The incidence and wage effects of overskilling among employed VET graduates

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The cover of Monograph 03/2009 features the artwork 'Stranded' by Peter Penn, a graduate of the Bachelor of Visual Arts and Applied Design course, 2003, Adelaide Institute of TAFE, Arts Campus. The work is an exploration into the mechanics of memory – the process and journey of a single strand of recollection.

This work is from NCVER's collection which features work from VET students.

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The NVETRE program is based upon priorities approved by ministers with responsibility for vocational education and training (VET). This research aims to improve policy and practice in the VET sector. For further information about the program go to the NCVER website <http://www.ncver.edu.au>. The author/project team was funded to undertake this research via a grant under the NVETRE program. These grants are awarded to organisations through a competitive process, in which NCVER does not participate.

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About the research

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The incidence and wage effects of overskilling among employed VET graduates

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When the skills workers have to offer do not balance with the skills jobs require, mismatch occurs.

Using data from the Household Income and Labour Dynamics in Australia (HILDA) survey, this study examines the extent to which workers can use their skills and abilities in their current jobs. The authors refer to the situation when a worker perceives that their job does not use all their skills as 'overskilling'. The persistence of overskilling is a particular focus.

Overskilling can be distinguished from overeducation. The former is based on perceptions that skills are not used in a job, while the latter refers to people working in a job that does not require their level of education. While the concepts are related, they do differ; for example, early school leavers can be overskilled if they work in particularly unskilled jobs, but they could not be described as overeducated.

Mavromaras and colleagues find that, by comparison with workers with no post-school qualifications or with university qualifications, those with vocational qualifications at the certificate III or IV level are less likely to experience overskilling, and if they do, suffer fewer adverse consequences, such as periods of unemployment.

Key messages

- Overskilling is, on average, most prevalent among those who are poorly educated. This is because poorly educated people end up in the most unskilled jobs.
- While overskilling is associated with lower educational levels, it does occur among those with post-school qualifications. And in their case it has worse consequences.
- The negative effects of overskilling are greatest for those with diplomas and degrees; persistence of the skills mismatch and of associated wage penalties is highest for the overskilled with a diploma or degree.

The finding that overskilling occurs among highly educated persons, and is persistent, suggests that individuals investing in education need to be aware of the range of possible outcomes—not everyone gets a high return.

Tom Karmel
Managing Director, NCVER

Informing policy and practice in Australia's training system …

* This work was mostly undertaken at the Melbourne Institute of Applied Economic and Social Research.

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Abstract

This research investigates the incidence and wage effects of overskilling for vocational education and training (VET) graduates in Australia between 2001 and 2006. Overskilling is defined as the extent to which workers are able to use their skills and abilities in their current job. We compare overskilling with other measures of skill mismatch and skill underutilisation in the workplace and explain why overskilling is our chosen mismatch measure. The Household Income and Labour Dynamics in Australia (HILDA) survey asks employed respondents a question about overskilling in every wave, which means that we have repeated information by the same individuals over time. The research estimates the likelihood of being overskilled and how the labour market outcomes of overskilled and comparable well-matched workers may differ.

The research focuses on the impact of four different levels of highest educational attainment: formal school qualification with Year 12; formal school qualification less than Year 12; formal post-school qualification (VET); and formal post-school qualification with diploma/degree. The research finds that many Australian workers report that they are overskilled in their workplace (30% moderately, and 15% severely overskilled). Almost counterintuitively, those with the lowest formal qualifications report the highest incidence of underutilisation. The lowest incidence appears among workers with post-school qualifications. By comparing different estimation methods, certificates I and II are shown to confer a modest, short-lived advantage, in terms of reduced mismatch, and certificates III and IV confer a substantial and long-lasting, reduced mismatch advantage. When comparing the estimated difference between the wage of an overskilled and an equivalent well-matched worker, a wage penalty from being overskilled is found. The wage penalty costs are highest for mismatched university graduates, followed by VET graduates, and subsequently school graduates. State dependence of overskilling, that is, the degree to which becoming overskilled will in itself increase the probability of remaining overskilled, is examined. This scarring phenomenon is common amongst many adverse labour market outcomes (for example, long-term unemployment and repeat unemployment). Overskilling is found to be self-perpetuating, but only for university graduates and school graduates. VET graduates show no overskilling state dependence, a result that suggests that a mismatched VET graduate can get out of their mismatched job and into a well-matched job more easily than their school or their university counterpart.

The research offers two main conclusions: first, post-school qualifications generate benefits that may go beyond the increased lifetime financial returns often referred to in the literature; and, second, different types of post-school education confer different benefits, in terms of employment possibilities and patterns, with VET being a safer but less well-remunerated education pathway.

