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Abstract

This paper uses panel data and econometric methods to estimate the incidence and the dynamic properties of overskilling among employed individuals. The paper begins by asking whether there is extensive overskilling in the labour market, and whether overskilling differs by education pathway. The answer to both questions is yes. The paper continues by asking whether overskilling is a self-perpetuating labour market state (state dependence), and whether state dependence differs by education pathway. The paper uses a dynamic random effects probit which includes Mundlak corrections and it models the initial conditions following Heckman's method. It finds that there is extensive overskilling state dependence in the workplace, and to the degree that overskilling can be interpreted as skills underutilisation and worker-job mismatch, this is an important finding. Overskilled workers with a higher degree show the highest state dependence, while workers with vocational education show none. Workers with no post-school qualifications are somewhere between these two groups. The finding that higher degree graduates suffer the greatest overskilling state dependence, combined with the well-established finding that they also suffer the highest overskilling wage penalty, offers an additional useful perspective to compare the attributes of vocational and degree qualifications.

JEL classification: J24, J31.
Keywords: Overskilling, education pathways, state dependence, dynamic estimation.

1. Introduction

This paper examines the dynamic properties of overskilling and its relationship with the level of qualifications of overskilled workers. Overskilling is defined as the situation where an employed worker reports that their skills are not fully utilised in their job. It is taken to reflect a form of skills underutilisation in the workplace, and the possibility of a mismatch between the worker and the job. Overskilling has been emerging as a key measure of mismatch in recent literature, in preference to the more commonly used overeducation variable (see Sloane 2003; McGuinness 2006; O'Leary et al. 2009 for overviews of this literature). One of the arguments put forward is that overskilling is a more general, and potentially more robust, measure of skills under-utilisation in the labour market than is overeducation (O'Leary et al. 2009). A well-documented adverse outcome resulting from overskilling is lower earnings, especially for university graduates. Overskilled workers use a smaller proportion of their skills. As a result they are less productive and command lower wages than their well-matched counterparts (see Green & Zhu 2008; Mavromaras et al. 2009).

This paper examines a novel aspect of overskilling, namely its dynamic properties and the possible presence of state dependence of overskilling. State dependence is defined as the degree to which the effect of any initial endowments (often referred to as individual heterogeneity, or simply characteristics) on an outcome may be attenuated or accentuated by the continued presence of that outcome (Lancaster 1979; Heckman 1981; 1991). State dependence is distinct from heterogeneity, and this distinction must be explicitly modelled in estimation for the correct understanding of outcomes that persist over time. This paper follows Heckman's (1981) method. The presence of state dependence in overskilling is important for policy reasons, as the cost of labour market mismatches for 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 & Galor 1990) predict that workers may deliberately enter their preferred profession at a level lower than is 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 could explain overskilling as a temporary phenomenon, but the presence of state dependence where being presently overskilled may influence the chances of continued overskilling could cast doubt on these predictions. Although these theoretical issues have been recognised in many instances, the empirical aspects of persistent mismatch have not received adequate attention in the literature, principally due to the lack of appropriate longitudinal data on overskilling.

The paper distinguishes employees by their highest educational attainment and considers the extent to which overskilling may differ by education level. The underlying theoretical motivation for this distinction draws on the potential differences in the way general and specific human capital can be utilised in the workplace. In particular, we examine overskilling differences between individuals who undertook specific vocational education and training, and those who obtained their qualifications via a more general academic education pathway. We build on our knowledge that overskilling varies by education pathway (Mavromaras et al 2009) and examine the possibility that state dependence may differ by education type and level. The outcome of this investigation will improve our understanding of the relative merits of rebalancing the current mix of vocational *versus* academic educational provision.

This paper is structured as follows. Section 2 describes the pertinent aspects of the Household Income and Labour Dynamics in Australia (HILDA) survey longitudinal data, which contains individuals' information on overskilling and education. Section 3 explains the econometric method we use for the estimation of overskilling state dependence. Section 4 presents and discusses the estimation results. Section 5 concludes. An Appendix contains full descriptive statistics and estimation results.

