0.000	-0.003***	0.000
Age – 25 to 39 years	0.010	0.009	-0.005	0.021
Age – 40 to 54 years	0.006	0.010	0.006	0.025
Age – 55 to 64 years	0.002	0.012	0.038	0.029
A Union Member	-0.001	0.005	-0.007	0.013
Have children aged between 5 and 14	0.005	0.006	0.023*	0.012
Have children aged below 5	0.003	0.006	0.018	0.014
Firm size- less than 5 people	-0.006	0.005	0.019	0.016
Firm size- between 5-9 people	-0.011**	0.005	0.018	0.016
Firm size- between 10-19 people	-0.004	0.005	-0.003	0.014
Firm size- between 20-49 people	-0.001	0.005	-0.002	0.013
Industry- Agriculture, forestry and fishery	0.028	0.020	0.035	0.037
Industry- Mining	-0.006	0.017	-0.005	0.047
Industry- Electricity, gas and water	-0.018	0.016	0.071	0.069
Industry- Construction	-0.021***	0.006	0.013	0.027
Industry- Wholesale	0.023*	0.014	0.064**	0.027
Industry- Retail	0.021*	0.011	0.057**	0.024
Industry- Accommodation, Cafes and Restaurants	0.007	0.012	0.019	0.032
Industry- Transport	0.002	0.012	0.017	0.033
Industry- Communication	-0.014	0.011	-0.024	0.042
Industry- Finance	-0.018**	0.009	-0.043	0.034
Industry- Property& Business Services	-0.026***	0.005	0.004	0.023
Industry- Defence	-0.035***	0.004	-0.025	0.028
Industry- Education	-0.041***	0.005	-0.092***	0.027
Industry- Health	-0.042***	0.004	-0.069***	0.025
Industry- Cultural & recreational Services	-0.028***	0.005	-0.051	0.031
Industry- Personal & other services	-0.022***	0.007	-0.043	0.031
Observations	29978		36198	
Restricted Log Likelihood	-11072.13		-20589.75	
Unrestricted Log Likelihood	-10630.14		-20496.34	

The suggestion of this last result is that, once unobserved heterogeneity is controlled for, the possession of certificates III and IV does not influence the chance of a better skills match. Results suggest that only individuals with advanced academic qualifications are less likely to be severely overskilled in the labour market.

Looking at the remainder of Table 3 we see that the marginal effects of firm size become much less consistent and significant while the marginal effects of sector become much more pronounced. Migrants from a non-English background are now more likely to be exposed to both severe and moderate overskilling. The influence of occupational tenure falls out of the model while employment tenure becomes a significant determinant of moderate but not severe overskilling and the small negative effect of weekly hours on overskilling remains significant. The changing nature of the marginal effects as we move from pooled to random effects estimation demonstrates that our earlier estimates were clearly affected by unobserved heterogeneity bias.

The estimations presented in Tables 2 and 3 do not allow any of the coefficients to differ by education category. It is, therefore, impossible to determine from these results the extent to which the determinants of severe and moderate overskilling may differ between different educational groups. Given the pronounced differences that we have estimated in the wage penalty by education category (Mavromaras 2007a) we examined the possibility that similar differences may exist by estimating separate models by education category.[9] Given the emphasis of this paper we concentrate on the differences between VET graduates and others.

The comparison of estimations of severe overskilling for all employees with VET graduates suggests that for holders of level III, IV certificates and apprenticeships age is a less important factor in the likelihood of mismatch. This suggests that the advantages derived from vocational training tend to be immediately apparent when individuals first enter the labour market. Similarly, individuals from a non-English speaking background are at no disadvantage when equipped with certificates III and IV vocational training. The intuition behind these results is that vocational labour markets tend to be less discriminatory in nature. Some sectoral differences are also apparent between VET

[9] For reasons of space we do not present full results here but can supply them upon request.

graduates and other education levels. Perhaps not surprisingly, while in general employment in the retail sector is associated with higher levels of mismatch, this proves not to be the case when VET graduates are estimated separately. When looking at moderate overskilling, again for VET graduates relative to tertiary education graduates, age is much less of a determining factor of overskilling. However, VET graduates with certificates III or IV in larger firms are more likely to be moderately overskilled compared to tertiary education graduates.

