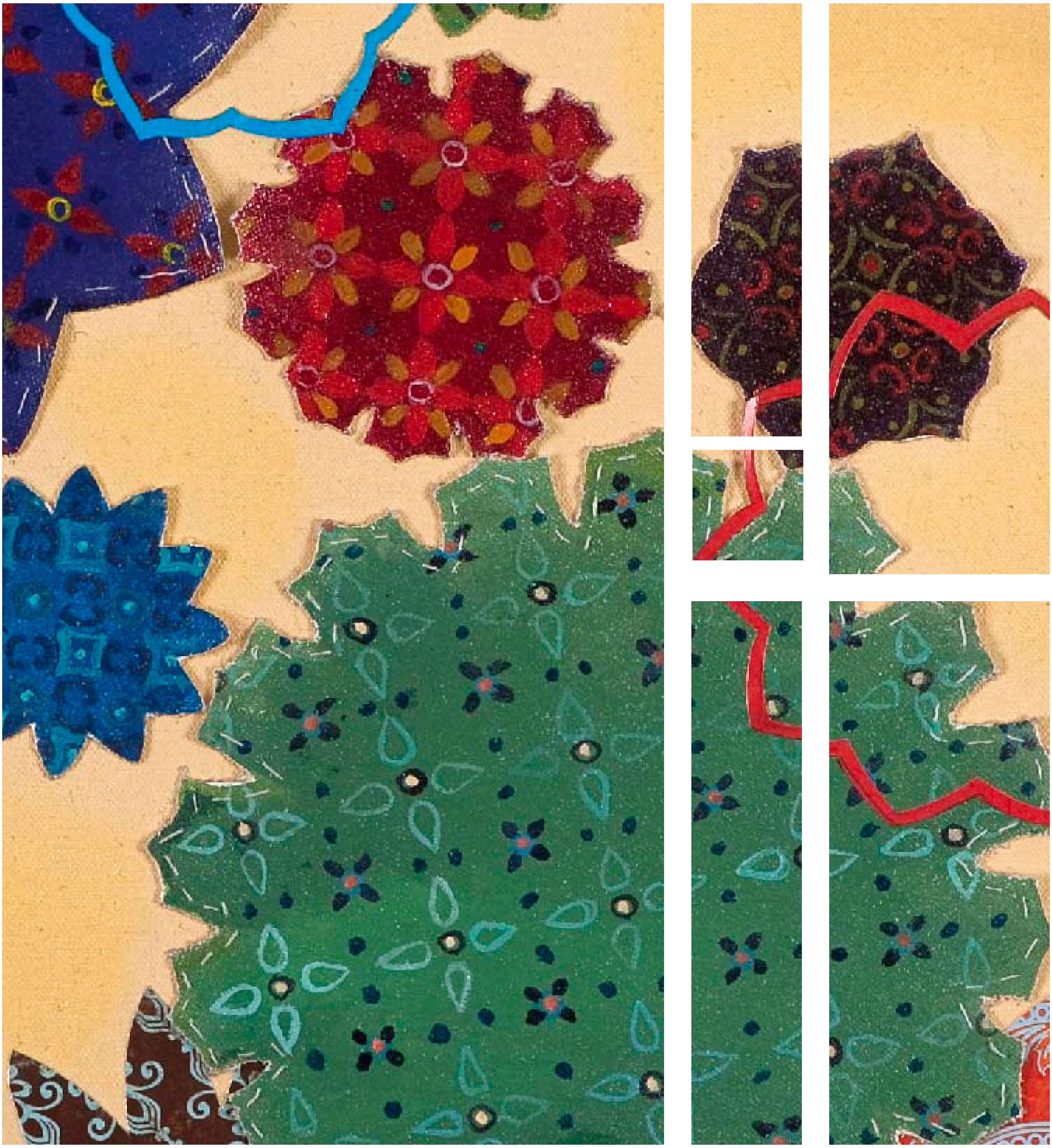

Over-education, under-education and credentialism in the Australian labour market

Alfred Michael Dockery and Paul W Miller
Curtin University

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About the research

Over-education, under-education and credentialism in the Australian labour market

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We know that, in general, the more years of education individuals acquire, the more money they are likely to earn. Recent responses from Australian governments to the demands for economic growth will see an increase in the proportion of workers holding educational qualifications, particularly higher-level qualifications. There is always a concern that there will not be enough jobs that require the proportionate level of education, and that the increase in those with higher-level qualifications will lead to credentialism rather than to a more skilled workforce.

Using data from the 2006 Census of Population and Housing and the Household, Income and Labour Dynamics in Australia (HILDA) Survey, Dockery and Miller examine the issue of credentialism by comparing the reference or required level of education for occupations and the actual education level held by an individual. They employ the 'ORU' model, where O refers to over-education (having more years of education than is required for the job); R refers to the reference or required level of education for a particular job; and U refers to under-education (having fewer years of education relative to the reference level). The credentialism dimension is captured by looking at whether the level of over-education is greater among younger cohorts and the extent to which there is a wage penalty attached to this 'over-education'.

Key messages

- Increasing education levels have given rise to a degree of credentialism, with young age cohorts having greater numbers who are over-educated relative to older cohorts.
- But the degree of credentialism is quite modest: the (wage) return from years of over-education is 6% compared with 9% for required years of education.
- The penalty for credentialism is about the same as that attached to labour market mismatch, whereby, as part of the usual dynamics of the labour market, individuals are in jobs for which they are over-educated.

While the authors find some evidence for credentialism, the results are somewhat reassuring for governments intent on improving education levels. While more members of younger cohorts with specific higher-level qualifications may end up in jobs not commensurate with their qualifications (relative to older cohorts), there is still a healthy return from the implied 'over-education'.

Tom Karmel
Managing Director, NCVER

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Abstract

It is well established that workers with more years of education earn higher wages. By establishing a reference or 'required' level of education for a worker's occupation, it is possible to decompose an individual's actual level of education into years of required education and years of over-education or under-education relative to that occupational norm. A richer picture of wage determination can be gained by substituting these three terms for actual education in the standard Mincer wage equation. Relative to the standard estimates of returns from years of actual education, international and Australian studies using this 'ORU model' (*over*-education, *required* education, *under*-education) typically find larger returns from years of required education and modest returns from years of over-education. Workers benefit from being employed in an occupation for which they are under-educated, because the positive effect of being in an occupation with a higher reference level of education outweighs the negative effect of their years of under-education.

This report shows how the ORU model can be used to inform consideration of the wage implications of credentialism, defined as an increase over time in the education standards for specific jobs and which is not necessary for the effective achievement of tasks across positions in the labour market. Data from the 2006 Census of Population and Housing are used to establish the required (mean) level of education in each of 46 two-digit occupations for a sample of employees from waves 1 to 8 of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Both standard ordinary least squares (OLS) and panel data models show that the estimated return from years of required education exceeds the return from years of surplus education. This result is robust to the augmentation of the ORU model with variables for the occupation of employment, and to estimation on separate samples of males and females. The years of educational attainment attributable to credentialism are associated with an increase in the hourly wage of the same order of magnitude as the years of over-education in the standard ORU model. Under extreme versions of credentialism, where the level of education is used only to match individuals to jobs and where the skills that are valued in the labour market are only learned on the job, it would be expected that the credentialism wage effect would be zero. The fact that this return is not zero indicates that, even if the higher levels of schooling of our younger cohorts are not needed for them to be assigned to jobs, the skills learned at school are valued in the labour market.

There are two key policy messages from this research. The first is that the additional years of schooling associated with credentialism are not wasted: these additional years appear to be linked to the development of skills that attract a reward of around 3—6%. This is comforting for advocates of the expansion of the education sector. Second, there are large gains that could be potentially achieved through a better matching of workers' actual educational attainment to job requirements.

Introduction

The relationship between the years of education an individual has accrued and their wage rate is one of the most studied relationships in labour economics. An extensive international body of empirical evidence is highly consistent in finding a positive and sizeable wage premium associated with each additional year of education attained. For Australia, estimation of a standard Mincer earnings equation reveals that each year of education is associated with roughly a 10% higher wage rate, a figure not dissimilar to that found in many other advanced economies. It is important to note, however, that for a number of reasons this cannot be taken to represent the causal effect of education on earnings.

There is also evidence from a growing international literature that individuals receive a lower return from years of education that are in excess of the requirements for the occupation in which they work. This is typically established by identifying a 'reference level' of education for each occupation and decomposing workers' own years of education into the reference (or 'required') level for the occupation they work in, and their shortfall or surplus relative to that reference level. Those with fewer years of education relative to the reference level are termed 'under-educated' and those with more years of education than the reference level are termed 'over-educated'. Then, separate variables for years of over-education (O), years of reference or required education (R) and years of under-education (U) are included in the earnings equation in place of the conventional single years of schooling variable. This is termed the ORU model.

When compared with standard estimates of the return from years of education, this ORU approach typically finds higher returns from reference years of education, quite modest returns from years of surplus education, while, for under-educated workers, the positive effect of being in an occupation with a higher reference level of education outweighs the negative effect of their years of under-education. The first study to apply the standard ORU approach to Australian data (Voon & Miller 2005) confirmed these findings.

Thus the over-education and under-education approach provides a much richer picture of the returns from years of education in the labour market and has appeal, in that it links demand-side considerations into the typical supply-oriented human capital approach to earnings determination. From a social policy perspective, this has important implications for the net benefit of additional years of education, once foregone earnings and the direct costs of education are taken into account, and for the importance of efficiently matching the supply and demand sides of the labour market according to job requirements and workers' skill levels. It also has potentially important implications for recent policy initiatives in Australia, which have sought to increase mandatory levels of schooling and which may be seen as one component of a more general issue of credentialism.

The issue of credentialism has quite broad intellectual roots. It is associated with education being an indicator of social class rather than a means of skill development (Evans & Kelley 2001). In the modern economics literature it is usually linked to education being used as a signalling device (Spence 1973). In this situation, levels of education emerge as indicators, or signals, of innate ability rather than reflecting human capital developed through the education system. Credentialism is often viewed as synonymous with an over-time and unnecessary increase in the education standards required for the effective achievement of jobs. This is the practical implication of credentialism, which is tested below using a framework based on the ORU model.

However, there are some important limitations to the over-education and under-education approach. Firstly, it is possible that those who are employed in jobs where there is a significant mismatch between their own level of education and that of the typical worker in that occupation have systematically different attributes, which may be unobservable to the researcher. Those who secure jobs when they have less than the 'reference' level of education may have other attributes that positively impact upon their productivity, such as a strong career focus or greater confidence. On the other hand, those who accept jobs for which they are overqualified may have attributes that negatively affect their productivity. The over-qualified could also simply be engaged in longer-term planning, with some arguing that the over-qualified are perhaps engaged in the accumulation of 'on-the-job' skills that will lead to future job success. These 'unobservables' can be controlled for if the analyst has panel data — sufficient repeat observations on the same individuals over time and in different jobs. A second limitation is that the reference level of education is often defined as the average years of education observed for each occupation, and an increase in credentialism will be reflected in the models as an increase in the reference level of education and in patterns of under-education and over-education that vary by age but which may not accurately portray the true extent of these phenomena.

This study presents evidence on the sensitivity of the findings from the over-education and under-education approach to estimation, using panel data to control for unobserved heterogeneity among individuals as well as incorporating estimates of the role of credentialism. The chapter following the literature review provides a descriptive overview of key variables. This includes the construction of the reference or required level of education by occupation, based on 2006 census data and patterns in over- and under-education gleaned from longitudinal data from the Household, Income and Labour Dynamics in Australia Survey. The next chapter presents the results from models comparing the standard Mincer wage equation with those from wage equations employing the ORU approach using cross-sectional and panel techniques. The results imply that much of the difference in the estimated effects of years of under-education, years of required education and years of over-education observed in cross-section models can actually be attributed to fixed and unobserved individual effects. These findings are consistent with the handful of previous studies that have applied panel techniques to the ORU model.

The next chapter uses the ORU framework to investigate the role of 'credentialism', the gradual increases in education levels over time that are unrelated to changes in actual job requirements. This may apply if employers use years of education as a screening device to allocate workers to jobs, or through the use of the job competition model conceived by Thurow (1975), in which individuals compete for jobs rather than for wages. Evidence is found that credentialism — defined, for the purposes of inclusion in the earnings equation, as years of education for younger workers above the occupational norm for older workers — results in the same modest increases in pay that are linked to years of over-education among the older workers. In other words, credentialism can be argued to contribute to over-education, as the educational mismatch arising from this source does not appear to have any inherently different effects on wages when compared with the mismatch arising from other sources.

Several tests of the sensitivity of the findings are presented. First, occupation-specific wage effects are taken into account in the ORU model. This is important, as the variation in required levels of education in the ORU model could reflect other general characteristics of the occupation (for example, short-run skill shortages) rather than skill requirements. The addition to the earnings equation of dummy variables for the broad occupational group of employment accounts for only a very small proportion of the variation in wages unexplained by the original sets of explanatory variables and results in only modest changes to the estimated partial effects in both the conventional Mincerian model and the ORU model. Second, the analyses are undertaken on separate samples of males and females. Similar findings in relation to the wage effects of under-education, over-education and required education are established for each gender group. However, positive returns from credentialism appear to be concentrated among females, a finding that is likely to reflect an added value from the signalling of innate ability as female employment has become less segregated by occupation since the 1970s, and hence is not applicable to males. These tests show that the findings in relation to the ORU model terms, and to some degree the credentialism term introduced in this research, are robust to the range of specification issues considered.