2. The data

The data for this paper come from the first six waves of the HILDA survey. HILDA is a nationally representative panel dataset of the Australian population that has been collected annually since 2001. The sample used here begins with the unbalanced panel of working-age employees (15-64 years for male; 15-59 for female) and contains a total of 42,255 person-year observations. The overskilling variable is constructed using the 7-

point scale responses 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 & van der Velden (2001) and Green & McIntosh (2002).[1] All respondents in the sample were classified into one of three groups for each yearly observation: (i) the severely overskilled (selecting 1, 2, or 3 on the scale); (ii) the moderately overskilled (selecting 4 or 5); and (iii) the well-matched (selecting 6 or 7). Sensitivity tests confirm that the cut-off points for severe and moderate overskilling are appropriate (Mavromaras et al. 2009).[2]

Table 1: Reported Overskilling in Paid Employment

Highest Education Level (Australia)	*Extent of Overskilling (%)*			%
	Well Matched	*Moderately Overskilled*	*Severely Overskilled*	
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

We group education by the highest educational qualification obtained: *below year 11* (no qualifications), *year 11 or 12* (accredited qualifications at compulsory schooling level),

[1] In the data employed by Allen & van der Velden (2001), a measure of skills underutilisation 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 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] A question arises in this context, namely whether in responding to the overskilling question, employees are not consistently factoring in skills that have no relevance to their current job. McGuinness & Wooden (2009) 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. They argue that this association demonstrates that the overskilling responses will not be biased by respondents having incorporated non-labour-market-relevant skills and abilities into these responses. 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.

certificates (vocational), *diplomas and other higher degrees*. 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 and shows high incidence and differences by education level.

An interesting observation is the high proportion of workers with few qualifications reporting themselves underutilised in the workplace (around 20 percent severely overskilled and 30 percent moderately) and the high proportion of workers with post-compulsory school qualifications reporting themselves well-matched (above 60 percent). This finding may relate to a high incidence of jobs requiring only very basic skills in the Australian labour market which, may, in turn, relate to its sectoral composition.

3 Estimation method

This paper utilises the panel nature of the HILDA data to estimate the dynamics of overskilling. We estimate the following equation:

(1) $$OS_{it} = X_{it}^{'}\beta + \gamma OS_{it-1} + \varepsilon_i + u_{it}$$

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 0 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. The first problem stems from the assumption of independence between the error terms and the covariates in the random effects model, and the second problem stems from the inclusion of a lagged dependent variable in the right-hand side of Equation 1 and its correlation with the error terms.

The problems arising from the unrealistic assumption of independence between the covariates and the error term can be resolved within the random effects framework through the application of Mundlak (1978) corrections. This is done by 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 right-hand side of Equation 1 the individual (over time) means for each of the time-varying explanatory variables. 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. It can be shown that assuming that OS_{it-1} and ε_I are independent amounts to assuming that the first observation of OS_{i1} is independent of the individual-specific error term ε_i. This assumption is difficult to justify on empirical or theoretical grounds. The problem was first examined in detail in the econometrics literature by Heckman (1981); it 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 be modelled by using the values of the first wave of a panel dataset to approximate the true values of the initial conditions. It is desirable when this method is applied, that some data that contain information that was finalised some time before the first observed period be included as a means of identification. This method is widely accepted in econometrics for its proven robustness and relative simplicity in estimation. The estimations that follow incorporate both the Mundlak corrections and Heckman's method of accounting for the initial conditions. Equation 1 can be re-written as:

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

And it has to be estimated simultaneously with the initial condition equation which is written as:

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

Note that Equation 2 utilises data starting from period 2 to the end of the observation frame, while Equation 3 utilises data exclusively from period 1. Further, Z_{i1}, the list of right-hand side 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. To this purpose the paper uses a number of questions that were asked at the first interview to collect individual background, historical, information. These are (i) a set of dummies which indicate the country of birth of the individual (Australia; not Australia but English speaking; not Australia; and not English speaking), as the country of birth will 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 individual's overskilling status in the first period. After experimentation, and considering previous results in the literature, we also decided to exclude the moderately overskilled from the analysis. This amounts to having restricted our sample to estimate the sharp contrast between the severely overskilled and the well-matched.[3] Estimations were carried out using the STATA procedure ***redprob*** developed by Stewart.[4]

4. Estimation results and discussion

4.1 Overskilling and state dependence

Estimating a random effects dynamic panel model that controls for both initial conditions and applied Mundlak corrections as in Equations (2) and (3) reveals the extent of overskilling state dependence. Table 2 contains a number of specifications that support two central findings. First, even after the application of a number of econometric corrections that are known to remove spurious state dependence (principally by removing heterogeneity that could contaminate the lagged dependent variable in the right-hand side of Equation 2), there remains considerable true state dependence of overskilling. Table 2 shows that the first lag of overskilling is highly significant statistically, which demonstrates that severe overskilling is a self-perpetuating state. The coefficient of lagged overskilling is robust to the different specifications, as one would wish it to be. The intuition behind this finding is that the negative effect of those characteristics that

[3] There is no evidence that moderately overskilled individuals incur significant wage penalties (Mavromaras et al 2009), or that they experience significant adverse mobility (McGuinness & Wooden 2007). Accepting this evidence we focus on the comparison between severely overskilled and well-matched workers. Thus our estimations exclude those who have been classified as moderately overskilled.

[4] The STATA ado files and a number of useful related papers can be found by visiting 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 researcher who wishes to use these estimation methods. The precise algebra of the likelihood function we estimate is presented by Stewart; we do not replicate it here.

were responsible for becoming overskilled in the first instance will be accentuated through the experience of continued overskilling, thus strengthening the labour market disadvantage associated with overskilling—such as lower wages.

Table 2: 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 (0.08)	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)
Higher degrees	-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)
Higher degrees	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 whether the initial conditions are exogenous. A clearly positive value of θ rejects the hypothesis that the initial conditions are exogenous, thus lending support for adopting Heckman's method.

This result would tend to weaken 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 longer than one year to grasp the basic elements of their chosen occupation and thus cease to report themselves as overskilled. Experimentation with two lags of the overskilling dependent variable indicated that overskilling state dependence remains significant for two and perhaps three periods, but the sample sizes were reduced too much to make these results statistically trustworthy. A longer HILDA panel will allow us to confirm this finding in the future.

Estimation results in Table 2 may appear to be at odds with previous research that was based largely on pooled or single cross-section data. In contrast with Mavromaras et al. (2009) where both vocational and degree-level educational variables were significant in an overskilling incidence equation, this paper finds that the effect of education level, entered in the right-hand side in the form of a set of dummies that reflect *completion* of a qualification between the previous and the present interviews, becomes statistically insignificant for vocational education. It remains significant for degree-level education (reference category 'no post-school education'). Careful comparison confirms intuition and suggests that the pooled estimation results in Mavromaras et al. (2009) and the panel results in this paper are not contradictory, as they are answering two different questions. The difference is informative. The estimates of Mavromaras et al. (2009), based on cross-section data, reflect the difference in overskilling between people with and people without a particular type of qualification, all observed at the same point in time. They suggest clearly that in the long run, education pathways that lead to either vocational or degree-level qualifications are associated with lower levels of overskilling. (Note that in the cross-section context a qualification may have been completed at any time in the past.) By contrast, the estimates in this paper reflect the effect that the completion of a qualification has had on the difference in the overskilling status that was reported in the last interview before completion, and the overskilling status reported in the first interview after the completion of the education course in question, controlling for unobserved individual heterogeneity. Our results suggest that those who obtain a degree qualification report an immediate reduction in their overskilling in the first interview after completion of their degree, while those who obtain a vocational qualification do not report such a clear-cut reduction in their overskilling right after they have completed their vocational qualification. The fact that the conditional associations between overskilling and vocational education and overskilling and degree-level education are both negative, and of a similar magnitude (in the pooled cross-section estimations of Mavromaras et al. 2009) would lead to the suggestion that the effect of vocational education on overskilling takes longer to emerge. This difference is not surprising when one considers the strong and often immediate effect that obtaining a higher degree has on a graduate's employment opportunities. This is especially so with low-skill work that often supports students during their study for degrees (although the data exclude full-time students). Results suggest that the same immediate effect is not present in the case of completing a vocational educational qualification. This section established that overskilling incidence differs by education level, and that overskilling state dependence is clearly present. It has also provided some indications that overskilling incidence by education level may be different in the short run suggesting that there may be differences in the dynamics of overskilling by education level. Therefore in next section we ask the question of whether overskilling state dependence may be different by education level.