Introduction

Mismatches in the labour market

Background

Skill mismatches in the labour market are a type of imbalance between the skills workers have to offer and the skills that jobs need. The most commonly discussed mismatch is the presence of skill shortages, which appear when firms cannot hire workers with the skills they need for specific jobs at an appropriate market rate. Skill shortages have been widely discussed in the last decade in Australia, to a large degree as a possible result of an economy close to overheating and also in the context of interventions—such as targeted immigration and education and training efforts—apparently not managing to eliminate the problem completely. Another type of mismatch is the presence of skill gaps in the workplace, where workers may not have all the skills necessary for the job they do, but who are nonetheless hired for the job, because the right skills are either not available, or available but too expensive for the specific production. This is often a problem that is hard to identify and measure. A third possible category of mismatch is when the worker has more qualifications and/or skills than required by the job. This mismatch has been called in the literature either *overeducation* or *overskilling*, depending on whether it measures excess qualifications (overeducation) or excess skills and abilities (overskilling). Of these types of mismatch, this is the hardest to identify empirically and our research focuses on its manifestation in the form of overskilling.

Mismatches, and in particular overeducation, have been measured in three main ways. The first way uses the so-called objective method, where a detailed list of jobs is used to make a systematic assessment of the qualifications required for each job. This is then compared with the qualifications of the worker to determine if there is a mismatch or not. The second way uses the workers' self-assessment of the requirements of their jobs by comparison with their skills. The third way uses the so-called empirical method, which finds the relative position of each worker within a meaningfully defined peer group. This could be their occupation, their workplace colleagues or other. The empirical method then defines mismatch as the distance (usually defined in standard deviations) of each worker's qualifications from the mean peer group qualifications. This research uses the second category—worker self-assessment—to measure overskilling.

There are other measures of labour market mismatches of importance which are essentially of a macro nature and which we do not consider explicitly in this research. These include the Beveridge curve, which measures the simultaneous presence of job vacancies and unemployed job seekers; youth unemployment, which arises principally in periods of contraction; skills obsolescence; and other. This research concentrates on overskilling as a mismatch measure, in recognition of the recent evidence in the literature showing that it can have both serious and invidious consequences, manifested through a number of important labour market outcomes.

Consequences of overskilling

Skill mismatches can lead to losses in productivity and a decline in international competitiveness. Although theory suggests that skill mismatches, and especially skill shortages, can lead to low-skill equilibria in the wider economy (with production adjusting to the available rather than the desired skills), there is insufficient direct empirical evidence to support this proposition. Empirically, this is a very hard macroeconomic proposition to test. A better understanding of the extensive and diverse consequences of skill mismatch has begun to be documented in empirical microeconomic research linking mismatch with productivity and efficiency losses, lower wages and a host of other adverse labour market outcomes.[1] It has been argued that skills underutilisation has severe economic and social consequences, including reduced tax revenue (Booth & Snower 1996), wasted human capital investment (Frenette 2004), lower job satisfaction (Jones et al. 2004; Green & Zhu 2008) and lower productivity (Haskel & Martin 1996; McGuinness & Bennett 2006). These consequences provide a strong policy justification for pursuing further research on skill mismatches.

This research concentrates on overskilling and argues that it is the most informative measure of skills underutilisation in the workplace available to researchers at present. It has been proposed that overskilling generates losses which include: (i) wage losses, (ii) job satisfaction losses, (iii) disadvantageous mobility, (iv) skills obsolescence, and (v) overskilling persistence. By investigating and quantifying each of the losses experienced by overskilled workers, we can increase our understanding of what it is that can make participating in education more or less attractive as a labour market investment. This is the motivation for this research. Of all the possible adverse outcomes of overskilling mentioned above, this research concentrates on overskilling state persistence or state dependence. State persistence is a term that defines the case where a labour market state may perpetuate itself. Self-perpetuating states are not uncommon in the labour market. A simple example is unemployment, where an employed worker may become unemployed for a number of reasons, and as soon as they have become unemployed they acquire an additional and independent reason for remaining unemployed; namely, the fact that they are presently unemployed. We explain below how this problem applies to overskilling and we test empirically for the presence of overskilling state dependence.