The concluding chapter discusses some of the implications of the analysis for theory, policy and for future research.

Background and literature review

Labour is a key ingredient in all of the various production processes that generate goods and services in the economy. The organisation of that labour, however, is infinitely more complex than that portrayed in the model found in introductory economics texts, in which labour is a homogenous input into a single production function, receiving in recompense wages equal to the value of its marginal product. Rather, workers need to be allocated to jobs, which are in turn organised around the idiosyncratic requirements of the relevant factor and product markets, the physical capital and technology used, and the structure of the firm, along with many other factors. Performing in these different jobs requires a wide variety of different combinations of general skills and knowledge, and of skills and knowledge that are specific to the particular firm, industry and technology used. Some skills and knowledge may be most efficiently accrued through work experience and others through school, post-school vocational education and higher education. An occupation is a categorisation of jobs that require similar sets of knowledge and skills and involve the performance of similar tasks.

Human capital theory assumes that a worker's productivity, and hence wage, increases with years of education. For the vast bulk of the workforce, however, realising that higher productive and earnings capacity is mediated though the processes of job formation and the allocation of workers to those jobs. Completing educational qualifications signals to employers the capacity to perform more difficult or complex jobs and increases a person's chances of being allocated to a job carrying a higher wage. Thus the wage can be seen as being a characteristic of either the job or the worker. Evidently, both views apply to some degree. On the one hand, even within the same firm, promotions and bonuses generate performance-based differences in earnings between workers in the same occupation. On the other hand, a highly paid medical specialist would not earn as much working as a cleaner. There are both individual and occupation-specific effects at play in determining wages.

Which effect dominates has important implications for the role of education. If there existed a known continuum of jobs ranging from 'low productivity' to 'high productivity' *and* workers could be similarly placed on a continuum measuring their suitability to perform higher-productivity jobs, *and* the labour market perfectly matched workers to jobs with a one-to-one correlation between the two hierarchies, then the two views would be indistinguishable. For a host of reasons, imperfect information, search costs and labour immobility among them, matching in the real labour market is not so clinical. Occupation, wages and educational attainment provide only very coarse signals of the positions of jobs and workers in the respective hierarchies. Educational attainment plays the dual role of increasing workers' actual capacity to perform higher-productivity jobs and of signalling to employers their position on the continuum. So while earnings increase with educational attainment, empirically it is very difficult to disentangle the impact of education on workers' actual productivity from the signalling effect that increases their likelihood of securing a higher-paid job.

If productivity and earnings are directly linked to the level of educational attainment of individuals, then we should observe a positive relationship between earnings and education, irrespective of occupation. If, on the other hand, productivity is primarily a characteristic of the job, then within occupations persons with relatively high levels of education should earn no more than persons in the same occupation with relatively low levels of education. In an approach attributed to Duncan and Hoffman (1981), these hypotheses have been tested empirically by distinguishing between the years of required education for an individual's occupation and the actual years of education accrued by the individual.[1] This allows estimation of the returns (or wage effects) associated with years of under-education, required education and over-education, or ORU.

Hartog (2000) provides a review of empirical findings from the ORU approach and a discussion of methodological issues.[2] He identifies four key findings from this literature (2000, p.135):

- The return from required years of education is higher than that obtained from the standard Mincer wage equation, a finding that has been confirmed in studies based on data from the United States, Portugal, the Netherlands and the United Kingdom.
- Returns from years of over-education are positive but smaller than for years of required education.
- Returns from years of under-education are negative but always smaller in absolute value than the returns from required education. Hence under-educated workers receive higher wages than their counterparts with the same level of education but in correctly matched occupations.
- These findings are robust to different methods of measuring the required education for an occupation, including job content analysis (in theory, the best approach, but also the most onerous for data collection), worker self-assessment and realised matches. Chiswick and Miller (2010a) have provided more recent evidence based on data from the United States, that the same general findings are obtained when required education is determined using realised matches or worker self-assessment. Similarly, Chiswick and Miller (2010b) apply the realised matches and job content analysis methods in a study of data for Australia and arrive at the same conclusion.

The results from the first study to follow the standard ORU approach using Australian data, Voon and Miller (2005), largely conform to these findings. Using 1996 census data for full-time workers, Voon and Miller decompose individuals' years of actual education into separate terms for their occupation's required years of education and their years of over- or under-education. The 'realised match' approach is used to define required education — basing the reference level of education on the average years of education of persons observed to be working in that occupation. They estimate around a 17% increase in earnings for each year of required education, much higher than the 9% return obtained for actual years of education using a standard Mincer wage equation for the same sample. By comparison, each year of over-education results in an increase in wages of just 6.3%. Individuals are also estimated to receive high returns from securing employment in an occupation for which the reference years of education exceed their actual years of education — about 13.7% for each year of under-education, comprised of the 17.1% gain per extra year of required education less a penalty of 3.4% for each year of under-education. Controlling for the incidence of over- and under-education is found to increase the estimated gender wage gap by around three percentage points: women receive lower returns from years of required education than do men.

Other ORU studies using Australian data include Kler (2005, 2006a, 2006b), Linsley (2005), Fleming and Kler (2005), Chiswick and Miller (2006, 2010b), Messinis and Olekalns (2006) and Green, Kler and Leeves (2007). These studies use the over-education and under-education framework to examine specific aspects of the labour market, such as the roles of birthplace and language skills, visa class and the lack of recognition of qualifications obtained abroad among immigrants, and whether training

[1] While the early literature opted for the term 'required' to describe the educational norm for an occupation, in recent studies the terms 'usual' or 'reference' have been preferred in recognition of the fact that workers are frequently employed with levels of education that diverge from the occupational norm, making the term 'required' something of a misnomer.

[2] Leuven and Oosterbeek (2011) provide a more recent review, though this covers only one study for Australia.

is useful in bridging the gap between actual and required education levels. These applications show that the framework provides a powerful tool for labour market analysis.

Two other Australian studies, Mavromaras, McGuinness and Fok (2009a, 2009b) and Mavromaras, McGuinness, O'Leary, Sloane and Wei (2010), use the HILDA data to analyse overskilling in the Australian labour market, based on workers' self-assessment of the degree to which their skills are fully utilised in their jobs, in contrast to over-education. They do not consider underskilling, since there is no comparable question in the survey by which to construct such a concept. Mavromaras, McGuinness and Fok (2009a) find that workers with certificate level III or IV vocational qualifications are the least likely to experience mismatch of the form of 'overskilling'. Perhaps perversely, workers with the lowest level of vocational qualifications are the most likely to report underutilisation of their skills. Akin to existing ORU results, Mavromaras, McGuinness and Fok (2009a, 2009b) find a wage penalty associated with being overskilled, relative to correctly matched workers.

Mavromaras et al. (2010) interact the definition of overskilling from the HILDA Survey with over-education, based on the realised match approach (using the occupational mode) from the same dataset. This generates four categories of workers: correctly matched; over-educated only; overskilled only; and both overskilled and over-educated. As with Mavromaras, McGuinness and Fok (2009a, 2009b), they do not consider underskilling or under-education; however, they do consider job satisfaction as an outcome variable in addition to wages. They find that overskilling and over-education are distinct phenomena; and that wage penalties are greatest for those who are both overskilled and over-educated. Job satisfaction, on the other hand, appears only to be reduced in the presence of overskilling. Of particular significance for this current paper, Mavromaras et al. (2010) utilise the longitudinal nature of the HILDA data to estimate panel models that control for unobserved heterogeneity, and this strongly reduces the estimated impacts of overskilling and over-education on wages. These findings mirror two other studies to have utilised panel data in estimating the effects of over-education, Bauer (2002) and Tsai (2010), which also find that unobserved individual effects account for much of the apparent wage penalty associated with over-education observed in cross-sectional data.

Over- and under-education in Australia: some descriptive data

The Household, Income and Labour Dynamics in Australia Survey is a household panel survey in which respondents are tracked and interviewed each year. The panel was established through a random sample of private households in Australia, and within those households all persons aged 15 and over are interviewed. The bulk of interviews are conducted between September and December each year and, as at the commencement of this analysis, data from eight waves, spanning 2001 to 2008, were available. Around 13 000 individuals from over 7000 households responded in each year, with year-on-year attrition rates averaging below 10%. (See <http://www.melbourneinstitute.com/hilda/ for further details on the survey>.)

For the purposes of this analysis the sample is restricted to employed persons who:

- are employees (as opposed to employers, self-employed or unpaid family helpers)
- are aged 15 to 64 years
- were not still at school
- usually worked between 0 and 112 hours per week (to remove outliers)
- did not have a long-term health condition that limited the amount of work they can do.

This results in a total sample of 40 644 person-year observations across the eight waves, or around 5000 observations per wave.

To establish the benchmarks for the reference level of education in each occupation, data from the 2006 census were accessed via the Australian Bureau of Statistics' (ABS) CData Online facility. These data provide a basis for applying a realised matches approach, which appears to be the only practical method, given that the main objective of this study is to assess the impact of credentialism, which requires establishing reference levels of education for various age cohorts. Tables of the highest level of schooling completed by highest level of non-school qualification were extracted for each two-digit occupation. For completion of Year 8 through to completion of Year 12, eight through to 12 years of education (or schooling) are assumed, respectively. For those who reported 'did not go to school', completion of seven years of primary school is assumed. The results are unlikely to be sensitive to this last assumption as it applies to less than one per cent of individuals. Table 1 shows the assumptions regarding the years of education associated with the categories of highest level of non-school qualification.

Table 1 Assumed years of (post-school) education for each level of non-school qualification reported

Census category for level of education: non-school qualification	Assumed years of education
'Not applicable'	0
Certificate level I/II, 'Certificate level nfd'	0.5
Certificate level III/IV	1
Diploma and 'Advanced diploma and diploma level nfd'	1.5
Advanced diploma/associate degree	2
Bachelor degree	3.5
Graduate certificate, graduate diploma and 'graduate diploma and graduate certificate nfd'	4
Master degree and 'Postgraduate degree nfd.'	5
Doctoral degree	8

The table of years of schooling by highest level of post-school education is in the form of a six by nine matrix (years of schooling by highest level of non-school qualification), with each cell representing a different level of schooling, defined as the sum of the years of schooling and the assumed years of education associated with the highest level of non-school education. For each two-digit occupation, populating the matrix by the number of individuals in each cell allows the average years of education to be derived by occupation. The estimates at the major (one-digit) occupation level are shown in the middle columns of table 2. It is possible to use much the same assignment rules to the schooling and educational attainment variables available in HILDA. (Note, however, the sample used in the calculations based on HILDA have been restricted, as set out above.) These are shown in the right-hand columns of table 2. It can be seen that there is a very close concordance between the census and HILDA-based means and standard deviations. The one notable disagreement is the average years of education for managers, for which the estimate based on the HILDA data, at 13.42 years, is notably higher than the census estimate (12.66 years). Most of this difference lies in the higher estimate of post-school education for managers identified in HILDA (1.99 years versus 1.44 years in the census). This is likely to be a result of the HILDA sample being restricted to employees only, for the purposes of the modelling. The census data, on the other hand, will include others describing themselves as managers, including employers and the self-employed.

Table 2 Average years of education by major occupation category, 2006 census and HILDA

	Census 2006		HILDA (waves 1–8)	
	Mean	Std dev.	Mean	Std dev.
Managers	12.66	2.40	13.42	2.32
Professionals	14.77	2.02	14.86	1.94
Technicians and trades workers	11.70	1.57	11.78	1.56
Community and personal service workers	12.08	1.82	12.09	1.74
Clerical and administrative workers	12.13	1.94	12.16	1.89
Sales workers	11.63	1.73	11.87	1.67
Machinery operators and drivers	10.88	1.66	10.81	1.54
Labourers	10.88	1.74	10.96	1.74
Total (employed)	**12.41**	**2.31**	**12.68**	**2.32**

Source: Authors' calculations based on 2006 census data accessed through CData Online (see <http://www.abs.gov.au/CDATAOnline>) and HILDA waves 1–8.

The close concordance between the means in the 2006 census and the HILDA data suggest that similar results would be obtained regardless of which dataset was used to determine the reference level of education. The census data are preferred in this instance as, when the more detailed two-digit occupational categorisation is used, the larger numbers in the population-based census data ensure more accurate measures than can be obtained from the sample-based HILDA data. The means and standard deviations derived from the census data by gender and at the more detailed two-digit occupation level can be found in appendix table A1.

To explore the extent of under- and over-education, persons are defined as being correctly matched to their occupation if their own years of education are within plus or minus one standard deviation of the mean for their occupation, with both the reference mean and standard deviation taken from the census and calculated at the two-digit level (see table A1). The very small number of persons with occupations classified at the major level but as ‘not fully defined’ at the two-digit level (such as ‘20 Professionals not fully defined’) were not included in the analysis, although technically they could be, as a mean and standard deviation can be calculated for such categories from the census. Persons are considered to be under-educated if they have years of education more than one standard deviation below their occupation’s mean, and over-educated if they have years of education more than one standard deviation above their occupation’s mean.

For the pooled sample in total, just under three-quarters (72.2%) are classified as correctly matched, with the remaining one-quarter split roughly evenly between the under- and over-educated categories. The result is not greatly sensitive to the level of occupation at which the analysis is done. If the means and standard deviations are calculated only for the eight major occupational groups, instead of the 43 two-digit groups, around 68% are classified as correctly matched. Table 3 shows the breakdown by gender and wave. It can be seen that, relative to females, males are more likely to be over-educated and, correspondingly, less likely to be under-educated. For both genders there is a trend of declining incidence of under-education and growing incidence of over-education in the HILDA sample between 2001 and 2008, possibly due to rising overall educational attainment or to a lower rate of attrition among more educated persons.