3.2 Assessing the relative demand for skills in vocational labour markets

We now extend the analysis further to assess the extent to which the incidence of overskilling among workers holding vocational qualifications varies by occupation. The very nature of VET leads to high proportions of vocationally trained workers taking up posts relevant to their education. It follows that in the RHS of an estimation, the variable occupation could provide a general indicator of the relative demand for particular skills. To test this we estimate the Mundlak corrected RE effects probit for Level III and IV certificate holders including a detailed set of occupation variables. We focus on certificates III and IV workers as they constitute the clear majority of vocationally qualified workers. Small sample size problems raise doubts over the potential reliability and robustness of a model estimated for VET graduates with certificates I and II. As occupation and sector are often highly correlated, the sector variables have been omitted from these estimations equations. Results are presented in Table 4.

The occupational groupings are constructed so as to provide a relatively disaggregated view of the demand for craft workers relative to other, more broadly defined groups such as managers and associate professionals. The reference category contains occupations of an elementary nature.[10]. Concentrating on the occupation marginal effects we see that, in the case of severe overskilling, training in the areas of Electrical/Electronics, Construction, Automotive Engineering substantially reduces the probability of overskilling mismatch. The intuition behind these marginal effects suggests that, in terms

[10] Reference category occupations by ASOC 2-digit code and name: 81 Elementary Clerks; 82 Elementary Sales Workers; 83 Elementary Service Workers; 90 Laborers and Related Workers n.e.c.; 91 Cleaners; 92 Factory Laborers; 99 Other Laborers and Related Workers.

of the vocational labour market, demand is highest for electricians, construction workers and mechanics and that this higher demand works towards these VET graduates being placed more in accordance with their skills and training than in other occupations.

Table 4: Incidence of Overskilling and Occupational Categories (Certificates III/IV)

	Certificates III-IV			
Explanatory variable	*Severely over-skilled*		*Moderately over-skilled*	
	M.E.	Std. Error	M.E.	Std. Error
Female	-0.009	0.006	-0.048**	0.021
Migrant from English speaking country	-0.004	0.007	0.024	0.027
Migrant from non-English speaking country	0.007	0.011	0.0003	0.030
Proportion of past year in unemployment	0.0002	0.0002	-0.0002	0.001
Urban	-0.009	0.014	-0.079*	0.045
Occupational experience (years)	0.0002	0.0004	0.001	0.001
Employment tenure (years)	0.0002	0.001	0.0004	0.002
Weekly hours worked	-0.001***	0.0003	-0.002*	0.001
Age – 25 to 39 years	0.038**	0.019	0.081*	0.045
Age – 40 to 54 years	0.009	0.016	0.042	0.051
Age – 55 to 64 years	-0.014	0.010	0.043	0.066
A Union Member	-0.007	0.007	0.017	0.027
Have children aged between 5 and 14	0.010	0.009	0.041*	0.023
Have children aged below 5	0.002	0.009	0.064**	0.031
Firm size- less than 5 people	-0.005	0.008	-0.021	0.030
Firm size- between 5-9 people	-0.009	0.007	-0.002	0.030
Firm size- between 10-19 people	0.010	0.010	-0.033	0.027
Firm size- between 20-49 people	-0.0005	0.008	-0.021	0.025
Occupation- Managers	-0.018***	0.006	-0.094**	0.037
Occupation- Professionals	-0.021***	0.005	-0.093***	0.034
Occupation- Associate Professionals	-0.020***	0.006	-0.071**	0.031
Occupation- Mecahnical &fabrication engineering tradespersons	-0.019***	0.007	-0.074	0.048
Occupation- Automotive tradespersons	-0.023***	0.005	-0.129***	0.044
Occupation- Electrical and electronics tradespersons	-0.024***	0.005	-0.040	0.056
Occupation- Construction tradespersons	-0.025***	0.005	-0.020	0.061
Occupation- Other tradespersons	-0.018***	0.006	-0.075*	0.040
Occupation- Clerk	-0.016***	0.006	-0.051	0.038
Occupation- Intermediate clerk and workers	-0.004	0.008	-0.030	0.032
Observations	6411		7929	
Restricted Log Likelihood	-2064.35		-4455.58	
Unrestricted Log Likelihood	-1975.33		-4434.23	

The much smaller marginal effect on the Clerical category suggests that VET leading to Clerical occupations provides a much weaker guarantee of avoiding working in a job where one is severely overskilled. The resulting differences in probabilities of overskilling by occupation give an indication of relative effectiveness of different VET directions in sheltering the VET graduate against severe overskilling. It should be noted that these estimates could also be reflecting skill shortages as well as well-targeted training. The data at hand does not contain sufficient information on the employer to be able to distinguish between the two possibilities.