4.2 Does overskilling state dependence vary by education level?

To answer the question of whether overskilling state dependence may be different by education level we carried out the same estimation on three separate sub-samples by highest education qualification at the time of interview. One sub-sample contains only school graduates, one contains only vocational education graduates, and one contains only higher degree graduates. The objective is to compare the direction and level of the lagged dependent variable as a reflection of differences in state dependence by education level. Apart from dropping the education variables from the right-hand side, the estimation is the same as in Table 2. Table 3 below reports the results, concentrating on the coefficients of the lagged overskilling variable.

It is clear that overskilling state persistence varies by level of education. The coefficient on lagged overskilling for vocational education graduates is the lowest amongst all education groups and is not significantly different to zero. This implies that vocational education graduates who are presently overskilled are clearly no more likely to be overskilled in the future than their presently well-matched vocational education counterparts. This means that here we find no evidence of state dependence within the vocational labour market.

Table 3: Dynamic RE Probit Estimations of Severe Overskilling by Education

	All School Including Year 12	*Certificates III and IV*	*Higher Degrees*
Overskilling at t-1	0.63*** (0.13)	0.31 (0.75)	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)	0.72 (0.25)	0.565 (0.064)
θ[2]	0.789 (0.130)	1.91 (3.16)	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 included in the estimation: gender, immigration status, age, family status and number of children, employer size and sector. The estimation of the Certificates III and IV category was difficult to converge, but then it did produce sensible results.

By contrast, there appears to be overskilling state dependence for both school graduates and for higher degree graduates. The significant coefficients in the lagged overskilling variable in Table 3 for these two educational outcomes suggests that graduates with higher degrees who are presently overskilled in their job are more likely to find themselves overskilled in the future than are their presently well-matched counterparts. The same applies, but not as strongly, to overskilled school graduates. The evidence supports the view that in the case of vocational education graduates, overskilling is more likely to be a short-term phenomenon that dissipates (relatively) quickly enough not to be present a year later at the next HILDA interview. The picture that emerges is one where vocational education graduates do not realise the benefits of lower overskilling straight after graduation (hence the incidence coefficients in Table 2 are not significant for vocational education), but they do so in later years. Indeed, the pooled regression results in Mavromaras et al. (2009) suggest that in the long run vocational education graduates end up with the lowest overskilling rates in the entire labour force. By contrast, degree-level graduates are, on average, more likely to realise the reduction of overskilling shortly after their graduation. However, for those who are unlucky enough to be the outliers and who remain overskilled after graduation, the chances of escaping overskilling are reduced through the greatest state dependence in the whole labour force.