There are several reasons why overskilling persistence should be of concern. To gain some understanding, we must first ask if overskilling is temporary or not. Temporary overskilling may be the result of choice. It may be an investment in human capital by the worker and as such it should not cause concern. A worker may accept a temporary sub-optimal job in order to open the door for future better jobs. Such behaviour could be efficient and possibly worth encouraging, as it leads to long-run improvements. Temporary overskilling may also be the result of lack of choice by job seekers with lower levels of human capital. Its temporary nature, however, makes it less of a worry, as it obviously does not trap workers and allows them to escape any associated disadvantage. Hence, temporary overskilling should be viewed as a lesser policy concern, if at all. Permanent overskilling, however, is a less clear-cut case. Although this may initially sound counterintuitive, sometimes permanent underutilisation of skills may be the result of choice, following personal and/or family preferences. But even this may be a policy concern, to the extent that the education that generated these skills may have received some public subsidy. Full skills utilisation may entail stress and responsibilities in the workplace, the removal of which can be traded off for lower pay and skills utilisation in a welfare-enhancing way. However, permanent skills underutilisation could be an inefficient and damaging trap for some workers and difficult to escape from. Our research suggests that overskilling is more of a permanent than a temporary state for some groups of workers. To understand the implications of such differences, we need to know the degree to which this may be due to state self-persistence or just the characteristics of the overskilled. As we explain below in some detail, the choice of policy levers for alleviating mismatch will depend crucially on whether overskilling is self-perpetuating or not. This research establishes the degree to which overskilling is persistent and relates this to different education pathways.[2]

1 See Mavromaras, McGuinness and King (2009a) and O'Leary et al. (2009) for a detailed exposition.

2 It should be noted that this research does not make any direct observations on the distinction between optimal and sub-optimal overskilling. The authors are currently engaged in research that makes this empirical distinction by combining aspects of job satisfaction with different types of mismatch, but this is at too early a stage to report results.

Overskilling and overeducation as measures of mismatch

Overskilling is defined as the extent to which workers are not able to utilise all their skills and abilities in their current employment. Overskilling is a labour market mismatch measure that has only recently emerged in contemporary survey data sets. Until recently, the bulk of the relevant literature used overeducation as a measure of labour market mismatch. Overeducation is defined as the situation where a worker has more formal qualifications than their job requires. It can be argued that some of the shortcomings of the overeducation measure in microeconomic research contributed to the emergence, in the international literature, of overskilling as an alternative and to the increased interest in overskilling as a mismatch measure. Notwithstanding the fact that this monograph concentrates on overskilling and not overeducation, the close links between the two concepts and the much more extensive use in the literature of overeducation as a measure of mismatch in the workplace suggest that we discuss briefly and compare both measures here.[3]

The literature contains a number of different definitions of overeducation. They all provide an indirect measure of mismatch by comparing the formal qualifications that a worker possesses with some qualifications benchmark. This benchmark is usually related to the qualifications required for the specific job they do, or the qualifications that are typical of their occupation. There are problems with using overeducation to study employer–employee mismatches. First, the possibility that a worker may hold the right level but the wrong type of qualification is not captured by the definition of overeducation. For example, a teaching degree would be of limited direct use for an individual working for an accounting firm. Second, the extent to which the informal skills and abilities of a worker may be underutilised in their employment cannot be captured accurately by the definition of overeducation. It is possible that a worker who is correctly matched, in terms of the qualifications they possess and those required by their job, may still be underutilising their skills and abilities if their time is not managed appropriately or if they are not motivated. The conclusion that the authors have reached on how useful the two measures of overeducation and overskilling can be in the context of labour market research is that both provide useful but distinctly different information regarding mismatches and that, when we are concerned with underutilisation of skills and abilities in the workplace, overskilling is a superior measure because it contains direct and specific information on utilisation rather than just qualifications.[4]

Education pathways and overskilling

This research builds on the past and ongoing work of the authors and provides evidence to reveal new aspects of overskilling and mismatch in the labour market. There is evidence that a large proportion of Australians in paid employment report that their skills are underutilised in their workplace: 30% report that they are moderately overskilled, and 10% that they are severely overskilled.[5] There is also evidence that overskilling differs by education level. The theoretical origins of skills underutilisation and mismatch are not easily explained by conventional market economics, unless consideration is given to the possibility that human capital is often built with imperfect information at hand, so that markets may not end up clearing when the time to use these skills comes, causing some skills to remain underutilised. A fundamental reason why education pathways matter in overskilling research is because job–worker matches differ by education level and type. The principal difference stems from the composition of the human capital (general versus specific) that underlies each job–worker match. Completely general human capital is the education and knowledge of a worker that would have the same value for all employers and in all jobs.

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3 Green and McIntosh (2002) investigate overskilling among the overqualified. For an extensive up-to-date review on overeducation see McGuinness (2006). Mavromaras et al. (2007) report joint overskilling and overeducation regressions for Australia and United Kingdom.

4 For a more detailed account see Mavromaras et al. (2007), where evidence of overskilling in Australia and the United Kingdom is presented (Manchester School, forthcoming)

5 See Mavromaras, McGuinness and King (2009) where some of the effects of overskilling in Australia are analysed

Literacy and numeracy are probably the closest to what we would call perfectly general human capital and they are perfectly transferable. The employer has a lower incentive to pay for the acquisition of these skills, as poaching is a problem.