Results on moderate overskilling for VET certificates III and IV are very similar in their qualitative direction as those of severe overskilling, however, only the Automotive tradespersons control is statistically significant. The results suggest that, with the exception of mechanics, individuals from all trade areas are equally likely to be moderately overskilled. Given that moderate overskilling is more prevalent than severe overskilling the lack of significance of the estimates is not due to sample size problems and reflects true weaker estimates.

3.3 How persistent is overskilling?

A major area of current empirical research in labour economics aims to answer the question of whether there is state dependence in some of the key labour market processes (e.g. unemployment, wages etc) after we have controlled for observed and unobserved individual heterogeneity. This question is clearly important in the context of overskilling. Overskilling state dependence can be defined as the situation where past and/or present overskilling may influence the probability of future overskilling. The presence or absence of state dependence has important implications regarding the effectiveness of policy. Labour market states that are ‘sticky’ will also be much harder to influence in a clean, direct and quick way. Given that it is not possible to influence the past values of overskilling, one has to work on current causal factors and wait for the effect of state persistence to be reduced with time. In some economic processes this can take time that can be afforded with difficulty. Clearly, state dependence makes policy design more complex and reduces policy effectiveness, hence it is crucial to know if it is present or not. As previously stated we assess the extent of state dependence by estimating a RE dynamic panel model that controls for both the initial conditions problem and the potential correlation between the error term and contemporaneous covariates. After considering the evidence that the cost of moderate overskilling is small, shown by the lack of strong evidence that individuals trapped in a state of moderate overskilling incur substantial wage penalties (Mavromaras et al 2007a), we concentrate on the dynamic persistence of severe overskilling only.

We present a number of specifications used to estimate severe overskilling in Table 5 below. Two central findings arise from the analysis of state dependence. First, even after we have applied a number of econometric corrections that are known to remove spurious state dependence, there remains considerable true state dependence of overskilling. Second, even after we have controlled for state dependence, the direction and significance of the education coefficients remain consistent with those in Table 3. Table 5 shows that the first lag of overskilling is highly statistically significant, demonstrating that severe overskilling is a self-perpetuating state which implies that an individual falling into severe overskilling is likely to maintain that labour market state in the following year. This result would tend to contradict the temporary mismatches predictions of matching theory. If overskilling mismatches were simply due to asymmetric information one would expect that overskilled workers would have achieved more suitable matches within a year. This result does not agree with theories of job mobility either, as it may not be as likely that individuals seeking core experience would require a period in excess of one year to grasp the basic elements of their chosen occupation and cease to report themselves overskilled.

Table 5: Dynamic Random Effects Probit Estimations for Severe Overskilling

Variable	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)
Overskilling at t-1	.78 (9.16)	0.81 (0.08)	0.84 (0.08)	0.77 (0.08)
Certificates III or IV	-0.28 (0.32)	-0.30 (0.31)	-0.30 (0.32)	-0.15 (0.32)(
Diploma or degree	-1.45 (0.43)	-1.23 (0.38)	-1.23 (0.37)	-1.10 (0.41)
Gender (Female=1)	0.17 (0.08)	0.07 (0.07)	0.07 (0.07)	-0.24 (0.09)
Occupational tenure	-	0.01 (0.005)	0.003 (0.12)	-
Occupational tenure sq.	-	-	0.01 (0.035)	-
Hours worked	-	-	-	-0.01(0.004)
Means over time				
Certificates III or IV	-0.20 (0.34)	-0.18 (0.34)	-0.16 (0.34)	-0.25 (0.34)
Diploma or degree	0.62 (0.43)	0.49 (0.39)	0.50 (0.38)	0.36 (0.42)
Occupational tenure	-	-0.06 (0.008)	-0.08 (0.13)	-
Occupational tenure	-	-	0.83 (0.33)	-
Hours worked	-	-	-	-0.03 (0.006)
Constant	-1.91 (0.09)	-1.25 (0.09)	-1.12 (0.097)	-0.27 (0.16)
ρ[1]	0.72 (0.02)	0.67 (0.03)	0.65 (0.26)	0.70 (0.024)
θ[2]	0.83 (0.08)	0.93 (0.11)	0.95 (0.11)	0.88 (0.09)
Log likelihood	-4130.72	-4023.22	-4016.17	-4019.35
Sample size	24057			

Notes: [1] ρ is an estimate of the cross-period correlation of the composite error term $\varepsilon_i + u_{it}$. [2] θ is the statistic used to test if the initial conditions are exogenous. A clearly positive value of θ rejects the hypothesis that the initial conditions are exogenous, thus lending support to the adoption of the Heckman method.