Table 3 Employees under-educated, correctly matched and over-educated, 2001 (wave 1) to 2008 (wave 8), by gender (%)

	Females			Males		
	Under-educated	Correctly matched	Over-educated	Under-educated	Correctly matched	Over-educated
Wave 1	20.1	70.4	9.5	17.7	70.6	11.7
Wave 2	18.0	71.9	10.1	15.6	71.8	12.6
Wave 3	17.1	72.0	10.8	15.6	71.4	13.0
Wave 4	16.5	72.6	10.9	14.8	71.8	13.4
Wave 5	15.7	71.5	12.8	14.0	72.7	13.3
Wave 6	15.0	72.5	12.5	14.0	72.6	13.4
Wave 7	14.9	73.8	11.3	14.0	73.0	13.0
Wave 8	14.1	73.9	12.0	14.1	72.4	13.4
Total (Waves 1–8)	**16.5**	**72.3**	**11.2**	**15.0**	**72.0**	**13.0**

Table 4 reports the proportion of workers within each occupation by over- and under-education status. Managers show the lowest proportion of correctly matched workers and in particular a high proportion of over-educated workers among both male and female managers. Professionals are very unlikely to be over-educated, and this holds most strongly for women. There are some noticeable differences between males and females within the occupation categories. Women who work as ‘technicians and trades workers’ are far more likely to be over-educated than their male counterparts, while men who work as ‘sales workers’ and to a lesser extent ‘clerical and administrative workers' are much less likely to be under-educated than their female counterparts. In part this may reflect differences in the occupations at the lower levels of aggregation in the two-digit categories in which men and women are concentrated. Appendix table A2 shows the incidence of over- and under-education at the more detailed two-digit occupation level.

Table 4 Employees under-educated, correctly matched and over-educated, by occupation (pooled sample) (%)

	Females			Males		
	Under-educated	Correctly matched	Over-educated	Under-educated	Correctly matched	Over-educated
Managers	16.8	62.6	20.6	16.4	63.9	19.7
Professionals	18.5	76.9	4.6	20.5	70.8	8.7
Techs and trades	13.3	67.8	19.0	13.0	74.2	12.8
Community and pers. service workers	14.2	73.8	12.0	10.8	75.5	13.7
Clerical and admin.	18.5	67.7	13.9	11.5	70.8	17.7
Sales workers	10.7	77.5	11.8	5.5	79.3	15.1
Machine operators and drivers	11.7	77.5	10.8	17.9	74.1	8.0
Labourers	17.6	70.9	11.5	14.5	72.6	12.8
Total	**16.5**	**72.3**	**11.2**	**15.0**	**72.0**	**12.9**

It is also of interest to see whether the state of being under- or over-educated tends to be a relatively transient or persistent one. To investigate this, transitions between the states were calculated over one-year periods and over the full eight years for which the HILDA data are available. The top half of table 5 shows the transition matrix for the employed observed in any one year and the immediately following year. It can be seen from the small percentages in the off-diagonal cells that there is relatively little movement between the states in a single year. Ninety per cent of individuals are in the same state the following year, and no movement is observed from over-education to under-education, or vice versa. Even over the longer period of eight years, the matrix shows surprisingly little increase in transition probabilities. Of those observed as employees in both waves 1 and 8, 83% are classified in the same educational state, and still almost no movement between the over-educated category and under-educated category is observed. Of those who were classed as under-educated (over-educated) in wave 1, for example, 72.5% (68.7%) are classified in that same state in wave 8. As an alternative indicator, if the years of mismatch are calculated as a continuous variable (actual education minus the occupation mean), the correlation coefficient calculated from one year to the next is 0.90, declining to 0.83 after seven years. Educational mismatch, therefore, seems to be a highly persistent labour market state.

Table 5 One-year and eight-year transitions between under-educated, correctly matched and over-educated states, HILDA

		State one year later (n = 25 904)			
		Under-educated	Correctly matched	Over-educated	Total
Initial state	Under-educated	13.1	2.4	0.0	15.4
	Correctly matched	2.3	67.6	2.6	72.6
	Over-educated	0.0	2.4	9.6	12.0
	Total	15.4	72.4	12.2	100.0
		State in wave 8 (n = 2 365)			
		Under-educated	Correctly matched	Over-educated	Total
State in wave 1	Under-educated	12.6	4.6	0.2	17.4
	Correctly matched	3.3	63.4	5.4	72.1
	Over-educated	0.0	3.3	7.2	10.5
	Total	15.9	71.2	12.8	100.0

Wage equations with panel data

The HILDA data present two main alternatives for measuring the wages of employed persons. Respondents are asked a series of questions about their pay (most recent and usual pay) and they also report how many hours they work per week. From this, both weekly wages and an hourly wage rate can be derived. As an earnings measure, weekly wages suffer from the lack of comparability between people who work differing numbers of hours per week. Derived hourly wage rates, on the other hand, are subject to a further source of reporting error, as they must be based on the individual's estimate of their usual working hours as well as their estimate of pay. One option is to limit the sample to full-time workers and use usual weekly earnings as the wage measure. The main reason this approach is not followed here is that it would mean rejecting a very large proportion of female workers. Instead, the analysis reported below is based on real hourly wages, derived as usual weekly wages before tax, divided by usual weekly hours worked. As the bulk of surveying for HILDA is undertaken during the December quarter of each year, the nominal hourly wage figure is deflated by the CPI index for December in each wave to give a real wage in 'December-quarter 2001 dollars'.

To estimate the relationship between years of education and earnings, a standard Mincer wage equation takes the form:

$$\ln Y_i = \alpha + \beta X_i + \gamma S_i + \mu_i \qquad \text{(Equation 1)}$$

where the subscript i denotes individuals, $\ln Y_i$ is the log of earnings, X_i is a vector of variables other than schooling known to impact upon earnings and S_i is the number of years of education the worker has undertaken. The constant term, α, the vector of coefficients, β, and the return from years of schooling, γ, are parameters to be estimated by ordinary least squares, and μ_i is a standard error term.

A reasonably rich specification of the vector X is considered, with variables for age (five dichotomous variables for five-year and ten-year age brackets), marital status (three dichotomous variables), disability status (one dichotomous variable), part-time work (one dichotomous variable), English proficiency (two dichotomous variables), and work experience (a quadratic specification of a continuous variable) included in the estimating equation. This follows other recent studies that have used the HILDA data, such as Mavromaras, McGuinness and Fok (2009b) and Cai and Waddoups (2011).

There are a number of features of this model that could limit its usefulness, the four major ones being functional form, omitted variables, measurement errors, and the potential endogeneity of the explanatory variables.

First, the model is additive in the right-hand-side variables. Mincer (1974) considered various interaction terms, although these more general models typically do not enhance the explanatory power of the earnings equation, and the estimates become cumbersome to interpret.

Second, the model does not include a measure of ability, thereby inviting speculation over the accuracy of the estimates of the coefficients of other variables correlated with ability, and particularly the schooling coefficients. Both Griliches (1977) and Card (1999) conclude from their surveys that the ability bias in the estimated schooling coefficient is small, and the 'return to education in a given population is not much below the estimate that emerges from a simple cross-sectional regression of earnings on education' (Card 1999, p.1855).

Third, as the data are self-reported, there is the potential for reporting/recall errors to lead to mismeasurement of the variables in the model. Of particular concern is the schooling variable. Measurement error is typically linked to a downward bias in the estimated return from schooling of around 10%, which is argued to approximately offset the upward omitted variables ability bias (Card 1999).

Fourth, we follow Mincer (1974) and use a measure of work experience in the model, although, unlike Mincer, we also include variables for the worker's age. This is similar to other recent studies using the HILDA database, such as Mavromaras, McGuinness and Fok (2009b) and Cai and Waddoups (2011). Mincer's (1974) work experience variables were included in the earnings equation to capture post-school investments via on-the-job training. Work experience, along with other elements of the vector X, could be endogenous. The theoretical response to this is to consider an instrumental variables estimator. This alternative estimator is not considered here due to a lack of variables in the dataset that would be suitable instruments (for schooling, experience, marital status, language proficiency, occupation), and the general disquiet in the literature over the sensitivity of the instrumental variables results (see, for example, Levin & Plug 1999). For discussion on the relative merits of age and work experience in the earnings equation, see Blinder (1976).

Following the existing literature (Hartog 2000; Voon & Miller 2005), years of education are further decomposed into years of under-education (S^U), required education (S^R) and over-education (S^O), where required education is defined as the mean years of education in a worker's occupation, as calculated from the 2006 census data at the two-digit level (and reported in appendix table A1). That is:

$$S^O = \begin{cases} S_i - S^R \text{ if } S_i > S^R \\ 0 \text{ if } S_i \leq S^R \end{cases} \qquad S^U = \begin{cases} S^R - S_i \text{ if } S_i < S^R \\ 0 \text{ if } S_i \geq S^R \end{cases} \qquad \text{(Equation 2)}$$

and hence the wage equation is extended to the form of:

$$\ln Y_i = \alpha + \beta X_i + \gamma_R S_i^R + \gamma_O S_i^O + \gamma_U S_i^U + \mu_i \qquad \text{(Equation 3)}$$

where γ_R, γ_O and γ_U are the estimated returns from years of required education, years of over-education and years of under-education, respectively. The potential limitations of the Mincer model (Equation 1) carry over to this ORU model.[3] In addition, it is noted that the required level of education for each occupation is assumed to be the same for all workers in the occupation, regardless of their age, birthplace or gender. This assumption is standard in the literature and appears to follow from the research using the job content approach to assessing the required level of education for each occupation, where a single standard is used.

Initially the data are treated simply as pooled independent observations and take no account of the fact that there are repeated observations on the same workers, other than adjustment for the standard errors within 'clusters' (individuals). Average nominal wages grew quite strongly over the period from 2001 to 2008, and while the dependent variable is real wages, allowance is further made for wave-specific effects that might arise through changes in aggregate labour market conditions and

[3] The measurement error issue could be more acute in the ORU model, as there are multiple schooling variables that may be mismeasured. While assessment of this with multiple measures of over-education appears to attest to the gravity of the potential problem (Leuven & Oosterbeek 2011), there are no systematic patterns in the estimates across the alternative methods for assessing education—occupation mismatch (the objective job content analysis, the subjective worker self-assessment and the realised matches procedure) that would lend support to this argument.

trends in real wage growth. Virtually identical results are obtained when individual dummy variables are included for each wave and when a continuous wave (or time) variable is used instead. Hence the latter more parsimonious specification is adopted.

The results from the estimation of the standard wage equation with a time trend (Equation 1) are presented in table 6 (Model 1). As the dependent variable is the logarithm of the hourly real wage, the coefficients can be taken as an approximation of the percentage effect on real wages. The coefficient of 0.02 on the wave variable implies real wage growth of around 2% per annum over this period. Males are estimated to earn 11% higher hourly wages than females. Wages follow a parabolic or inverted-U relationship with age. The pure age effect reaches a maximum for workers between the ages of 25 and 34 years; however, this must be considered in conjunction with the effect of work experience. Wages increase with years of experience in the workforce, but at a declining rate. Taking the effects of age and experience together, the wages of a person who works continually from age 21 would peak in their early 50s. Married persons display higher wages, while those with a long-term health condition, disability or impairment earn around 4% less per hour.[4] People who speak a language other than English as their main language at home and rate their English ability as poor or 'no English at all' face a wage penalty of around 28%. These results are all broadly consistent with existing estimates of wage determination in Australia.[5]

Turning to the main parameter of interest, the coefficient on years of education of 0.07 implies an increase in hourly earnings of 7% per additional year of schooling or post-school education. This estimate is comparable with results in Australian studies, which use hourly wages as the dependent variable or which limit their focus to full-time workers. Studies based on weekly or annual earnings often report a higher return from schooling, as they also capture labour supply responses that vary by level of education.

4 Recall that the sample restrictions mean that this health condition, disability or impairment does not limit the amount of work they can do.

5 While the sample has been restricted to persons who report usually working 1—112 hours, no further removal of outliers based on the value of the hourly wage has been applied. MacDonald and Robinson (1985, p.133) suggest that retaining all observations is preferable to arbitrary truncation rules.