At the other end of the spectrum, completely employer-specific human capital is the education and knowledge that can only be used and would only have any value when an individual works for a specific employer and, as a result, is not transferable. Workers have little incentive to pay for the acquisition of skills that are perfectly employer-specific. They know that they will not be able to derive any surplus from a profit-maximising employer who uses those skills, and that they will not be able to use these skills at all when they move job. Most bundles of education, knowledge and training that make up the human capital of individuals in the workplace contain both general and specific elements. This general–specific split depends not only on the worker but also on the requirements of the job. Another reason why the education pathway matters is that the generation of skills through education and training involves sometimes considerable time lags. Time lags differ by the type of education and training and we have to keep these differences in mind when we examine overskilling because, other things equal, the longer the lags, the more likely that the circumstances under which the education decision was initially made may have changed by the time it is completed.

Data and definitions

The HILDA survey and overskilling

The data for this study come from the first six waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey, which began in 2001 with a national probability sample of Australian households. Interviews were completed at 7682 of the 11 693 households identified as in scope for wave 1. The members of these participating households form the basis of the panel pursued in the subsequent waves of interviews, which are conducted approximately one year apart. Interviews are conducted with all adults (defined as persons aged 15 years or older on the 30 June preceding the interview date) who are members of the original sample, as well as any other adults who, in later waves, are residing with an original sample member.[6] The sample used in this monograph is based on the unbalanced panel of working-age (17–64 years for men and 17–59 years for women) persons.[7] The data are used in this monograph in two main ways. We use a pooled cross-section sample, where all observations are treated as if they are part of a single cross-section data set. In this set each individual contributes a number of observations equal to the number of interviews to which they responded. We also use a sample, where each individual's responses are part of a single contribution ordered in their time sequence: this is often called a time series cross-section, or simply a panel data set. The statistical method we use depends on the question asked and, in some parts of the analysis, we use more than one method and compare the results.

The data used to construct the overskilling variable are derived from the self-completed questionnaire of the HILDA survey. Overskilling is defined as the extent to which a worker is utilising their skills and abilities at work in response to the statement 'I use many of my skills and abilities in my current job'. The extent of overskilling is measured using a 7-point scale. A response of 1 corresponds with strongly disagree and 7 with strongly agree. The question is similar to that used in the United Kingdom by both Allen and van der Velden (2001) and Green and McIntosh (2007).[8] It is also very similar to the questions that appear in the European Community Household Panel, a data set similar to the Australian survey that has now been discontinued but which is still sufficiently topical for labour market research. All respondents in the HILDA sample were classified for the purposes of this analysis into one of three groups for each yearly observation: (i) the severely overskilled (individuals selecting 1, 2 or 3 on the 1 to 7 scale); (ii) the moderately overskilled (those selecting 4 or 5); and (iii) the well matched (individuals selecting 6 or 7). The data suggest that, in Australia between the years 2001 and 2006, approximately 56% of workers

6 Further information on the HILDA survey can be found at <http://www.melbourneinstitute.com/hilda/>.

7 A balanced panel data sample is one that includes only individuals who responded to all interviews in the survey. An unbalanced sample is one where all available interviews are present, including those of respondents who may have missed some but not all interviews. Working with an unbalanced sample is preferable in the sense that it utilises all the information contained in the data. However, on some occasions and for some statistical methodologies, a balanced data set is necessary. This analysis will be based on an unbalanced sample unless explicitly otherwise stated.

8 In the data employed by Allen and van der Velden (2001), a measure of skills underutilisation is constructed from responses, scored on a 5-point scale, to the statement: 'My current job offers me sufficient scope to use my knowledge and skills'. By contrast, Green and McIntosh (2007) combine responses to two items, both of which have four possible response options. These items are: 'In my current job I have enough opportunity to use the knowledge and skills that I have'; and 'How much of your past experience, skills and abilities can you make use of in your present job?'

considered themselves to be well matched with their job, 29% moderately overskilled and 15% severely overskilled (table 1).

Sensitivity tests confirm that the cut-off points for severe and moderate overskilling are appropriate and that results from multivariate analysis do not change in a significant way when these cut-off points are altered.[9] Furthermore, it has been suggested that, in responding to the overskilling question, workers do not consistently factor in skills that have no relevance to their current job. McGuinness and Wooden (2009) cross-tabulated the overskilling variable with a measure of job complexity to confirm that the more overskilled the worker, the less difficult they consider their job to be.[10] Their finding would suggest that the overskilling measure used in the present analysis will not be biased by respondents incorporating skills and abilities not relevant to the labour market into their response.