Note that, after controlling for state dependence in overskilling, the higher education variable remained strong and statistically significant while the vocational education variable remained insignificant. These results are the same in all four specifications we present here, but have also been observed in a large number of regressions which we carried out in order to test the robustness of our model and which we do not report here. The results in Table 5 demonstrate that the effectiveness of a tertiary qualification as a guard against severe overskilling remains unaffected by the presence of persistent dynamic effects. However, that is not to say that once a state of severe overskilling has been acquired, graduates are more likely to exit to a improved match more quickly. The extent of transitions out of overskilling will depend heavily on the degree to which the nature of dynamic persistence varies across vocational and tertiary labour markets. To gain further insight it is necessary to re-estimated Table 5 for each educational grouping and present the results in Table 6.

Table 6: Dynamic RE Probit Estimations of Severe Overskilling by Education

	All school incl. Year 12	*Certificates III and IV*	*Adv. Diploma and Tertiary*
Overskilling at t-1	0.63*** (0.13)	0.28 (0.22)	1.11*** (0.17)
Observations	9607	5205	9245
Restricted Log Likelihood	-1883.94	-828.62	-1091.84
Unrestricted Log Likelihood	-1781.01	-733.23	-984.19
ρ[1]	0.704 (0.044)	0.818 (0.043)	0.565 (0.064)
θ[2]	0.789 (0.130)	1.855 (0.430)	1.818 (0.584)

Notes: [1] ρ is an estimate of the cross-period correlation of the composite error term $\varepsilon_i + u_{it}$. [2] θ is the statistic used to test if the initial conditions are exogenous. A clearly positive value of θ rejects the hypothesis that the initial conditions are exogenous, thus lending support to the adoption of the Heckman method. A large number of control variables were include in the estimation. Gender, immigration status, age, family status and number of children, employer size and sector. The estimation of the Certificates III/IV category was difficult to converge, but then produced sensible results.

Table 6 shows how state persistence varies by level of education. The coefficient on lagged overskilling for VET graduates is the lowest amongst all education groups and is not significantly different than zero. This implies that VET graduates who find themselves to be presently overskilled are clearly no more likely to be overskilled in the future than their presently well matched counterparts. This means that we find no evidence of state dependence within the vocational labour market. By contrast, there appears to be overskilling state dependence for both Year 12 and higher education groups. Presently severely overskilled workers holding Advanced Diplomas / Degrees are more likely to find themselves severely overskilled in the future than their presently well matched counterparts. The same applies but not as strongly to severely overskilled workers with year 12 education. The evidence supports the view that in the case of VET graduates severe overskilling tends to be a short-term phenomenon that dissipates relatively quickly enough to not be present a year later when the next HILDA interview takes place. This implies that concerning the long-term costs of severe overskilling to the workers, VET graduates score very well with the lowest costs. The opposite is true for workers qualifying by more conventional academic routes.

There may be a number of theoretical explanations regarding the differences in overskilling state persistence between VET and other graduates and our results suggests that further research should be carried out in this direction. One major difference between the type of education and skills provided by schools and universities on the one hand and VET institutions on the other hand is the degree of sectoral and occupational specificity. School knowledge is very general and transferable between sectors and occupations. The same applies to a large component of university education (in terms of developing analytical and related skills), but not to all of it. Some degrees are intensely occupation specific (e.g. medical degrees) but a very large number of degrees is rather general and can be utilised in a wide range of occupations and sectors. By contrast, VET graduates have a great proportion of their skills taught with a specific occupation in mind. In terms of providing a possible explanation for lower levels of persistence in vocational labour markets the distinction between general and specific human capital becomes important. Our results suggest that being overskilled and in possession of general human capital can be a problem for the worker as it may convey a negative signal. Whilst being overskilled and in possession of specific human capital is not so much of a problem as it may generate a lesser negative signal if any at all. The intuition is that while employers are more likely to expect that workers with general human capital should be more able to adapt to the needs of the specific job given to them (hence, in the case of those with school and university education the presence of overskilling will be a signal of lower individual ability to adapt) they understand that without further formal training it may be unreasonable to have similar expectations that the worker will adapt to a job that requires the very specific human capital that VET graduates bring to their jobs (hence, overskilling creates a lesser negative signal in the case of VET graduates). Simply put, overskilling is less acceptable for people with general human capital and they may be considered responsible for changing their jobs, than it is for people with specific human capital in jobs that require specific human capital.