4.2 Discussion

It is worth remembering at this point a well-established result in the literature: the wage penalties from overskilling are the lowest in the labour force for vocational graduates and are the highest for higher degree graduates. A complex picture arises from looking jointly at the incidence and state dependence findings presented in this paper and the wage penalty findings. First, overskilling is less likely for vocational education and for degree-level graduates than for school graduates (Mavromaras et al, 2009). In other words, post-school education in general reduces the chances of overskilling. Second, the consequences of overskilling are nowhere near as serious a problem for vocational education graduates as they are for higher degree graduates. Overskilled vocational education graduates suffer a much lower overskilling wage penalty (Mavromaras et al, 2009) and they have a higher probability of escaping overskilling if they have been unlucky enough to be overskilled.[5] By contrast, overskilled higher degree graduates suffer the highest overskilling wage penalty and have the lowest probability of escaping overskilling if they have been unlucky enough to be overskilled. School graduates appear to be somewhere in the middle between the two post-compulsory education pathways.

A number of theoretical explanations relate to the differences in overskilling state persistence between vocational education and higher degree graduates, but this paper only provides some speculative suggestions. One difference between the type of education and skills provided by schools and universities on the one hand, and vocational education institutions on the other 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. Although some degrees may be intensely occupation-specific (for example medicine, law, accounting, and others) a very large proportion of study for most degrees develops rather general analytical skills that can be utilised in a wide range of occupations and sectors. By contrast, vocational education

[5] Mavromaras et al (2009) find considerable overskilling wage penalty using a number of econometric methodologies and the HILDA data. They distinguish their sample by the level of the highest qualification of workers and report overskilling wage penalty estimates that range from 6.3 to 7.3 percent for workers with vocational education and training to 13.7 to 19 percent for workers with higher degrees. Workers without post-school qualifications are somewhere in the middle, depending on whether they completed school or not.

graduates have a bigger 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, and the expectations and signals associated with each type of educational pathway are pertinent considerations. Results in this paper suggest that being overskilled and in possession of general human capital can be a problem for the worker in terms of lower wages and higher state persistence, especially for those workers with higher levels of general human capital. By contrast, being overskilled and in possession of the specific human capital developed by vocational education does not appear to be much of a problem either in terms of lost wages or in terms of state dependence. The intuition is that while employers are more likely to expect that workers with general human capital should be better able to adapt to the specific needs of their job, they may be less attractive than workers who have already developed a set of work relevant skills through vocational education and training This type of information cannot be found in the conventional, large datasets typically used for the analysis of workplace mismatch. A combination of qualitative and quantitative data would be most appropriate for generating this valuable information.

5. Summary and conclusion

This paper was motivated by the growing evidence in the empirical labour economics literature that overskilling is an important labour market phenomenon, and by the emergence of the HILDA dataset that provides up to date panel information on overskilling. Research to date, including that of the authors of this paper, has concentrated primarily on the wage penalty that overskilled workers are faced with when compared with their well-matched counterparts. This paper adds a new dimension to the debate by estimating the factors that are associated with the incidence and with the state dependence of overskilling, and by showing that using dynamic panel econometric methods makes a difference. Our findings suggest that overskilling incidence differs by educational pathway among other factors. These findings also suggest that overskilling, like other adverse labour market outcomes, exhibits considerable state dependence and that this overskilling state dependence differs strongly by education pathway.

Overskilling state dependence is shown to be at its worst for higher degree graduates, lower but still present for school graduates with no post-compulsory school education, and not present for vocational training graduates. The paper combined these novel findings on overskilling incidence and state dependence with existing evidence on overskilling wage penalties to suggest that workers who complete vocational education and training suffer the least damage by the various outcomes of overskilling in the labour market.