Table 6 Wage equation estimates, HILDA, 2001—08

Variable	Standard wage equation		Over- and under-education models					
			OLS		Random effects		Fixed effects	
	(Model 1)		(Model 2)		(Model 3)		(Model 4)	
	Coef.	*Pr>|t|*	*Coef.*	*Pr>|t|*	*Coef.*	*P>|z|*	*Coef.*	*P>|t|*
Intercept	1.65	0.000	1.09	0.000	1.22	0.000	1.32	0.000
Wave	0.02	0.000	0.02	0.000	0.02	0.000	0.00	0.879
Male	0.11	0.000	0.14	0.000	0.14	0.000		
Age (yrs):								
15–19	-0.23	0.000	-0.20	0.000	-0.19	0.000		
20–24	-0.02	0.167	0.00	0.877	0.01	0.579		
25–34	0.03	0.006	0.04	0.000	0.03	0.000		
35–44	—		—		—			
45–54	-0.06	0.000	-0.07	0.000	-0.04	0.000		
55–64	-0.08	0.000	-0.09	0.000	-0.06	0.000		
Marital status:								
Married	—		—		—		—	
Never married	-0.10	0.000	-0.09	0.000	-0.07	0.000	-0.06	0.000
Separated	-0.04	0.000	-0.03	0.000	-0.02	0.009	0.00	0.886
Widow	-0.05	0.001	-0.05	0.001	-0.04	0.000	-0.02	0.176
Has disability	-0.04	0.000	-0.03	0.000	-0.01	0.065	0.00	0.854
Job is part-time	-0.01	0.136	0.01	0.369	0.08	0.000	0.11	0.000
English ability:								
1st language	—		—		—		—	
2nd language &:								
English good/v. good	-0.03	0.003	-0.02	0.143	-0.02	0.057	-0.01	0.470
English poor/none	-0.28	0.000	-0.21	0.000	-0.17	0.000	-0.10	0.048
Work experience (yrs)	0.02	0.000	0.02	0.000	0.03	0.000	0.07	0.000
Work exp. squared/1000	-0.26	0.000	-0.26	0.000	-0.39	0.000	-0.79	0.000
Years of education								
Actual	0.07	0.000						
Required			0.12	0.000	0.10	0.000	0.06	0.000
Over-education			0.05	0.000	0.05	0.000	0.03	0.000
Under-education			-0.04	0.000	-0.06	0.000	-0.04	0.000
Obs	39 812		39 783		39 783		39 783	
Individuals	10 703		10 698		10 698		10 698	
Obs/indiv.	3.7		3.7		3.7		3.7	
R-squared	0.30		0.32		0.31		0.16	
R-sq: within					0.10		0.10	
between					0.35		0.19	
F value	408	0.000	395	0.000			141	0.000
Wald chi2					6 636	0.000		

Notes: All models estimated in STATA using XTREG with robust standard errors. Clustering is at the level of the individual.

Model 2 presents the results of the same model, but with years of education now decomposed into years of required education, under-education and over-education. This change to the model specification has little impact on the estimated effects associated with the non-schooling explanatory variables. At 12%, the estimated return from years of required education is significantly higher than the 7% return from actual years of education. However, there is a much lower return of 5% from years of education in excess of that required for an individual's occupation. In this sense, persons working in occupations requiring less education than they possess face an opportunity cost from not being employed in an occupation matching their educational attainment. Each year of under-education is associated with a 4% reduction in wages. This in fact implies that under-educated workers are better off than they would be if they were correctly matched. Take, for example, a worker who has one year of education less than the required level for the occupation in which s/he is employed. This worker is estimated to receive 8% higher wages than s/he would if employed in an occupation correctly matched to his/her years of education: 12% higher wages for the additional year of required education less 4% for his/her year of under-education.

Voon and Miller's (2005) estimates, based on the earnings of full-time workers as reported in the 1996 census, show a similar premium for each year of actual education: 9% compared with this current estimate of 7%. However, using the ORU approach, they find a much larger return from required years of education (17% as opposed to 12% here), and roughly similar returns from years of over-education (6.3% as opposed to 5.1%) and years of under-education (-3.4% compared with -4.0%). The lower return from years of required education in the current study relative to Voon and Miller's (2005) estimate for full-time workers may reflect the fact that, among full-time workers, working hours tend to be longer in occupations with higher educational requirements, thus reducing the wage premium calculated on an hourly basis. Also, Chiswick and Miller (2010b) report a return from required education of around 15% in their analysis of 2001 census data. Thus there could be a pattern of decline over time in this particular payoff.

Models 3 and 4 of table 6 test the robustness of these results to estimation using panel models that take into account the fact that the data consist of repeat observations on the same individuals. The 39 783 observations available for the estimation of the over- and under-education models actually comprise observations on 10 698 individuals. On average, each individual contributed 3.7 observations, with a minimum of one and a maximum of eight observations for any one individual. The results do not vary greatly when estimated using the random-effects model. However, results from the fixed-effects model suggest a much lower return from years of required education.[6] Importantly, the fixed-effects specification results in a much smaller difference between the coefficients on years of required education and years of either under- or over-education.[7] The return from years of over-education is only three percentage points lower than that for years of required education. Under this specification, our worker with one year of education less than the required level for the occupation in which s/he is employed is now estimated to receive only 2% higher wages than if s/he were correctly matched: 6% higher wages for the additional year of required education less 4% for his/her year of under-education.

Once the workers' levels of education relative to their occupational norm are taken into account, the estimated gender wage gap actually increases. The standard wage equation indicates that males receive a wage premium of 11%. The ORU approach suggests a male wage premium of 14%, and the figure of 11% lies well outside the normal confidence intervals for the ORU estimate. In short, none of the gender wage gap can be explained by females being more likely to be over-educated or to be working in occupations for which they are under-educated. This is explored further in the robustness tests reported in the following section. Voon and Miller (2005) also report a greater standardised female wage disadvantage in their ORU model than in the conventional Mincerian model of wage determination.

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6 By way of comparison, random-effects and fixed-effects estimation of the conventional Mincer wage equation (Model 1) result in estimates of the return from years of education of 7% and 4%, respectively.

7 The Hausman test statistic is highly significant, suggesting that the fixed-effects model is the more appropriate specification for the ORU models.

From a methodological perspective, it is interesting to note that the findings are remarkably insensitive to whether or not the reference level of education is defined at the ANZSCO[8] major occupational category (eight categories) or the more disaggregated two-digit level (43 applicable categories[9]). Table 7 reports the corresponding coefficients on the education variables when the reference level and years of over-education and under-education are defined only at the major occupational level. None of the estimates differs by more than one percentage point from those reported in table 6.

Table 7 Wage equation estimates, HILDA 2001–08, with reference level, years of over-education, and years of under-education defined at major occupational categories

Variable	Standard wage equation		Over- and under-education models					
	(Model 1)		OLS (Model 2)		Random effects (Model 3)		Fixed effects (Model 4)	
	Coef.	*Pr>|t|*	*Coef.*	*Pr>|t|*	*Coef.*	*P>|z|*	*Coef.*	*P>|t|*
Years of education								
Actual	0.07	0.000						
Required			0.12	0.000	0.09	0.000	0.06	0.000
Over-education			0.06	0.000	0.06	0.000	0.04	0.000
Under-education			-0.05	0.000	-0.06	0.000	-0.04	0.000

Notes: All models estimated in STATA using XTREG with robust standard errors. Clustering is at the level of the individual.

In terms of these findings, most interest lies in the OLS model and the fixed-effects model, which is favoured by the Hausman test over the random-effects model. The advantage of the fixed-effects model is that it can take account of any time-invariant fixed effects that might be associated with omitted variables bias in the OLS model. The disadvantages of the fixed-effects model include that the estimates will also be inconsistent if these individual specific effects are in fact time-varying. As Leuven and Oosterbeek (2011, p.26) point out:

> Job changes can however be preceded, accompanied or followed by many other changes that are unobserved and affect wages. In such cases the strict exogeneity assumption that is necessary for the fixed effects estimates to be consistent fails.

A further potential disadvantage of the fixed-effects estimator is that it relies on changes in education-occupation match/mismatch status for identification. Table 5 shows that this support for the model comes from around 10% of the sample. Finally, measurement error is often viewed as being of greater importance in the fixed-effects specification. For these reasons, we focus in the following section on the results from the random-effects estimator.

Nevertheless, it is interesting to note that the payoff from actual years of education, from years of required education, and from years of surplus education are all approximately halved under the fixed-effects specification.[10] Research into the heterogeneity in the return from education has shown that it is related to factors such as school quality, and that the factors associated with higher returns are also typically associated with higher levels of education. The additive influences of these fixed effects

8 ANZSCO = Australian and New Zealand Standard Classification of Occupations.

9 Recall that employees in the two-digit 'not fully defined' categories were not included.

10 The earnings advantage of an under-educated worker compared with a worker with the same actual years of schooling who is correctly matched to the requirements of his occupation is 2% under the fixed-effects estimation (2 = 6 – 4) and 8% under the OLS model (8 = 12 – 4). This lends support to the earlier argument that this earnings advantage was due to under-educated workers being relatively well endowed with unobservables linked to favourable earnings outcomes.

are accommodated in the fixed-effects model. It would appear, therefore, that their relative importance is the same across the three coefficients noted above.

The most important conclusion, however, is that, regardless of the set of estimates used, the fixed effects or the ordinary least squares, the same basic pattern arises. In other words, the relative magnitudes of the earnings effects associated with over-education, correctly matched education, and under-education reported in the literature are not distorted by the fixed effects that can be accommodated via the use of longitudinal data. Similarly, the policy findings, which are based largely on these relativities across the various payoffs rather than on absolute magnitudes, will not be sensitive to the particular method of estimation employed.

Credentialism versus over-education

Human capital theory assumes that education increases an individual's productivity, with likely synergies between education, experience and the use of technology and capital. Hence more education results in an individual commanding a higher wage in the labour market. Some models of wage determination in the labour market depart from this notion that wages are linked to individuals' productivity levels, arguing instead that the wage distribution is determined by the distribution of available jobs in the labour market rather than the distribution of workers' skills. Two such models are the screening hypothesis and Thurow's job competition (or job queuing) model. The screening hypothesis suggests that the achievement of higher levels of education merely signals the pre-existing abilities of individuals, which employers then use as a means to allocate potential workers to available jobs (see Layard & Psacharopoulos 1974 for an early discussion). Thurow (1975) argued that a substantial proportion of workplace skills are accumulated on the job, and that the market is not so much one of competition on the basis of existing productivity but of allocation to training slots. Employers select applicants from the queue of potential workers based on the perceived cost of their training, which is influenced by the workers' level of education. Educational attainment hence affects the worker's position in the queue, but Thurow saw wages as attached to the job and determined by the power balance and sense of justice between workers and firms.

Both the screening hypothesis and Thurow's job competition model provide a possible theoretical basis for the empirical findings from the ORU approach. As McGuinness (2006, p.392) notes, Thurow's model predicts that returns from education above that required to gain entry to the job will be zero. Undoubtedly, elements of both theories are at work in the real labour market, and their relative importance in explaining wage distributions is an empirical issue. The first part of this section uses variation in educational attainment by age cohort as a proxy to test for a trend of credentialism in the Australian labour market, and whether or not this can account for the findings in the ORU approach. The second provides two tests of the robustness of the findings, by considering the role of occupational fixed effects and differences in the wage determination process between males and females.

Credentialism

The optimal level of education 'required' for jobs will change over time as a result of the underlying characteristics of the work undertaken, such as the technology used and the industrial structure. Such changes can create a 'real' increase in the educational requirement of jobs, but can also work in the other direction, as in the case of the de-skilling associated with automation in many manufacturing processes. Credentialism can be defined as a general increase in the level of education of workers that is unrelated to these underlying requirements of the jobs in which they are employed. It can arise through workers using educational attainment to compete with each other for better jobs in the knowledge that employers use this as an imperfect signal of ability or lower training costs.

Other than through the resource-intensive process of detailed job-content analysis, it is difficult to assess the proportion of change in the average level of education in an occupation that could be attributed to 'genuine' changes in the nature of the work done and the proportion that could be attributed to pure 'credentialism'. As an admittedly imperfect indicator of trends in credentialism, differences in levels of educational attainment by age cohort are used. The rationale is that the higher levels of education accumulated by younger Australians represent a general increase in education levels rather than a response to the requirements of specific jobs. If this is the case, then we would expect to observe a negligible earnings return from the extra years of education that the younger cohorts have relative to the older cohorts. However, where the extra years of schooling are associated with the development of productive skills (reading, numeracy), which enhance the worker's value in the workplace, then we would expect to see an earnings return to the cohort effects similar to that documented above for years of surplus education. In this situation, the workers would get a modest return from the skills learned at school, but they would not get the high return associated with a greater likelihood of entering an occupation in which a higher level of skills is needed. This is simply because the occupational requirements of jobs have not really changed.

Table 8 shows the average number of years of education accrued by age cohort for all persons, as derived from the 2006 census.

Table 8 Average years of education by age cohort: 2006 census

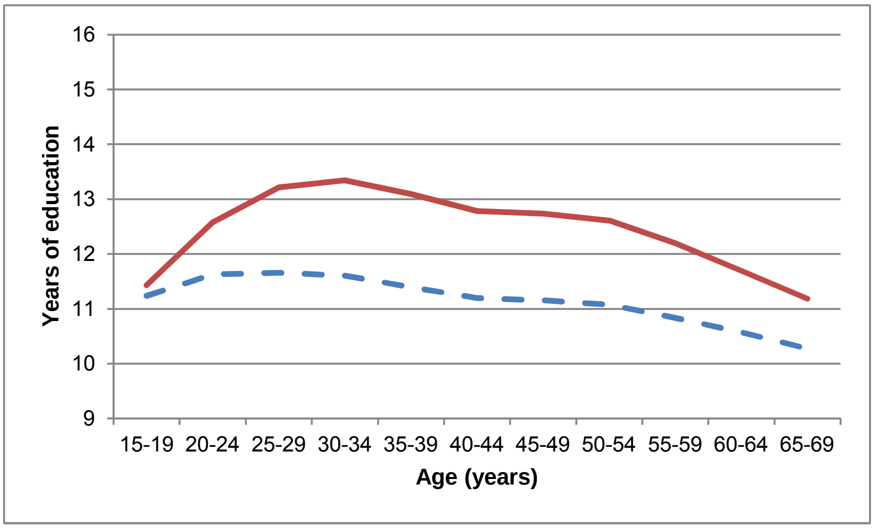
	School	Non-school qualifications	Total
15–19 years	10.66	0.06	10.72
20–24 years	11.50	0.85	12.35
25–29 years	11.46	1.48	12.94
30–34 years	11.36	1.48	12.84
35–39 years	11.12	1.35	12.47
40–44 years	10.93	1.25	12.18
45–49 years	10.85	1.24	12.10
50–54 years	10.72	1.20	11.92
55–59 years	10.47	1.05	11.52
60–64 years	10.24	0.90	11.14
65–69 years	10.00	0.75	10.74

Ignoring the 15 to 19-year-old cohort, of which many would have still been attending school, it is clear that the average number of years of schooling completed falls off steadily for older cohorts, reflecting a trend of increasing school retention over time. Similarly, for the cohorts older than 20—24 years, the average number of years of post-school education completed falls with age, suggesting an upward trend over time. It seems unlikely that these trends are due to the changing occupational composition of the labour force, such as a decrease in the proportion of labouring and related unskilled jobs, since, as figure 1 demonstrates, the trend of rising accumulated education applies in all occupations. Likewise, Karmel (2011) concludes from his analysis of the employment and qualifications data in the 1996 and 2006 censuses that one result of the large increase in persons with qualifications in Australia 'is that individuals with a certain level of qualification are being pushed toward less skilled occupations than were their peers from earlier cohorts' (Karmel 2011, p.82).