Having established that true state dependence is present (in the form of a significant lagged overskilling variable in the right hand side of our overskilling incidence estimation) a crucial question to ask is how far back this effect may stretch. A number of additional regressions were estimated in order to try to answer this question by including further lags of the overskilling variable in the RHS of the overskilling estimations. We do not present these here because we do not believe that they are reliable. Our view is that once further lags are introduced, the data available for estimation becomes too short for detailed and robust estimation. In all attempts we made the second lag of overskilling was significant and, as one would expect had a weaker effect than the first lag. The majority of the remaining coefficients however, lost in significance and a small number of them assumed values that cannot be reconciled with other existing evidence. Adding a third lag in the RHS did not result in a significant coefficient, indicating that the lagged effects do not carry further than two periods back. Although we could be tempted to argue that this is evidence of short-lived state persistence of overskilling, we believe that we should not and we should simply acknowledge that our data is not sufficient for testing longer lags hypotheses. The reason is that, once all three lags were included in the RHS, the overall model was not reliable and all other variables (except the lagged overskilling ones) lost their significance and assumed coefficient values that make no empirical or theoretical sense. Nevertheless, if we look at our persistence results as a whole we can argue that once an individual becomes severely overskilled, they have a pretty good chance to remain so for one more year and possibly for two years. There is therefore some evidence that casts doubt on the assumed predominance of job mobility and matching theories in the labour market. Given that in international standards the Australian labour market can be thought of as a well de-regulated market with considerable flexibility, this is an interesting result..

3.4 Wage effects

After examining the incidence of overskilling, we look at its wage consequences. On the grounds that we cannot totally rule out the influence of unobserved heterogeneity bias from our wage estimates we follow Mavromaras 2007a et al. by estimating the wage impacts using both the standard Ordinary Least Squares and the more robust approach of Propensity Score Matching (PSM). PSM works on the principle of matching individuals who belong to a treatment group, (in this research the treatment group will be those who are moderately or severely overskilled in their jobs) with individuals who belong to a control group (in this research the control group will be those who are well matched in their jobs). Matched pairs in the PSM context consist of two individuals (one from each group) who are similar in every observable respect apart from their overskilling. Having matched all workers we can assess the extent to which wages may differ between the control and the treatment group.[11] A number of PSM techniques are available to researchers and, on the grounds that none are considered superior to the others, have been applied here, for further details on PSM matching see the appendix. [12]

The results from both the OLS and PSM models are presented in Table 7. The first thing that becomes apparent is that the OLS estimates are generally similar to the PSM estimates, confirming the finding of Mavromaras et al. (2007a) that the OLS estimates are not subject to a high degree of bias. Table 7 compares the wage impact of moderate and severe overskilling within each educational grouping.[13] Looking at the complete sample,, the majority of our estimates suggest that individuals who are severely overskilled earn between 10.0 and 13.5 per cent less than their well matched counterparts[14]. In line with Mavromaras et al. 2007a, the analyses does not find wholly consistent evidence of a pay penalty to moderate overskilling. Splitting the sample by education level, the penalty to severe overskilling was highest among graduates ranging from between 16.2 to 18.9 per cent. The severe overskilling wage penalty among vocationally qualified workers was lower at between 11.6 and 14.4 per cent.

[11] Studies by McGuinness 2007 and Mavromaras et al. 2007a have demonstrated that the principal determinant of present mismatch is an individuals history of mismatch. Therefore, we again harness the panel characteristics of our sample to include a measure of overskilling in the previous wave as a covariate in the propensity score estimates. In doing this we effectively compare the wages of individuals who are overskilled with those with the same characteristics who were previously overskilled but are now matched. Thus, to the extent that lower levels of ability may be evident in the treatment group they will also be present in the control group by nature of their previous overskilling.