Appendix

Table A1: Extended results on Table 3 estimations

	All schooling (incl. Year 12)		*Certificates III & IV*		*Higher degrees*	
	Coeff.	*Std.Error*	*Coeff.*	*Std.Error*	*Coeff.*	*Std.Error*
<u>*Main panel estimation results*</u>						
Overskilling at t-1	0.63	0.13	0.31	0.75	1.11	0.17
Female	-0.04	0.16	-0.13	0.24	-0.05	0.15
Occupational tenure	0.01	0.01	0.03	0.02	0.00	0.01
Hours worked	-0.01	0.01	0.00	0.02	-0.01	0.01
Firm size up to 4	-0.10	0.28	-0.02	0.48	0.05	0.32
Firm size 5 to 9	-0.08	0.27	0.22	0.56	-0.13	0.34
Firm size 10 to 19	-0.38	0.26	0.35	0.44	-0.42	0.30
Firm size 20 to 49	-0.27	0.21	0.12	0.39	0.14	0.23
Sector						
Agriculture	-0.88	0.68	2.36	1.19	0.19	0.78
Mining	-1.91	1.17	0.28	1.12	3.02	1.04
Electricity	-1.82	1.27	-0.71	2.09	0.70	1.31
Construction	-0.87	0.47	1.30	1.00	0.66	0.66
Wholesale	0.81	0.40	-0.09	0.63	0.34	0.50
Retail	0.36	0.36	0.55	0.59	1.13	0.50
Accommodation	0.27	0.49	-0.54	1.29	1.30	0.91
Transport	0.16	0.46	-0.62	0.82	0.61	0.70
Commerce	0.80	0.78	1.18	1.16	1.95	1.49
Finance	0.28	0.62	-0.79	2.09	0.18	0.86
Property	-0.27	0.39	0.69	0.65	-0.17	0.46
Defence	-0.17	0.55	1.19	1.29	0.13	0.58
Education	-0.75	0.64	2.44	1.45	0.59	0.56
Health	-0.60	0.49	0.53	0.89	0.17	0.55
Cultural	-0.83	0.62	-0.74	1.73	0.63	0.77
Personal	-1.83	0.73	0.19	0.76	0.38	0.73
<u>*Mundlak corrections*</u>						
Occupational tenure	-0.05	0.01	-0.07	0.05	-0.03	0.01
Hours worked	-0.03	0.01	-0.04	0.02	-0.02	0.01
Firm size up to 4	-0.02	0.36	-0.17	0.54	0.08	0.40
Firm size 5 to 9	-0.35	0.39	-1.25	1.69	0.22	0.46
Firm size 10 to 19	-0.14	0.37	0.13	0.51	0.63	0.41
Firm size 20 to 49	0.48	0.36	-0.70	0.48	0.09	0.36
Sector						
Agriculture	0.45	0.80	-2.65	1.24	0.03	0.96
Mining	0.79	1.35	-0.80	1.10	-3.03	1.32
Electricity	0.87	1.43	1.27	2.70	-0.23	1.57
Construction	0.48	0.59	-1.86	1.01	-0.62	0.80
Wholesale	-1.08	0.58	-0.08	1.15	0.38	0.65
Retail	-0.52	0.47	-0.25	0.82	-0.12	0.67
Accommodation	-0.20	0.64	0.24	1.46	-0.13	1.32
Transport	-0.03	0.60	0.30	0.91	0.09	0.92
Commerce	0.01	0.94	-0.16	1.41	-3.28	2.14
Finance	-1.36	0.75	1.63	2.39	-0.91	0.97