Overskilling by education group: Preliminary findings

The Household, Income and Labour Dynamics in Australia data reveal that overskilling differs considerably by level and type of education and training. The categorisation of educational attainment used in this monograph is based on the highest education qualification obtained. The educational groupings provided within HILDA are: school completion below Year 11, completion of Year 11 or Year 12, vocational education and training (VET) graduates with certificates, graduates with diplomas and tertiary degrees. We subdivide the VET graduates category into (a) certificates I and II and below, and (b) certificates III and IV and apprenticeships.[11]

Table 1 reports the incidence of overskilling for all workers by highest education level. The data here are pooled across all six waves of HILDA and have been weighted using cross-sectional weights to ensure that they are representative of the population. VET graduates in employment account for just fewer than one-quarter of the total employed sample, with fewer than 2% having certificates I or II and 21% with certificates III or IV.

The relatively small number of VET graduates with certificates I or II in the sample restricts the extent to which this category can be examined separately when we come to more detailed analyses. Table 1 suggests that the incidence of both moderate and severe overskilling is more pronounced among lower education levels. The data suggest that, within the Australian labour market, 18–20% of workers within the three lowest levels of educational attainment in table 1 are employed in jobs that they consider to be severely underutilising their skills and abilities, while 31–36% consider themselves to be moderately underutilising their skills and abilities. Although the HILDA data do not provide any direct and objectively verifiable information on specific jobs and their attributes, it would be reasonable to think that these overskilled workers who are reporting being underutilised are more likely to be employed in menial and low-skill jobs. In contrast, VET graduates with certificates III or IV are on a par with the diploma and tertiary graduates in terms of a much lower incidence of both moderate (26–28%) and severe (10–11%) overskilling.

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9 Note that, whenever we apply a data reduction of this type without having any theoretical guide as to where the cut-off points may need to be, we carry out extensive sensitivity tests as a matter of course. In the numerous overskilling estimations we have performed sensitivity results suggest overwhelmingly that the estimates are very robust to the specific definition of overskilling in terms of the cut-off points we use.

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

11 This definition suffers from the potential problem that, once the highest qualification has been achieved, all past lower-level qualifications are concealed, irrespective of whether or not they may be important in explaining, at least in part, past and present labour market outcomes. This may well be important in the case of advanced vocational training which was complemented at a later stage by a university degree. It may also conceal the effect of school completion, especially in the case of VET graduates, as some of them will and some will not have completed Year 12 of schooling. Especially in the case of certificate I or II holders, the school-completion information may be as important as that of the certificate completion.

Table 1 Reported overskilling in employment

Highest education level	Extent of overskilling (%)			%
	Well matched	Moderately overskilled	Severely overskilled	
All employed				
Year 10 and below	50.99	30.68	18.32	18.69
Year 11–12	47.39	32.25	20.36	25.79
Certificates I and II and below	45.19	35.88	18.92	1.73
Certificates III and IV and apprenticeship	62.13	27.88	9.99	21.02
Diploma/degree	62.46	26.33	11.21	32.78
All qualifications	56.06	29.16	14.78	100.00
No. of observations	23 688	12 322	6 245	42 255

Note: HILDA waves 1 to 6 (years 2001–06) were used with population weights.

To the degree that overskilling represents skills underutilisation and mismatch in the workplace, the difference of overskilling by education level is in itself an important finding. It suggests that the highest levels of skills underutilisation in the workplace are not reported by highly educated workers, but by workers with the lowest levels of education and training in the labour market. Our finding that there is considerably more overskilling amongst the less well-educated allows us to make a number of pertinent observations and raise a number of important questions. First, the finding highlights one of the shortcomings of overeducation as a human capital underutilisation measure; namely, that it cannot be used for the complete labour force. The concept of overeducation has little meaning amongst workers with only the lowest level of qualifications. By contrast, overskilling captures the complete labour force and shows underutilisation to be present across the full educational spectrum. Second, by suggesting that reported skills underutilisation is higher amongst the lower education segments of the labour market, our finding raises the question of why this may be the perception of so many workers with no formal education, training, or qualifications.