[12] Given that no lagged information exists for wave 1 the models are estimated on pooled waves 2 through to 6.

[13]Reliable PSM estimates could not be generated for the Certificate I II grouping due to their small sample size.

[14] As was the case in Mavromaras et al 2007a, the nearest neighbour technique generated estimates well below those of the other approaches and is discarded on this basis.

Table 7: OLS *versus* PSM estimates for the effect of overskilling on wages (wave 2-6)

Dependent variable: Log (wage)	**OLS**	**PSM (neighbors matching)**	**PSM (radius matching)**	**PSM (kernel matching)**
All sample				
Severely overskilled	-0.106***	-0.074***	-0.135***	-0.100***
	(0.009)	(0.023)	(0.018)	(0.018)
Moderately overskilled	-0.014**	-0.011	-0.068***	-0.027**
	(0.007)	(0.014)	(0.012)	(0.012)
Graduates				
Severely overskilled	-0.179***	-0.138***	-0.189***	-0.162***
	(0.016)	(0.039)	(0.031)	(0.031)
Moderately overskilled	-0.028**	-0.005	-0.038**	-0.023
	(0.011)	(0.021)	(0.017)	(0.017)
Certificates III and IV				
Severely overskilled	-0.128***	-0.082**	-0.144***	-0.116***
	(0.018)	(0.040)	(0.033)	(0.034)
Moderately overskilled	-0.012	-0.016	-0.029	-0.021
	(0.012)	(0.022)	(0.019)	(0.019)
Certificates I and II				
Severely overskilled	-0.131*			
	(0.067)	-	-	-
Moderately overskilled	0.041			
	(0.050)	-	-	-
Year 11-12				
Severely overskilled	-0.034**	0.00004	-0.036	-0.006
	(0.016)	(0.043)	(0.034)	(0.035)
Moderately overskilled	0.008	0.024	-0.049**	0.001
	(0.013)	(0.030)	(0.024)	(0.025)
Year 10 and Below				
Severely overskilled	-0.060***	-0.073	-0.102**	-0.077*
	(0.020)	(0.051)	(0.041)	(0.042)
Moderately overskilled	0.0002	0.031	-0.018	-0.003
	(0.017)	(0.038)	(0.031)	(0.031)

Note: Sample sizes in the category Certificates I and II were too small to allow for the necessary matching for PSM estimation.

There is no evidence for the presence of an overskilling pay penalty among the year 11-12 grouping, but there is evidence of a wage penalty (of between 6.0 and 10.2 per cent) among the completely unqualified workers (that is, highest education attainment to school year 10 or less) who deem themselves to be severely overskilled. This final result could lend support to the view that those individuals at the very bottom of the labour market and the education distributions who are undertaking the most menial of tasks are doing so for a very low wage.

4. Summary and Conclusions

This paper uses the HILDA survey, to assess the incidence, persistence and wage effects of overskilling among workers by educational pathway. The HILDA survey offers the unique opportunity of panel information on overskilling so that we can use dynamic panel methods to test hypotheses that have not been tested before in the literature. The rationale for and contribution of this study is twofold. First, we assess the extent of state persistence of overskilling in order to shed more light on the extent to which severe mismatches in the labour market represent a permanent or a transitory phenomenon. We find that, as a whole, the labour market exhibits overskilling state persistence. Second, we explore the extent to which overskilling state persistence may vary by the type of education and, by extension, by the degree of generality of the human capital of overskilled workers. We find that vocationally qualified workers, who tend to be equipped with a higher level of job relevant skills, are less exposed to the adverse impacts of overskilling.