Property	-0.20	0.52	-2.58	3.07	-0.52	0.55
Defence	-0.76	0.72	-1.83	1.21	-0.57	0.66
Education	-0.41	0.76	-4.68	2.34	-1.58	0.64
Health	-0.89	0.62	-0.99	0.88	-1.00	0.62
Cultural	-0.13	0.80	0.98	2.11	-1.33	0.94
Personal	0.85	0.78	-0.11	0.83	-1.98	0.98
Constant	0.72	0.35	0.11	0.49	-0.12	0.36
Initial conditions estimation						
Female	0.11	0.13	0.16	0.54	-0.04	0.27
Occupational tenure	-0.02	0.01	-0.03	0.06	-0.03	0.02
Hours worked	-0.02	0.01	0.00	0.04	-0.05	0.02
Firm size up to 4	0.39	0.27	-0.16	0.70	-0.48	0.51
Firm size 5 to 9	0.33	0.28	-1.09	1.01	-0.82	0.64
Firm size 10 to 19	0.28	0.27	0.54	0.59	-0.55	0.53
Firm size 20 to 49	-0.31	0.24	0.01	0.92	0.24	0.47
Sector						
Agriculture	-0.82	0.60	-0.85	0.80	0.24	1.50
Mining	1.31	1.16	-0.16	2.79	-4.92	3.35
Electricity	-7.98		-2.71	4.81	-1.21	3.16
Construction	-1.28	0.51	-2.81	2.56	-1.91	1.37
Wholesale	0.33	0.39	-0.75	2.74	-0.20	1.04
Retail	-0.02	0.35	0.21	1.94	-0.56	0.87
Accommodation	0.03	0.46	0.14	0.91	-0.32	1.39
Transport	1.02	0.53	0.21	0.94	-1.70	1.44
Commerce	-0.51	0.74	-1.89	2.84	3.07	2.01
Finance	-0.27	0.66	-41.33		-1.29	1.35
Property	-0.71	0.41	-0.48	1.20	-1.06	0.70
Defence	-0.01	0.59	-2.64		-2.13	1.19
Education	0.05	0.58	-2.55	2.02	-1.99	1.08
Health	-0.83	0.49	-3.37	3.47	-2.23	1.15
Cultural	-0.50	0.60	-7.55	9.08	-0.90	1.03
Personal	0.10	0.65	-1.99	1.49	-1.80	1.16
Mundlak corrections						
Occupational tenure	-0.02	0.01	-0.08	0.08	-0.06	0.03
Hours worked	-0.02	0.01	-0.05	0.03	0.00	0.02
Firm size up to 4	-0.65	0.33	0.10	0.81	0.98	0.69
Firm size 5 to 9	-0.43	0.34	0.30	1.18	1.20	0.75
Firm size 10 to 19	-0.62	0.35	-1.01	.	0.73	0.71
Firm size 20 to 49	0.44	0.32	-0.41	1.33	-0.06	0.65
Agriculture	0.86	0.68	0.78		-0.38	1.86
Mining	-2.59	1.23	-0.63	4.16	4.61	3.31
Electricity	-1.17	2.19	1.72	4.40	1.11	3.55
Construction	0.91	0.55	2.09	1.90	0.91	1.48
Wholesale	-0.34	0.51	-0.13	1.48	0.21	1.33
Retail	-0.43	0.42	-0.35	1.55	0.96	1.18
Accommodation	-0.11	0.55	-1.34		2.28	1.97
Transport	-1.37	0.62	-0.46		2.58	1.70
Commerce	1.34	0.81	2.12	2.22	-2.99	2.26
Finance	-0.44	0.73	3.87	4.33	0.07	1.64
Property	0.03	0.49	-1.31		-0.38	0.86

Defence	-0.66	0.67	-0.08	2.86	0.70	1.12
Education	-1.62	0.67	0.39	2.20	-0.12	1.08
Health	-0.22	0.52	2.49	2.96	1.20	1.22
Cultural	-0.19	0.71	6.57	7.88	-1.23	1.35
Personal	-0.83	0.77	1.23	1.44	-0.32	1.56
Historical variables						
Immigrant: English spk cntry	0.12	0.19	-0.16	0.67	-0.45	0.35
Immigrant: Non-English spk cntry	0.13	0.17	-1.60	1.74	0.37	0.30
Professional father	0.26	0.13	-0.27	0.57	0.18	0.22
Professional mother	-0.41	0.17	-1.09	1.11	-0.46	0.33
Constant	0.96	0.29	0.09	1.03	0.63	0.64
ρ[1]	0.86	0.04	0.72	0.25	0.56	0.06
θ[2]	-0.24	0.13	1.91	3.16	1.82	0.58
Restricted Log-L	-1883.94		-799.032		-1091.84	
Unrestricted Log-L	-1781.01		-712.728		-984.187	
Cases	9607		5205		9245	

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.

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