Although answering this question is beyond the scope of the present analysis and, possibly, the capabilities of the data at hand, it is worth considering some ideas. Workers with no qualifications who declare themselves overskilled are simply stating that they could do a more complex (and one would justifiably presume) better remunerated job. Why would this not be happening? What is it that could be stopping people who want to do better from doing better? It could be that we are faced with a fair amount of over-reporting. Over-reporting, often called justification bias, is defined to be present when someone justifies their disadvantageous status by some external factor, for example, people who may feel bad about remaining unemployed for long periods may overstate their health problems by way of justification for their unsuccessful job search. If that were to be the case with overskilling, we should be asking why people do not train. One reason why currently employed individuals may not train could be that there are no on-the-job training opportunities available to them, and/or that it is too costly for them to take time off in order to train. Especially for full-time low-paid workers with family responsibilities and commitments, training outside their workplace may simply not be a financially viable option. Another reason for not training may be the expectation that a better job may not be forthcoming after training. Research has generated a mixed picture on this front. On the negative side, recent research by Lee and Coelli (2010) suggests that returns from undertaking VET qualifications are not significantly higher than those of school leavers, so perhaps the expectation that training would not confer a pay improvement is, in a number of cases, supported by evidence. On the positive side, recent research by Mavromaras, McGuinness and King (2009a) suggests that the wage penalty from a skills mismatch is lower for those with VET qualifications than for school leavers. This research has also found that VET qualifications result in better-matched employment, which also shows no persistence of mismatch for those who may end up in a job–skills mismatch through bad luck. On balance, however, the very fact that such a large proportion of employed Australians have no post-school qualifications and at the same time report that they are underutilised in their workplace may suggest that we live in a lower-than-necessary skills equilibrium and that there may be obstacles to shifting to a higher level of demand for additional skills. A higher level of demand would make training more attractive from the point of view of both employers and workers. We consider addressing these questions to be a high priority for the development of informed policy on upskilling in Australia.

Estimation methods

Cross-section and panel estimation

Before we move to the presentation of multivariate analysis results we outline the main estimation methodologies that are utilised in the analysis that follows. More detail can be found in Mavromaras et al. (2007), Mavromaras, McGuinness and King (2009a, 2009b), as well as in the appendix to this monograph. We present results using a range of regression methods. As the variable of interest (the dependent variable) is binary (that is, it takes two values: yes [or 1] for those who are overskilled and no [or 0] for those who are not), we use the probit method. This is designed to estimate the probability that a variable will take the value of 1 or 0. Estimation results are presented in terms of 'marginal effects' (ME), which are in essence a measure of the probability differences in the dependent variable associated with a unit change in each of the independent variables. For example, if a migrant from a non-English speaking country (value 1 for yes and 0 for no) has a ME of 0.038 in the severely overskilled estimation (see table A2), we can interpret this result as a suggestion that, on average, migrants from non-English speaking countries are 3.8 percentage points more likely to be overskilled than Australian-born workers (the reference category). Note that the comparison is made between two distinctly different sub-groups in the sample and that the interpretation depends on the unit of measurement of the variables. Table A2 suggests that for every ten extra years of occupational experience, and for every ten more hours worked per week, the probability of severe overskilling is lower by four and five percentage points respectively.

When using cross-section data and probit estimation methods, the correct interpretation is that, other things equal, those workers who work more and those who have more experience are also less overskilled. It is crucial to note the core limitation of these results, in that we cannot base predictions of the nature that 'if a worker who works for, say 20 hours per week swaps their job for a 30 hours per week job they will also reduce their overskilling level because they made this change'. This is because estimation compares different parts of the sample and there may be some unobserved factor that is responsible for the lower overskilling of those with higher hours worked. For example, better-motivated workers may be more likely to work longer hours and also be less overskilled because they are more motivated. The presence of unobserved factors such as motivation can mislead if the results of cross-section data are wrongly interpreted. The problem of unobserved factors is in part addressed by using panel data estimation. Unlike cross-section estimates, which measure differences between different groups, panel estimates measure changes that happen to specific individuals as time goes by. Commonly these estimates are called between (groups) and within (individuals). Where there may be unobserved factors that remain constant over time, these are controlled for by the panel estimation and the results (the within estimates) tell us what has happened to those individuals in the data who experienced a specific change during the time that we observed them. It is crucial to see that the two types of estimation are not right or wrong; they simply convey different information. The art of using these methods is in the careful interpretation of the results, especially by comparing different methodologies. For this reason we present and discuss both methods in table 2.

Dynamic panel estimation

The next estimation method we use is called dynamic panel analysis. The feature that distinguishes this method from the simple panel analysis is that we also model the possibility that the labour market outcome of today may depend on its own past values, which is the basis of the term 'dynamic analysis'. For example, the probability of finding a job today may not only depend on the human capital of each unemployed individual, but also on how long they have been unemployed.

The ability to measure the extent to which past disadvantageous outcomes may influence the probability of future disadvantageous outcomes is very important in labour markets, as it reveals the possibility that past disadvantage may scar the future of individuals. There is clear empirical evidence that having been out of work for a long time does not only damage human capital, but it also creates further lower re-employment probabilities in itself. There is no available evidence on the dynamics of the damage caused by mismatch and overskilling, but the similarities between unemployment and overskilling are very strong, in that both states entail skills underutilisation.