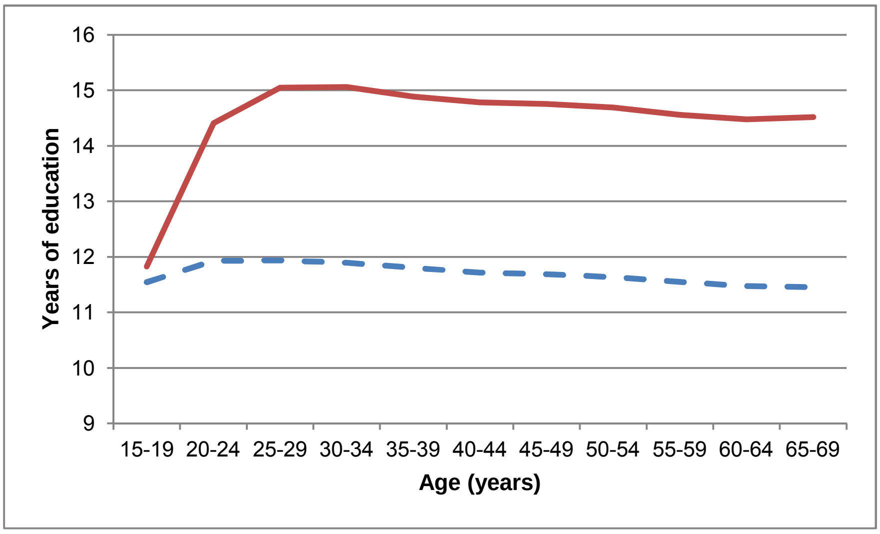
The important implication of these pictures is that it seems likely that what the previous literature, and our own previous section, has labelled 'over-education' and 'under-education' will partly be a cohort effect, whereby older workers are more likely to be classified as under-educated and younger workers classified as over-educated due simply to the norms in educational attainment that applied at the time of their formative years.

Figure 1 Trends in years of schooling and total education, by occupation, 2006 census

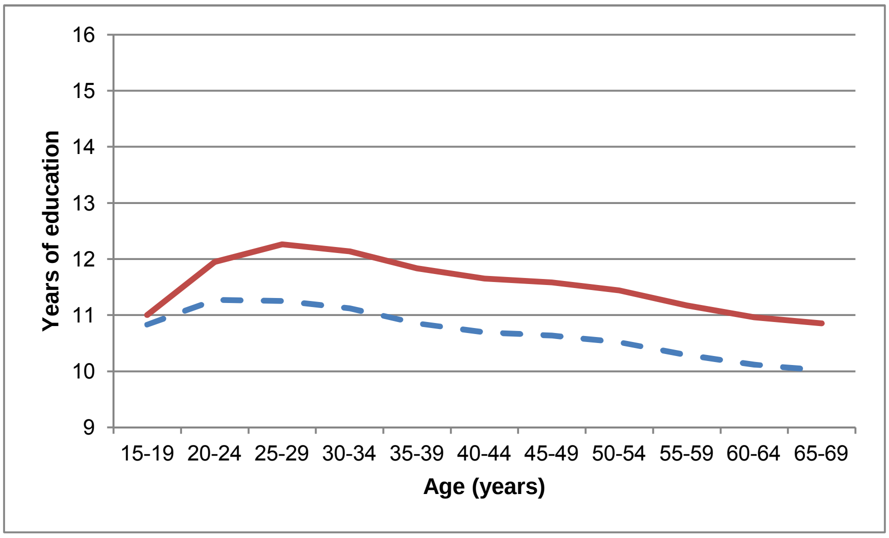
Managers



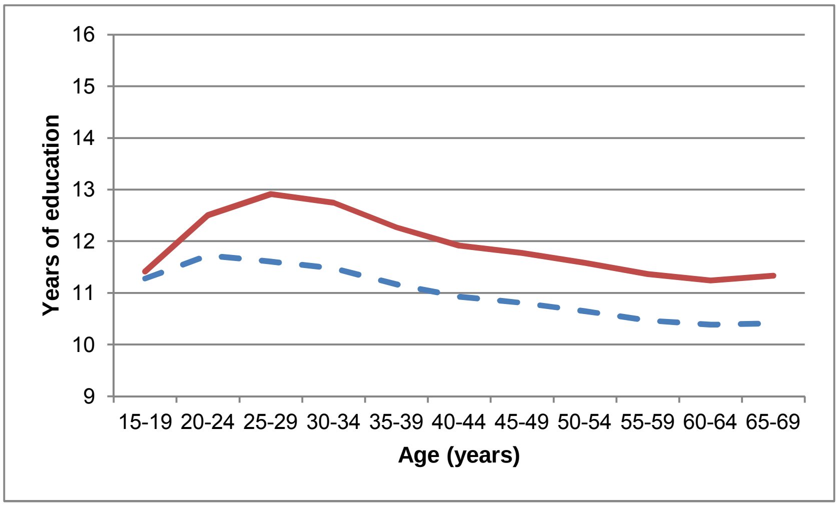
Professionals



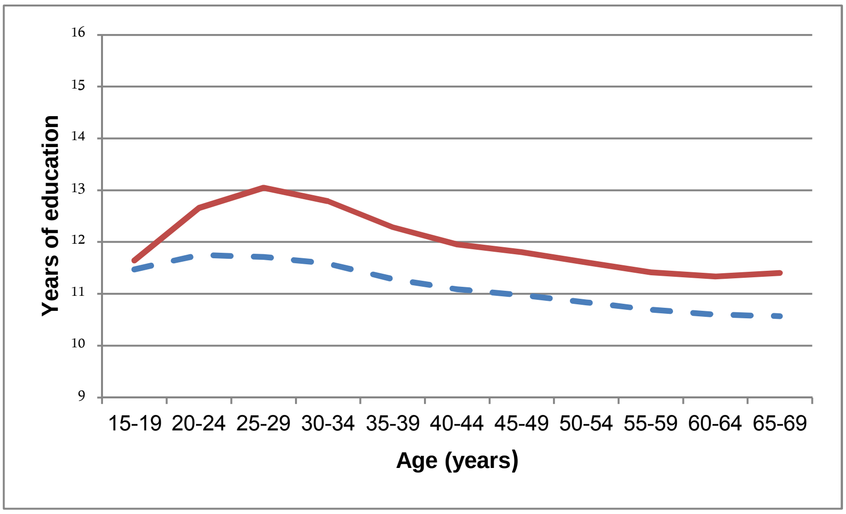
Technicians and trades



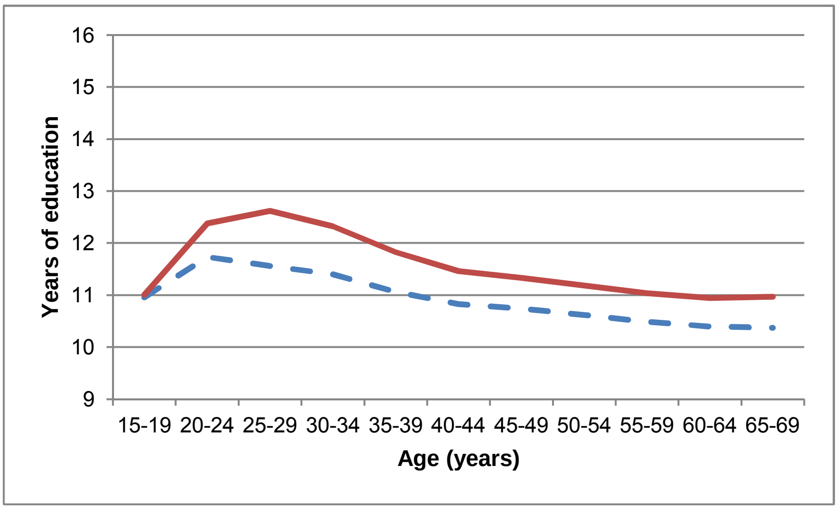
Community and personal service workers



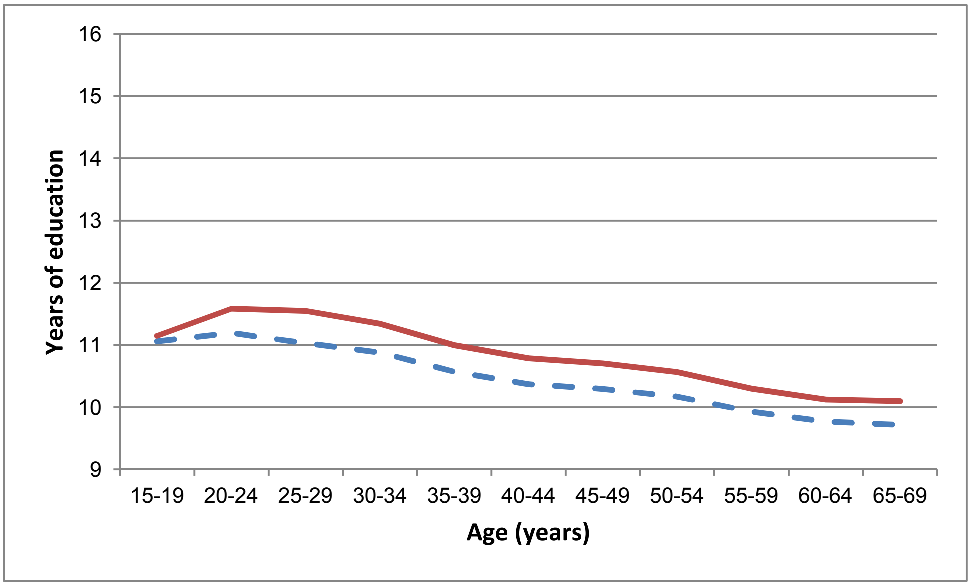
Clerical and administration workers



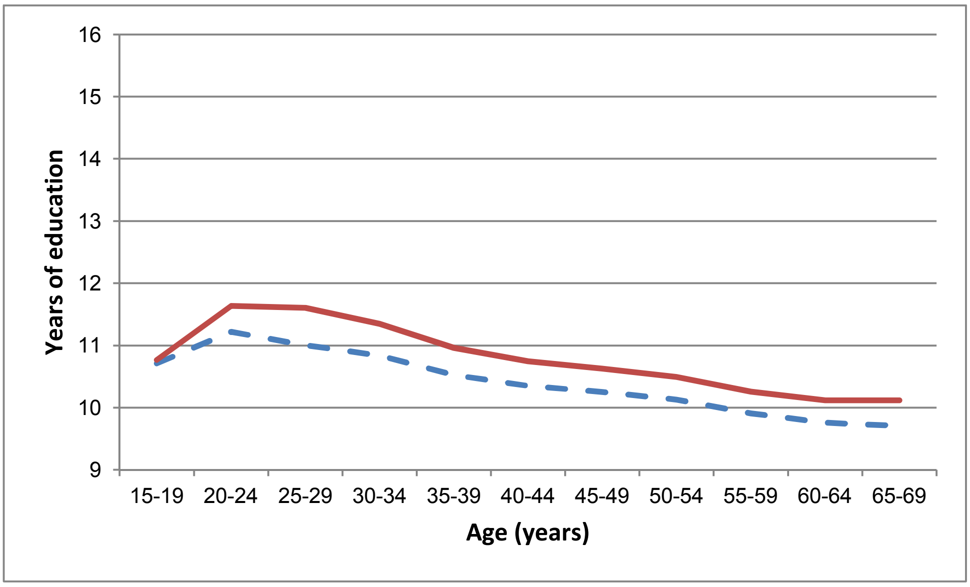
Sales workers



Machine operators and drivers



Labourers



To incorporate this into the wage equations, the differences in years of education across cohorts will be used as a proxy for credentialism. This is consistent with the view articulated in the introductory chapter that credentialism is synonymous with an unnecessary increase over time in the education standards for jobs. With this definition of the cohort or credentialism effect, each individual's years of schooling can be decomposed into an occupation reference level, the deviation from that level within the occupation associated with the individual's age cohort, and the level of over- or under-education relative to that cohort. The census data are again used to calculate a reference level of education for each of the major occupations. The 'required' level of education for each one-digit occupation is taken to be the mean years of education for persons employed in that occupation and aged 50—54 years. Divergences from that benchmark by age cohort are taken as a proxy for credentialism, such that the younger cohorts, which have typically accumulated more years of schooling, are assessed as having positive years of schooling, which are, under this definition, pure credentialism. This decomposition of an individual's years of education is thus given as:

$$S_i = S_i^{A50-54} + (S_i^C - S_i^{A50-54}) + (S_i - S_i^C) \qquad \text{(Equation 4)}$$

where S_i^{A50-54} represents the mean of years of education for employed persons aged 50—54 in individual i's occupation, taken from the 2006 census; S_i^C represents the average level of education of individual i's own cohort (in five-year intervals) and occupation; and S_i is the individual's own accumulated years of education.