We use a dynamic panel framework, to demonstrate the lack of evidence that labour market mismatch, as measured by severe overskilling, is a transitory phenomenon due to a temporary poor job match that will diminish with repeated job search (Jovanovic 1979) or because mismatch is a one-off deliberate strategy undertaken to enhance future career mobility ((Rosen 1972; Sicherman and Galor 1990). The results of this study demonstrate clear overskilling state persistence with workers falling into an severely overskilled state likely to remain in that state for at least one year. Our results suggest that the educational pathway matters in the context of overskilling. Only tertiary qualifications are associated with a lower probability of becoming overskilled. However, this is not to say that, once an overskilled state has been acquired, graduates will be quicker to move on to an improved match. In fact, our analysis shows that the persistence of severe overskilling is lower among vocationally qualified workers relative to both graduates and those holding school level qualifications. This suggests that while vocational workers are at least, and in some instances more, likely to become overskilled, they also have a higher likelihood of improving their job match relatively quickly. Thus, to the extent that severe mismatches are less persistent in themselves, they will be more of a relatively transitory phenomenon for vocational workers, and their long-run costs will be the lowest for VET graduates. These lower levels of persistence among vocationally qualified workers could result in less substantial labour market scarring among VET graduates who will typically have high levels of occupation-specific human capital. This suggests that being overskilled and in possession of general human capital is likely to be associated with a more substantial negative signal regarding the workers ability levels. Using both OLS and PSM methods, the paper compares the wage penalty of overskilling by qualification pathway. In line with previous research we do not find any evidence of a wage penalty to moderate overskilling. The results show that the penalty to severe overskilling was highest for graduates, then for VET graduates and then for employees without formal education.

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Appendix

Table A1: Distribution of Occupational Employment by Highest Qualification Level

	Highest Education Attainment				
Occupation	*Year 10 and below*	*Year 11 -12*	*Certificates I and II*	*Certificates III and IV*	*Adv. Diploma & Degree*
Generalist Managers	0.02	1.05	0.14	0.02	0.03
Specialist Managers	0.82	2.66	0.43	1.76	2.05
Farmers and Farm Managers	1.27	2.00	3.01	2.65	9.01
Professionals n.e.c.		0.01		2.47	1.29
Science, Building and Engineering Professionals	6.24	0.31	3.15	0.67	0.05
Business and Information Professionals	0.22	3.64	0.29	3.46	4.81
Health Professionals	1.34	1.54	1.29	1.25	12.76
Education Professionals	0.8	0.94	0.57	0.76	9.09
Social, Arts and Miscellaneous Professionals	0.37	2.24	0.14	2.00	16.45
Science, Engineering and Related Associate Professionals	1.1	1.11	0.29	2.56	8.69
Business and Administration Associate Professionals	0.66	4.95	0.86	3.72	1.94
Managing Supervisors	2.93	4.95	3.15	5.23	6.10
Health and Welfare Associate Professionals	4.42	0.32	4.87	2.02	2.92
Other Associate Professionals	0.34	1.65	0.29	0.91	1.12
Tradespersons And Related Workers		0.01		0.03	1.71
Mechanical and Fabrication Engineer Tradespersons	0.65	1.24	0.14	6.35	0.31
Automotive Tradespersons	1.12	0.57	2.72	3.16	0.06
Electrical and Electronics Tradespersons	0.61	1.15	0.43	5.99	0.67
Construction Tradespersons	0.59	1.47	2.01	6.36	0.44
Food Tradespersons	2.59	0.95	0.86	1.58	0.12
Skilled Agriculture and Horticulture	0.99	0.89	2.29	1.78	0.50
Other Tradespersons and Related workers	1.33	1.6	1.58	5.30	0.83

Secretaries and Personal Assistant	1.45	2.38	3.87	1.00	0.70
Other Advanced Clerical and Service workers	2.6	2.54	0.57	1.25	1.59
Intermediate Clerical workers	2.48	12.63	13.75	6.69	5.45
Intermediate Sales and Related workers	10.32	1.91	2.01	1.78	0.80
Intermediate Service workers	1.76	9.18	9.31	8.66	3.97
Intermediate Production And Transport workers	6.53	0.01			
Intermediate Plant Operators	3.7	1.73	3.30	2.58	0.19
Intermediate Machine Operators	1.48	0.94	1.43	0.55	0.12
Road and Rail Transport Drivers	6.03	2.13	5.16	3.35	0.48
Other Intermediate Production and Transport workers	3.68	3.61	4.44	2.42	0.52
Elementary Clerks	1.18	1.35	1.15	0.62	0.52
Elementary Sales workers	10.96	14.64	8.02	3.45	2.18
Elementary Service workers	2.39	1.57	4.73	0.86	0.34
Labourers and Related n.e.c	0.04	0.02			0.01
Cleaners	5.18	2.32	2.87	1.57	0.54
Factory Labourers	3.92	2.16	4.30	1.64	0.45
Other Labourers and Related workers	7.93	5.65	6.59	3.58	1.18