One could view unemployment as the extreme case of skills underutilisation. In policy terms the recommendations differ. Where there is no scarring, effort should concentrate on human capital improvements and we should not worry too much about when re-employment (or a better-matched job) occurs. However, where there is scarring, effort should also be made to avoid unemployment (overskilling) from occurring, and when it does to try to interrupt it as soon as possible. The relative weight to put on the two interventions will depend on the relative strength of the scarring revealed by the dynamic estimation. This type of estimation presents a new conceptual problem, which is called the initial conditions problem and refers to the fact that one needs to assume a starting point to analyse dynamic situations. In the case of individuals in the labour market, this would be their first day in the market (or, perhaps, in education?). Clearly, this information would be very hard to come by in large representative samples, so there have been a number of proposed solutions to the problem (see Heckman 1981; Wooldridge 2005; Mundlak 1978). All of these solutions use the first observation for each individual in the data at hand (usually the first wave of a panel) in order to approximate the (unobserved) initial conditions. The variant we use here is probably the most advanced in the literature and is a two-stage process that was devised by Heckman (1981) and implemented by Stewart (2006). Intuitively put, it uses the information in the first wave of a panel, including as much relevant historical information as there is in the data, to estimate a starting point for the outcome we analyse. The estimation results from the first stage are then used as the starting point of the second stage, which utilises the full data set (minus the first wave that has already been used). This method has been shown in the literature to produce statistically robust results.

Propensity score matching (PSM) estimation

The last estimations in this monograph extend and validate previously published results of the authors (Mavromaras, McGuinness & King 2009a, where we only used waves 1 to 4) but with the advantage of two more HILDA waves (2001–06) to estimate the wage penalty that results from overskilling by level of education. The method we use is propensity score matching, adapted to include past overskilling in the way the matching is performed. In essence, matching divides the sample into those who are overskilled and those who are not. Then, it uses observable characteristics to find, for each person who is overskilled in their job, another similar person who is matched in their job. The success of this method depends on the degree to which the matching works well for the whole sample (that is, the degree of common support). This is data-dependent and has to be tested and reported. Provided that some good matching has been achieved, this method allows us to compare the wages of the overskilled with their matched pairs of not-overskilled. This is in essence a regression methodology which contains elements of controlling for selection on observables by way of the matching. Our innovation in this work has been that we introduce past matching into the comparison, so that we take all those who were overskilled (well matched) for a number of periods in the past and then compare the wages of those who have subsequently become well matched (overskilled) with the wages of those who remained overskilled (well matched). This variation of the propensity score matching method allows us to control for the group of unobservable characteristics that may be common amongst those who have been overskilled (well matched) for some time and those who have not. We use the three main methods for matching and report that the findings they produce are very similar. The comparison of the propensity score matching results with those of ordinary least squares regression, which will be subject to bias due to possible non-random selection into overskilling, is of some interest as it can indicate the presence or absence of selection problems in the data.

The incidence of overskilling

The incidence of overskilling by educational attainment

We begin our empirical analysis by estimating the factors determining the incidence of severe and moderate overskilling. We estimate exactly the same model using two different methodologies, first a pooled cross-section binary probit model and, second, a random effects panel binary probit model. Extracts from both estimations are presented in table 2, where we concentrate on the differences by education level, with the full results in the appendix table A2. Depending on the overskilling level (severe or moderate), we use two different sub-samples to retain the same reference category. In the first case of severe overskilling the dependent variable takes the value of 1 if the individual is severely overskilled and zero if they are well matched, with the moderately overskilled excluded from the estimation, so that the comparison being made is between severely overskilled and well-matched workers. In the second case of moderate overskilling the dependent variable takes the value of 1 if the individual is moderately overskilled and zero if they are well matched, with the severely overskilled excluded from the estimation, so that the comparison being made is between moderately overskilled and well-matched workers.[12] Before we move to the presentation of estimation results in table 2, we remind the reader that the education reference category in the estimations is those with highest attained education level of below school Year 11. Consequently, the reported marginal effects refer to the difference in the probability of overskilling between this reference category and the category examined.