The cohort effect can be included in an augmented ORU model. Letting:

$S_i^R = S_i^{A50-54}$ be the required level of education;

$C_i = S_i^C - S_i^{A50-54}$ be the cohort or credentialism effect; and

S_i^O and S_i^U be years of over-education and under-education, now defined with reference to S_i^C,

Equation 3 can be augmented as:

$$\ln Y_i = \alpha + \beta X_i + \gamma_R S_i^R + \gamma_C C_i + \gamma_O S_{C.i}^O + \gamma_U S_{C.i}^U + \mu_i \qquad \text{(Equation 5)}$$

Note that for this part of the analysis S^U, S^O, C and S^R are defined at the major (one-digit) occupation level, rather than at the two-digit level due to the intensive data extraction and computation required to generate the reference levels of education for each two-digit occupation and age group. Tests of the sensitivity of estimates to the level of occupational disaggregation noted in the previous section suggest that this should not have any major bearing on the results.

As discussed above, if the skills that are valued in the labour market are only learned on the job, the years of education above the level needed to gain entry into a job will be associated with a zero earnings return. Hence, under this extreme, we would expect $\gamma_C = \gamma_O = 0$. However, where the skills learned at school have value in the workplace, we would expect $\gamma_C = \gamma_O \neq 0$. There is no reason to expect the effect of years of over-education within a cohort (γ_O) to differ from that of the cohort or credentialism component of years of schooling (γ_C), as both represent the same skills learned at school that are not matched to the requirements of the job. However, it is expected that $\gamma_C = \gamma_O < \gamma_R$. In the usual interpretation of the coefficients of the ORU model, the impact of a year of over-education (γ_O) records the impact on earnings of the skills learned at school, and the difference between this return and the return from years of required education (γ_R) records the impact of mobility to an occupation where the higher level of education is needed. Provided that the inter-occupational mobility is rewarded, and all the empirical literature suggests that it is, it is expected that $\gamma_O < \gamma_R$. Similarly, as this inter-occupational mobility component is not a characteristic of the years of schooling that represent credentialism, it is expected that $\gamma_C < \gamma_R$.

For the estimation, the sample used is again the pooled data from waves 1 to 8 of HILDA. It is now restricted to persons aged 25 and over, given that the average level of education of a cohort is largely unrealised until this age, as is apparent from table 8. The regression results reported in table 9 are for random-effects models. For the purposes of comparison, the initial model reported in table 9 is the random-effects estimation of the standard Mincer wage equation (Equation 1), and it implies an increase in real wages of 7.2% for each year of education. Model 2 represents the corresponding 'standard' ORU model, with education decomposed into the three components of S^U, S^O and S^R. This reveals a slightly higher return from years of required education (9.6%), and returns from years of under- and over-education of around 6%, consistent with results reported above (table 6, Model 3).

Model 3 in table 9 reports the results of fitting Equation 5, now incorporating the cohort effect. The estimated effect of each additional year of education associated with the cohort effect is to raise earnings by 5.7%, which is very similar to, and not statistically different from, that for over-education. It is possible that some of the cohort effect using this approach will be obscured by the inclusion of the dummy variables capturing age in ten-year cohorts. Note that the age dummies relate to the individuals' contemporaneous age at the time of the survey, and hence many individuals will be observed to move from one age group to the next over the eight-year period of the survey. In contrast, their occupation-specific and cohort-specific years of education are based on their age at the time of the 2006 census and, hence, time-invariant unless a change in occupation occurs. So while there will be some variation in the cohort effect on education, which is independent of age effects, the models reported in table 9 were also estimated without the age dummies. The results relating to the education-related variables are not sensitive to the inclusion of the age variables.

That additional years of education associated with the cohort effect are similarly associated with a lower return from education, as observed for years of over-education, is suggestive of a degree of 'credentialism' associated with growing education levels over time. However, the positive and significant return from years of education associated with the cohort effect means that we cannot reject the hypothesis that such increases in average education levels do reflect higher productivity. Most importantly, the estimates from required, over-education and under-education are only marginally affected. The basic story, of lower returns from years of over-education relative to years of required education, and a net benefit of securing a job in an occupation for which one is under-educated, remains the same. It seems, therefore, that the typical findings from the ORU approach are not simply an artefact of the higher average years of education accumulated by younger workers relative to older workers.

In the ORU model, the comparatively high return from years of required education is a payoff to two factors: the acquisition of the educational qualification; and the job mobility to where this higher level of education is typical. By comparison, the payoff from a year of education that is surplus to the usual requirements of the worker's occupation is a payoff simply from the acquisition of the qualification. Thus, the difference between the payoffs from the required years of education and the years of over-education represents the payoff from job mobility to an occupation where the higher level of education is a match to the job requirements.

From this perspective, the similarity of the estimated impacts for the cohort effect and the years of over-education suggest that the increase in the average level of education over time has played a very minor role in the allocation of people across jobs. This is what one might expect if it is a general increase in education, rather than the result of increasing skill requirements in certain occupations. There is, however, the same monetary benefit from credentialism over time as there is to surplus education at a point in time. Presumably, they are part of the same upward creep in educational attainment that has characterised Australia and most Western countries over the past 100 years.

Table 9 Wage equation estimates, random effects, HILDA 2001–08, persons aged 25–64

Variable	Standard wage equation (Model 1)		Over- and under-education models: Standard ORU model (Model 2)		With cohort effects (Model 3)	
	Coef.	*Pr>|t|*	*Coef.*	*Pr>|t|*	*Coef.*	*P>|z|*
Intercept	1.621	0.000	1.319	0.000	1.387	0.000
Wave	0.017	0.000	0.018	0.000	0.018	0.000
Male	0.150	0.000	0.161	0.000	0.159	0.000
Age (yrs):						
25–34	0.012	0.158	0.013	0.137	0.013	0.132
35–44	—		—		—	
45–54	-0.027	0.000	-0.028	0.000	-0.028	0.000
55–64	-0.053	0.000	-0.057	0.000	-0.057	0.000
Marital status:						
Married	—		—		—	
Never married	-0.069	0.000	-0.069	0.000	-0.069	0.000
Separated	-0.019	0.004	-0.018	0.006	-0.018	0.006
Widow	-0.041	0.000	-0.039	0.000	-0.039	0.000
Has disability	-0.011	0.112	-0.011	0.111	-0.011	0.108
Job is part-time	0.058	0.000	0.060	0.000	0.061	0.000
English ability:						
1st language	—		—		—	
2nd language &:						
English good/v. good	-0.041	0.000	-0.035	0.001	-0.035	0.001
English poor/none	-0.197	0.000	-0.180	0.000	-0.181	0.000
Work experience (yrs)	0.021	0.000	0.020	0.000	0.020	0.000
Work exp. squared/1000	-0.280	0.000	-0.273	0.000	-0.274	0.000
Years of education						
Actual	0.072	0.000				
Required			0.096	0.000		
Required (mean aged 50–54)					0.092	0.000
Cohort effect					0.057	0.000
Over-education			0.060	0.000	0.058	0.000
Under-education			-0.062	0.000	-0.063	0.000
Obs	32 621		32 615		32 615	
Individuals	8 337		8 336		8 336	
Obs/indiv.	3.9		3.9		3.9	
R-squared	0.21		0.23		0.23	
R-sq: within	0.05		0.05		0.06	
between	0.21		0.23		0.23	
Wald chi2	2 695	0.000	3 048	0.000	3 076	0.000

Notes: All models estimated in STATA using XTREG with robust standard errors. Clustering is at the level of the individual.

Tests of robustness

This section reports the results of two tests of the robustness of the findings discussed above. In the first instance the estimating equation is augmented with dummy variables for occupation. Wages could vary across occupations if there are labour market imbalances or compensating differentials. As the reference years of education are defined using the occupation of employment, it is possible that variation in the reference years reflects these more basic determinants of wages (that is, labour market imbalances, compensating differentials) rather than the skill requirements of jobs. The second test of robustness investigates whether or not the findings are consistent for males and females. In each case the sample for estimation is restricted to persons aged 24—64 years, as above.

Inclusion of dummy variables for occupation

The three wage equations reported in table 10 — random-effects estimates of the standard Mincer model, the standard 'ORU' model, and the ORU/cohort model — correspond with the models reported in table 9 but with dummy variables included for the worker's major occupation (at the one-digit level). Professionals, as the most numerous group, comprise the omitted category. Note that the variables for the reference levels of education in the ORU models ('required' years of education in the standard model and 'required — mean aged 50—54' in the ORU/cohort model) cannot be included due to collinearity with occupation dummies.

The introduction of these controls for occupation into the Mincer model results in a minor reduction in the estimated return from each year of education, from 7.2% to the 5.9% reported in Model 1. The coefficients on the occupation dummies can be interpreted as wage premiums associated with employment in that occupation relative to being employed as a professional. All occupations are estimated to be associated with lower hourly wages than those earned by professionals: 2.0% lower for managers, the next most highly paid; and 16.1% lower for labourers, the lowest paid.

As expected, these inter-occupational wage differentials are accentuated in Models 2 and 3, as the occupational dummies now capture differences in the reference levels of education. Under this specification, labourers are estimated to earn around 40% less than professionals. Thus there are relatively high wages predicted from the ORU model for workers in the high-status occupations, such as professionals and managers, compared with that which can be accounted for by the high mean levels of education in those occupations. This suggests that much of the inter-occupational wage structure typically reported in the literature and which presents the professional and managerial occupations as high paid, is more correctly associated with differences across occupations in job requirements.

However, the main finding here is that the pattern in the estimated ORU wage effects and the cohort effect are essentially the same as reported previously, which suggests that this pattern is not driven by the characteristics of the occupations other than the educational requirements as measured in the ORU model. The estimated returns from years of over-education remain at around 6% in each case, and from under-education at around -6%. The estimated return from years of education associated with the cohort effect is slightly larger, at 7.2% (Model 3), but the estimate for years of over-education remains well within the 95% confidence interval of [0.04:0.10] for the cohort effect. That is, the findings are robust to the control for the one-digit level of occupations.

Table 10 Wage equation estimates, random effects with occupation dummies, HILDA 2001—08, persons aged 25–64

Variable	Mincer model (Model 1)		ORU model (Model 2)		ORU model (Model 3)	
	Coef.	Pr>|t|	Coef.	Pr>|t|	Coef.	P>|z|
Intercept	1.864	0.000	2.735	0.000	2.739	0.000
Wave	0.018	0.000	0.018	0.000	0.017	0.000
Male	0.152	0.000	0.152	0.000	0.151	0.000
Age (years):						
25–34	0.011	0.178	0.011	0.196	0.009	0.306
35–44	—		—		—	
45–54	-0.027	0.000	-0.027	0.000	-0.026	0.001
55–64	-0.055	0.000	-0.054	0.000	-0.052	0.000
Marital status:						
Married	—		—		—	
Never married	-0.069	0.000	-0.069	0.000	-0.069	0.000
Separated	-0.018	0.007	-0.018	0.006	-0.018	0.007
Widow	-0.038	0.000	-0.038	0.000	-0.038	0.000
Has disability	-0.011	0.096	-0.011	0.104	-0.011	0.102
Job is part-time	0.068	0.000	0.068	0.000	0.068	0.000
English 1st language	—		—		—	
English 2nd language &:						
English good/v. good	-0.033	0.002	-0.033	0.002	-0.032	0.002
English poor/none	-0.177	0.000	-0.176	0.000	-0.175	0.000
Work experience (yrs)	0.019	0.000	0.019	0.000	0.020	0.000
Work exp. squared/1000	-0.261	0.000	-0.260	0.000	-0.261	0.000
Occupation (1-digit):						
Managers	-0.020	0.029	-0.135	0.000	-0.143	0.000
Professionals	—		—		—	
Technicians and trades	-0.071	0.000	-0.242	0.000	-0.267	0.000
Community, personal services	-0.134	0.000	-0.282	0.000	-0.324	0.000
Clerical, administrative	-0.073	0.000	-0.219	0.000	-0.260	0.000
Sales workers	-0.135	0.000	-0.310	0.000	-0.349	0.000
Machinery operators, drivers	-0.110	0.000	-0.331	0.000	-0.360	0.000
Labourers	-0.161	0.000	-0.381	0.000	-0.415	0.000
Years of education						
Actual	0.059	0.000				
Cohort effect					0.072	0.000
Over-education			0.056	0.000	0.055	0.000
Under-education			-0.063	0.000	-0.064	0.000
Obs	32 621		32 616		32 615	
Individuals	8 337		8 337		8 336	
Obs/indiv.	3.9		3.9		3.9	
R-squared	0.24		0.24		0.24	
R-sq: within	0.06		0.06		0.06	
between	0.24		0.24		0.24	
Wald chi2	3 211	0.000	3 210	0.000	3 222	0.000

Notes: All models estimated in STATA using XTREG with robust standard errors. Clustering is at the level of the individual.

Estimates by gender

As the second test of robustness, table 11 reports separate models by gender. For comparison purposes the random-effects estimates for the standard Mincer model are reported (Models 1 and 3) and for the ORU models incorporating the cohort effect (Models 2 and 4). Some differences in the estimates by gender are that men experienced faster real wage growth from 2001 to 2008, possibly due to the boom in the male-dominated mining sector during that period; males experience a greater fall-off in earnings with age; and married males receive a higher wage premium over their unmarried counterparts than is the case for women, possibly due to a division of labour among couples, in which the woman specialises in household production, freeing up time for the male to specialise in market production (see Gray 1997).

Turning to the education variables, the results of the Mincer models suggest no difference in returns from years of actual education between males (7.1%) and females (7.3%) aged 25 to 64 years. Using the ORU model, augmented by cohort effects, the results are again broadly similar for males and females with respect to under-education, while females are estimated to receive a marginally higher return from years of required education. Some differences do emerge in the relative effects of over-education and the cohort effect. For females the return from years of education associated with the cohort effect is slightly larger, but not statistically different from, the return from years of over-education, as was observed for the full sample. For males, in contrast, the cohort effect is markedly smaller and not significantly different from zero.

These results essentially provide information on the impacts on earnings of the vertical (in terms of chronological age) and horizontal dimensions of surplus years of schooling. The vertical dimension is the credentialism or cohort effect. The horizontal dimension refers to the value of years of surplus schooling within a cohort. The results indicate that the vertical dimension of the surplus schooling has value for females, but not for males. The horizontal dimension has modest value for both males and females.

The fact that the vertical dimension has value for females but not for males could indicate that there is a signalling role for the extra years of schooling for females but not for males.[11] The 1970s was the labour market entrance decade for the 50—54 year olds, who are used to establish the reference level for education. Since then, an increasing proportion of females have been entering the labour market and this has included movement into non-traditional female jobs. Therefore, within the broad categories of occupation used to establish the reference levels of education, extra years of schooling may have played a role in allocating women to higher paid and non-traditional occupations. In order to do this, they have needed to signal their innate abilities, or value, to employers. By contrast, males have continued to enter the same types of jobs over time, and hence signals of their worth by comparison with earlier cohorts have not been needed. This could also help to explain why the school and tertiary participation rates of females have increased relative to those of males since the 1970s.

At the same time, there is a premium in any cohort to being able to demonstrate superior innate ability within any occupation, for both males and females. This is why there is the premium attached to years of surplus schooling within a specific cohort (the horizontal dimension). Alternatively, the return from the horizontal dimension of surplus schooling could reflect the value of skills learned at school. In this case we have three possibilities:

- Additional years of schooling are used in job assignment at a point in time and this is why there is the relatively high return from years of required schooling.
- Additional years of schooling for specific jobs where there have been no changes over time in labour market circumstances, particularly those on the demand-side of the market, such as in

[11] As a first approximation, a year of schooling will impart similar skills for males and females (abstracting from differences in subjects studied, types of qualifications pursued), and hence it is difficult to envisage a situation where the different payoffs to the vertical dimension are linked to gender differences in skills learned at school.

traditional male jobs, are essentially redundant and hence are associated with a minimal impact on earnings.

- Additional years of schooling within an occupation at any point in time can reflect either skills learned at school or the associated higher innate abilities of the better-educated, and hence are associated with higher earnings, albeit to a lower extent than where the additional years of schooling are associated with the inter-occupational movement to where the skills can be effectively utilised.

Table 11 Mincer and ORU/cohort wage equation estimates by gender, random effects, HILDA 2001–08, persons aged 25–64

Variable	Females				Males			
	Mincer model (Model 1)		ORU model (Model 2)		Mincer model (Model 3)		ORU model (Model 4)	
	Coef.	*Pr>|t|*	*Coef.*	*Pr>|t|*	*Coef.*	*Pr>|t|*	*Coef.*	*Pr>|t|*
Intercept	1.621	0.000	1.298	0.000	1.743	0.000	1.602	0.000
Wave	0.015	0.000	0.015	0.000	0.019	0.000	0.021	0.000
Age (yrs):								
25–34	0.030	0.015	0.025	0.050	0.002	0.856	0.006	0.625
35–44	—		—		—		—	
45–54	-0.017	0.094	-0.015	0.145	-0.032	0.004	-0.034	0.002
55–64	-0.033	0.066	-0.031	0.078	-0.058	0.011	-0.063	0.006
Marital status:								
Married	—		—		—		—	
Never married	-0.045	0.001	-0.046	0.001	-0.080	0.000	-0.079	0.000
Separated	0.001	0.885	0.002	0.810	-0.036	0.000	-0.035	0.000
Widow	-0.016	0.222	-0.014	0.268	-0.064	0.001	-0.063	0.002
Has disability	0.001	0.956	0.001	0.941	-0.020	0.018	-0.020	0.017
Job is part-time	0.057	0.000	0.061	0.000	0.059	0.002	0.062	0.001
English ability:								
1st language	—		—		—		—	
2nd language &: English good/v. good	-0.019	0.198	-0.008	0.563	-0.060	0.000	-0.057	0.000
English poor/none	-0.256	0.000	-0.227	0.000	-0.152	0.000	-0.145	0.000
Work experience (yrs)	0.021	0.000	0.020	0.000	0.024	0.000	0.023	0.000
Work exp. squared/1000	-0.313	0.000	-0.295	0.000	-0.329	0.000	-0.332	0.000
Years of education								
Actual	0.073	0.000			0.071	0.000		
Required (aged 50–54)			0.099	0.000			0.085	0.000
Cohort effect			0.077	0.000			0.033	0.131
Over-education			0.053	0.000			0.063	0.000
Under-education			-0.061	0.000			-0.062	0.000
Obs	15 883		15 883		16 738		16 732	
Individuals	4 156		4 156		4 181		4 180	
Obs/indiv.	3.8		3.8		4.0		4.0	
R-squared	0.20		0.23		0.18		0.20	
R-sq: within	0.04		0.05		0.07		0.07	
between	0.21		0.24		0.18		0.19	
Wald chi2	1 428	0.000	1 852	0.000	1 260	0.000	1 360	0.000

Notes: All models estimated in STATA using XTREG with robust standard errors. Clustering is at the level of the individual.

Decomposition of the gender wage gap incorporating the cohort effect

The contribution of the differences in returns from under-education, over-education and the cohort effect to the gender wage gap can further be examined using a standard decomposition. Econometric studies of the determinants of earnings have consistently identified an earnings premium associated with being male. As is well known, women earn lower wages on average than men, and only a portion of this difference can be accounted for by observable characteristics relating to productivity. Wage equations therefore return a positive and significant coefficient on a dummy variable for male gender (or negative coefficient on a female dummy), even when an extensive range of other control variables are included. This portion of the gender wage gap that cannot be accounted for by differences in the mean observable characteristics of men and women is termed the 'unexplained' component of the wage gap and is sometimes inferred to represent an indication of gender-based discrimination. Borland (1999) provides an overview of the relevant Australian literature.

For the estimation sample included in the ORU/cohort wage equations reported above, the raw difference in mean wages by gender is a 17.7% higher hourly wage for men: $23.59 per hour as opposed to $20.04 per hour for women. The coefficient on the male dummy variable in Model 1 of table 9 implies a 15% wage premium for males after controlling for a relatively basic set of explanatory variables, and this persists even when occupational dummies are included (table 10), implying only around one-sixth of this wage gap is readily accounted for by differences in characteristics. The estimated male earnings premium increases marginally using the ORU approach (Models 2 and 3, table 9). The increase observed once individuals' levels of over- and under-education are controlled for is to be expected, given that women are more likely to be under-educated and less likely to be over-educated than males, since these are characteristics associated with higher earnings. This was also observed by Voon and Miller (2005); however, the results reported in table 10 suggest this may be accounted for by occupation-specific effects.

By way of comparison with another study based on HILDA data, Cobb-Clark and Tan (2011), using waves 1—6 and a sample restricted to persons aged 25—65 years, find an overall wage gap of 14.3%. The 'unexplained' gap remains at around 11.0% with the inclusion of controls for occupation and measures of individuals' 'non-cognitive skills'. Using cross-sectional data for full-time workers from the 1996 census, Voon and Miller (2005) estimate a 17.9% male wage premium from a standard Mincer wage equation, and a 20.6% premium from the ORU model.

Following the method proposed by Blinder (1973) and Oaxaca (1973), the difference in the mean rates of pay between males and females can be decomposed into components attributable to differences in the means of observable characteristics for men and women, and differences in the returns from characteristics. Consider separate wage regressions for males and females:

$$\ln Y_i^M = \alpha^M + \beta^M X_i^M + \mu_i^M \qquad \text{(Equation 6)}$$

$$\ln Y_i^F = \alpha^F + \beta^F X_i^F + \mu_i^F \qquad \text{(Equation 7)}$$

Once the right-hand-side parameters for these equations have been estimated, differences in mean hourly wages of males and females can be decomposed in either of the following ways:

$$\overline{\ln Y^M} - \overline{\ln Y^F} = \hat{\alpha}^M - \hat{\alpha}^F + (\hat{\beta}^M - \hat{\beta}^F)\bar{X}^F + \hat{\beta}^M(\bar{X}^M - \bar{X}^F) \qquad \text{(Equation 7a)}$$

$$\overline{\ln Y^M} - \overline{\ln Y^F} = \hat{\alpha}^M - \hat{\alpha}^F + (\hat{\beta}^M - \hat{\beta}^F)\bar{X}^M + \hat{\beta}^F(\bar{X}^M - \bar{X}^F) \qquad \text{(Equation 7b)}$$

The decomposition given in Equation 7a assumes that the coefficients from the wage equation estimated for men are the non-discriminatory norm at which the characteristics for both males and females are evaluated. The alternative decomposition set out in Equation 7b takes the estimated coefficients for women as the non-discriminatory benchmark. Here we follow Voon and Miller (2005) in reporting the average of the results from these two approaches, thus enabling a more direct comparison with their results from a comparable decomposition using 1996 census data.

The decomposition exercise set out above has previously been used to investigate whether the added information contained in the ORU approach can explain more of the gender wage gap than the standard Mincer wage equations (Voon & Miller 2005). It is now possible to also account for the cohort effect based upon the results reported in table 11, and the results of this decomposition analysis are presented in table 12. In fact, both specifications suggest that gender differences in observable characteristics should lead to higher wages for women — 1.7% higher under the Mincer model and 2.7% under the ORU/cohort model — and thus account for none of the wage gap at all. The main effects here are the higher proportion of women working part-time, which carries a positive wage premium, and the education variables. The decomposition suggests that the higher average years of actual education 'should' contribute a 1.6% higher wage for women on average. The standard ORU variables have a slightly larger effect: the sum of the effects of the higher proportion of women who are under-educated and correctly matched and the lower proportion who are over-educated is to reduce the explained gap by 2.2 percentage points. The estimated contribution of the cohort effect, however, is inconsequential. These variables thus lead to a higher unexplained wage gap under the ORU/cohort model. The constant term and females' lower returns from years of work experience are the main drivers of the 'unexplained' component.

Table 12 Decomposition of gender wage gap: Mincer and ORU models

	Mincer models	ORU/cohort models
Explained		
Education variables		
Actual years of education	-0.016	—
Cohort effect	—	-0.001
ORU variables	—	-0.022
Other observables	-0.001	-0.004
Total explained	**-0.017**	**-0.027**
Unexplained	0.157	0.165

Although Voon and Miller (2005) find a substantially larger gender wage gap among full-time workers than is observed here for all workers, their findings are largely confirmed, in that accounting for the incidence of over-education and under-education cannot explain the gender wage differential observed in the standard Mincer models. Indeed, it exacerbates the unexplained component of the wage differential.

Conclusions

When compared with the conventional Mincer wage equation, the ORU approach offers a potentially richer model of wage determination. While the Mincer model typically considers only supply-side factors, such as the educational endowments of the workforce, the ORU approach incorporates both the supply and the demand sides of the labour market. It potentially makes allowance for the possibility that workers have endowments in excess of those required by employers, or that in times of high demand employers will appoint workers to positions with less education than would normally be required; it also allows for a less-than-perfect matching process between the supply and demand sides. Evidence of significantly lower returns from over-education relative to the returns from required education would have important policy implications for the optimal level of investment in education and in improving the efficiency of the matching processes in the labour market.

This paper has sought to present further evidence on the intricacies of the returns from education in the Australian labour market through new applications of the ORU approach, making use of Australian datasets to test the robustness of the standard findings from ORU models when confronted by several conceptual challenges. The 2006 census data, covering almost the full population of Australian employees, allows the mean level of education by occupation to be identified with a degree of certainty and at a fine level of disaggregation — in this study for 43 two-digit occupations. Combining this information with data from the HILDA Survey allows the ORU model to be estimated — and tested by — the additional information provided by a large longitudinal panel spanning eight years.

The results confirm the key findings from the ORU approach: relative to the return from years of actual education estimated in a conventional Mincer model, the estimated returns from years of required education are substantially higher, and the returns from years of over-education are substantially lower than the returns from years of required education. Workers employed in occupations for which they are under-educated receive, on average, a positive wage premium over their similarly educated but correctly matched counterparts, because the return from years of required education is greater than the penalty associated with years of under-education. Using a random-effects panel model, the estimated return from each year of required education is 10%, from years of over-education 5%, and from years of under-education minus 6%. A comparable Mincer equation shows a return from years of actual education of 7%.

However, it appears that much of the difference between the returns from years of required education relative to both over- and under-education can be attributed to fixed individual effects, rather than to educational mismatch per se. These findings are consistent with two other studies of which we are aware that have applied the ORU approach to panel data for Germany (Bauer 2002) and the US (Tsai 2010).Other studies using the HILDA data and panel techniques to assess the wage effects of overskilling confirm the importance of fixed effects, although they do not strictly follow the ORU approach (Mavromaras et al. 2010). The pattern of differences in the estimated returns from actual years of education, years of required education, years of surplus education, and from years of under-education was the same under the various methods of estimation. As many of the policy conclusions that flow from research using the ORU model are based on the relative rather than the absolute magnitudes of returns, the robustness of the pattern here is reassuring.

In addition to testing whether previous findings are robust to estimation with panel data, an important conceptual challenge to the ORU approach has been explored: is what is measured as over-education simply a manifestation of credentialism — a general increase in the level of education of workers over time that is unrelated to the underlying requirements of the jobs in which they are employed? The average number of years of both schooling and post-school education that young people complete has continually increased over time. Data from the 2006 census show that 25 to 29-year-olds had completed, on average, 1.2 more years of schooling and 0.6 of a year more post-school education than 60 to 64-year-olds. This rising tide of credentialism will mean that, within occupations, younger people will tend to be classified as over-educated and older workers as under-educated.

By taking cohort effects on educational attainment as a proxy for credentialism, it is possible to extend the ORU approach by distinguishing between the over- or under-education associated with credentialism and the over- or under-education that arises independently of cohort effects. Strong evidence of credentialism is identified in the sense that years of education associated with the cohort effect are found to provide a substantially lower return (around 5.7%) than years of required education (9.2%). However, accounting for credentialism in this way has little impact on the estimates for other ORU variables. It can be concluded that the findings from the ORU approach do not simply reflect credentialism; rather, credentialism is just one of the sources of over-education captured in the ORU models. The fact that the estimated impact of years of education associated with credentialism is so similar to the impact of years of over-education (5.8%) suggests that the rise in educational attainment over time has not increased mobility to higher-paying occupations. Rather, the payoff is the same as returns from additional years of education within the one occupation.

This is consistent with deadweight loss arising through individuals competing for jobs: while there may be inter-occupational gains for any one individual accruing more years of education, it is a zero-sum game (in terms of inter-occupational mobility) if all individuals accrue more education. However, a more nuanced picture arises when the effects of credentialism are investigated separately by gender. Trends in educational attainment have resulted in young women employees now possessing more years of education than their male counterparts, the reverse of the situation for the older cohorts. This rise in the general level of education for women does appear to have generated returns in excess of those from years of over-education, and thus to represent more than a within-occupation effect. Moreover, this gain in occupational mobility has come at the expense of males, who display a markedly lower return from rising general levels of educational attainment, consistent with the 'zero-sum game' observed for the overall labour market.

The findings from the ORU approach to estimation, including the incorporation of credentialism, were robust to two extensions to the analysis. First, the model was augmented with dummy variables for occupation of employment. Second, the model was estimated on separate samples of males and females. While the point estimates of the key parameters differ across these various estimations, in each instance the estimates support the central findings from the standard ORU model. The one potential exception relates to the differential results for the cohort effect for men and women, and this has an intuitively appealing explanation. These results, together with the similarity of the pattern in the estimated coefficients across the ordinary least squares, random-effects panel model and fixed-effects panel model suggest that a high degree of confidence can be attached to the policy recommendations.

The key policy message from the results reported here — both the confirmation of the general findings of the ORU approach and those with respect to credentialism — is the large gain that could be potentially achieved through a better matching of workers' actual educational attainment to job requirements. It is true that a year of over-education still offers a positive return in terms of higher hourly wages, in the general magnitude of 3—6%. Note, however, this is only the wage premium at a point in time. The full impact is lower if that year of education is at the expense of a year of work experience and does not take into account the private direct costs associated with that education or the public costs associated with the provision of education. Promoting stronger links between industry and the school and VET systems, so that students engage with the workforce as early as possible, may help to better align workers' educational attainment with the requirements of their occupational destinations, at least initially. Better matching can also be achieved through more intensive counselling in the education sector, and through minimising the effects of barriers to worker mobility, which can include location barriers such as poor public transport and the high costs of selling and buying residential property.

The results relating to credentialism should at least offer a warning that the ongoing trend of increasing general educational attainment for young people needs to be monitored and critically assessed. However, this is the first study of which we are aware to estimate such an effect, and more empirical evidence is needed in this area. Devising alternative approaches to distinguishing credentialism from required education would offer an important contribution in this regard. Job content analyses for selected occupations where technological changes have had a significant impact upon job requirements over time or more general proxies for technological change that differentially impact upon the requirement of different occupations may provide possible sources of such measures. The difference between men and women in the estimated impact of credentialism suggests that further investigation of this outcome using a gender-specific measure may be worthwhile. This was beyond the scope of the current paper and remains a topic for future research.

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Appendices

Table A1 Years of education by two-digit occupation and gender: means and standard deviations, 2006 census

	Male		Female		Persons	
	Mean	Std dev.	Mean	Std dev.	Mean	Std dev.
Managers						
Managers, nfd	12.89	2.40	12.79	2.50	12.86	2.43
Chief executives, general managers and legislators	13.51	2.47	13.76	2.49	13.56	2.47
Farmers and farm managers	10.97	2.00	11.36	2.18	11.09	2.06
Specialist managers	13.28	2.37	13.84	2.33	13.45	2.37
Hospitality, retail and service managers	12.08	1.96	12.02	2.00	12.05	1.97
Professionals						
Professionals, nfd	15.70	2.86	15.51	2.51	15.60	2.69
Arts and media professionals	13.30	2.20	13.96	2.23	13.60	2.24
Business, human resource and marketing professionals	14.23	2.08	14.14	2.08	14.19	2.08
Design, engineering, science and transport professionals	14.76	2.21	15.07	2.06	14.84	2.17
Education professionals	15.49	2.10	15.24	1.52	15.32	1.72
Health professionals	15.60	2.00	14.77	1.67	14.98	1.80
ICT professionals	14.49	1.93	14.42	2.03	14.47	1.95
Legal, social and welfare professionals	15.24	1.85	15.11	1.89	15.17	1.87
Technicians and trades workers						
Technicians and trades workers, nfd	11.86	1.63	12.24	2.05	11.88	1.65
Engineering, ICT and science technicians	12.71	1.84	13.07	2.05	12.80	1.90
Automotive and engineering trades workers	11.47	1.25	11.54	1.77	11.47	1.26
Construction trades workers	11.29	1.33	11.26	1.80	11.29	1.33
Electrotechnology and telecommunications trades workers	11.98	1.27	12.19	1.79	11.99	1.28
Food trades workers	11.48	1.66	11.34	1.75	11.43	1.69
Skilled animal and horticultural workers	11.36	1.69	11.91	1.76	11.51	1.72
Other technicians and trades workers	11.60	1.53	11.73	1.55	11.65	1.54
Community and personal service workers						
Community and personal service workers, nfd	12.49	2.52	12.65	2.23	12.61	2.31
Health and welfare support workers	12.82	1.95	12.85	1.92	12.84	1.93
Carers and aides	11.97	1.97	11.77	1.76	11.79	1.79
Hospitality workers	12.14	1.63	11.70	1.63	11.83	1.64
Protective service workers	12.18	1.75	12.61	1.93	12.26	1.79
Sports and personal service workers	12.38	1.93	12.55	1.78	12.49	1.84
Clerical and administrative workers						
Clerical and administrative workers, nfd	13.04	2.17	12.56	2.10	12.70	2.13
Office managers and program administrators	13.36	2.23	12.52	2.10	12.75	2.17
Personal assistants and secretaries	13.07	2.27	11.79	1.75	11.82	1.77
General clerical workers	12.49	2.01	11.82	1.83	11.92	1.87
Inquiry clerks and receptionists	12.64	1.86	11.85	1.70	11.96	1.75
Numerical clerks	12.95	2.02	12.03	1.87	12.21	1.94
Clerical and office support workers	11.63	1.86	11.71	1.94	11.67	1.90
Other clerical and administrative workers	12.17	1.94	12.36	1.98	12.27	1.96

	Male		Female		Persons	
	Mean	Std dev.	Mean	Std dev.	Mean	Std dev.
Sales workers						
Sales workers, nfd	12.16	1.88	11.87	1.83	12.01	1.86
Sales representatives and agents	12.21	1.87	12.26	1.92	12.23	1.89
Sales assistants and salespersons	11.69	1.70	11.39	1.62	11.49	1.66
Sales support workers	11.79	1.82	11.40	1.64	11.50	1.69
Machinery operators and drivers						
Machinery operators and drivers, nfd	10.79	1.54	10.40	1.79	10.75	1.57
Machine and stationary plant operators	10.96	1.63	10.91	1.94	10.95	1.69
Mobile plant operators	10.59	1.47	11.14	1.62	10.61	1.48
Road and rail drivers	10.80	1.71	10.89	1.64	10.80	1.71
Storepersons	11.23	1.57	11.08	1.69	11.20	1.59
Labourers						
Labourers, nfd	10.62	1.59	10.58	1.70	10.62	1.60
Cleaners and laundry workers	11.03	1.96	10.56	1.75	10.74	1.85
Construction and mining labourers	10.86	1.50	11.14	1.80	10.86	1.50
Factory process workers	10.93	1.77	10.79	1.88	10.88	1.82
Farm, forestry and garden workers	10.76	1.68	11.09	1.83	10.84	1.72
Food preparation assistants	11.12	1.74	10.86	1.67	10.97	1.71
Other labourers	11.08	1.66	11.01	1.67	11.06	1.67

Table A2 Employees under-educated, correctly matched and over-educated, by two-digit occupation (pooled sample), HILDA (%)

	Females			Males		
	Under-	Matched	Over-	Under-	Matched	Over-
Managers						
Chief executives, general managers and legislators	22.7	70.5	6.8	19.1	72.8	8.1
Farmers and farm managers	*a.*	*a.*	*a.*	7.4	82.8	9.8
Specialist managers	12.6	61.6	25.8	18.2	59.9	21.9
Hospitality, retail and service managers	22.6	64.1	13.2	13.1	68.4	18.4
Professionals						
Arts and media professionals	7.5	72.2	20.3	15.6	76.3	8.1
Business, human resource and marketing professionals	19.8	73.3	6.9	21.2	70.2	8.6
Design, engineering, science and transport professionals	14.4	76.9	8.8	19.9	74.3	5.8
Education professionals	14.0	83.3	2.6	17.1	72.5	10.4
Health professionals	24.8	72.1	3.2	12.7	70.7	16.6
ICT professionals	21.4	61.1	17.6	30.2	61.1	8.8
Legal, social and welfare professionals	20.1	79.1	0.8	19.0	77.9	3.1
Technicians and trades workers						
Engineering, ICT and science technicians	18.8	54.1	27.1	7.0	72.8	20.2
Automotive and engineering trades workers	*a.*	*a.*	*a.*	16.4	68.1	15.5
Construction trades workers	*a.*	*a.*	*a.*	12.2	76.9	10.9
Electrotechnology and telecommunications trades workers	*a.*	*a.*	*a.*	11.7	80.4	7.9
Food trades workers	11.5	86.0	2.5	5.7	90.2	4.1
Skilled animal and horticultural workers	8.6	58.1	33.3	11.3	79.9	8.8
Other technicians and trades workers	9.3	74.8	15.9	23.5	63.0	13.6
Community and personal service workers						
Health and welfare support workers	17.0	65.0	18.1	11.5	64.2	24.3
Carers and aides	10.2	81.7	8.2	0.5	77.0	22.4
Hospitality workers	21.6	64.6	13.8	12.8	71.9	15.3
Protective service workers	12.7	70.9	16.4	13.6	81.5	4.9
Sports and personal service workers	16.5	65.1	18.4	7.8	65.6	26.6
Clerical and administrative workers						
Office managers and program administrators	20.1	56.4	23.5	8.6	56.4	35.0
Personal assistants and secretaries	19.6	71.9	8.6	*a.*	*a.*	*a.*
General clerical workers	19.3	68.3	12.4	13.1	67.0	19.9
Inquiry clerks and receptionists	20.0	69.1	10.8	3.0	76.2	20.8
Numerical clerks	17.7	70.6	11.7	5.5	71.8	22.7
Clerical and office support workers	10.9	76.0	13.1	3.7	87.2	9.2
Other clerical and administrative workers	14.5	63.7	21.8	20.0	70.7	9.3
Sales workers						
Sales representatives and agents	15.5	75.0	9.5	11.0	70.4	18.5
Sales assistants and salespersons	9.6	79.0	11.5	3.5	83.8	12.7
Sales support workers	12.1	73.8	14.1	1.4	79.6	19.0
Machinery operators and drivers						
Machine and stationary plant operators	12.5	79.8	7.7	19.9	73.2	6.9
Mobile plant operators	*a.*	*a.*	*a.*	19.2	73.7	7.0
Road and rail drivers	5.9	88.2	5.9	17.0	76.3	6.7
Storepersons	*a.*	*a.*	*a.*	13.9	70.4	15.7

	Females			Males		
	Under-	Matched	Over-	Under-	Matched	Over-
Labourers						
Cleaners and laundry workers	14.9	76.5	8.6	6.9	78.8	14.3
Construction and mining labourers	*a.*	*a.*	*a.*	20.2	70.0	9.9
Factory process workers	25.1	64.5	10.3	14.2	73.6	12.3
Farm, forestry and garden workers	10.6	62.5	26.9	16.2	70.0	13.9
Food preparation assistants	14.4	73.2	12.3	6.6	77.6	15.8
Other labourers	17.9	70.1	11.9	15.5	71.2	13.3
Total	**16.5**	**72.3**	**11.2**	**15.0**	**72.0**	**13.0**

Note: a. Percentages not reported where number of employees in the sample is less than 50.

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