Pooled estimation

Both severe and moderate overskilling vary by the level of education. Certificates I and II appear to be more likely to be moderately overskilled (relative to those with education below Year 11), although the small cell size for this category should be borne in mind when looking at this result. Education above certificate II or above Year 12 is associated with lower levels of overskilling and better job matches. Most of the other covariates in table 2 suggest that the determinants of both severe and moderate overskilling are very similar, a somewhat unexpected result, given that the wage effects of both types of mismatch tend to be very different.[13]

The main limitation of the pooled estimation results reported at the top part of table 2 is that all observations are treated as independent of one another, so that changes that happen to specific individuals over time cannot be identified, as the estimates reflect the comparison between two separate groups in the data. This makes it possible for the estimates presented in table 2 to be biased because some variables may be picking up unobserved individual differences, such as innate

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

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

ability or motivation, which may be driving the likelihood of overskilling, thus causing unobserved heterogeneity bias. This is a very common problem in the empirical estimation of data relating to the effect of education on labour market achievement, largely because education tends to be treated as an investment and is non-randomly obtained at higher levels by those with higher levels of ability. As a result, when positive returns from undertaking education are estimated without taking into account non-randomly distributed ability levels, these returns are biased upwards, reflecting in part returns from education and in part returns from (unobserved) ability. In the following analysis we control for those unobservable characteristics that are constant over time by utilising the panel aspect of our data and adopting a modelling approach that 'differences out' these constant unobservable characteristics.

Table 2 Overskilling and educational attainment

Explanatory variable	Severely overskilled		Moderately overskilled	
	Marginal effect	Standard error	Marginal effect	Standard error
Pooled estimation				
Education: Year 11–12	-0.004	0.009	0.005	0.011
Education: certificate I and II	-0.003	0.024	0.053**	0.026
Education: cert. III/IV, apprenticeships	-0.054***	0.008	-0.044***	0.010
Education: diploma/degree	-0.036***	0.009	-0.043***	0.010
Random effects panel estimation				
Educational attainment: Year 11–12	0.013	0.013	-0.002	0.032
Education: certificate I and II	-0.025*	0.013	0.131*	0.079
Education: certificate III and IV and apprenticeship	-0.009	0.012	-0.002	0.037
Education: advanced diploma or degree or higher	-0.036***	0.013	-0.038	0.043
Observations	29 978		36 198	

Notes: Given the extremely few cases of those with certificates I and II, the estimates of this specific variable should be treated with caution and should not be deemed trustworthy. Full results for pooled estimation are in appendix table A2 and for random effects estimation in table A3. Reference education category is *Year 10 or below*.
***/**/* denote statistical significance at the 1/5/10 per cent level.

Panel estimation

We estimate a random effects (RE) probit model with a Mundlak correction and report results in the bottom part of table 2.[14] First note that the lack of statistical significance in the results for the Year 11 and 12 category suggests that this category behaves in the same way as the lower education category of up to Year 11. This introduces a clear distinction between those with and those without any post-school education. Obtaining a post-school qualification significantly reduces the probability of severe overskilling. However, this result is not statistically significant for the moderately overskilled. Obtaining certificates III and IV does not have a statistically significant impact on overskilling.

Interpretation of results

It is useful and informative to look at the pooled and the panel results in table 2 together as they look at the same data but from a different angle. Remember that the pooled results largely account for differences between two different groups that are observed at the same time (this is what we called the 'between' variation), while the panel results place their emphasis on changes that happen

[14] The Mundlak effects are specially constructed variables which allow us to estimate a random effects model that removes some of the potential bias in the estimates and produces results that are closer to the fixed effects estimates. These are only present for variables that are time-varying and are constructed by the means of each variable for each person in the sample. The intuitive interpretation after the inclusion of Mundlak corrections is that the RE estimates get closer to the (unbiased) FE panel estimates.

to individuals over time (what we called the 'within' variation). Given that qualifications typically confer a long-term labour market advantage to workers, it will be useful to interpret the pooled results as representing the average position of all those who have a qualification against all those who do not, independently of when this qualification was obtained. There is an element of observing a long-run position in these results and we will use this interpretation. By contrast, the panel results are emphasising the immediate effect of obtaining a new qualification. As such, it will be useful to interpret the panel results as being a better representation of the short-term result of a change (with the 12-month distance between the HILDA interviews as the limit), bearing in mind that the beneficial effects of education can be of a much longer-term nature. Following this thinking, it becomes clear that the two estimation methods will each tell a different story.

The first result to note in this light is that, no matter how we look at it, in the context of overskilling incidence, those with no post-school education appear to behave as a single group. Both panel and pooled estimation results suggest that completing school Years 11 or 12 does not result in any discernible short- or long-run overskilling differences for those who do not go on to obtain some post-school qualification. This is not an easy result to interpret. Especially in the case of the panel estimation, we should take this message with caution, principally because of the relatively small number of school completions that are contained in the six waves of the HILDA data we analyse. To the degree to which differential school completion outcomes may result in different probabilities to obtain post-school qualifications in the future (which is only observed within a very narrow time frame in this data and analysis), the results presented here may be biased.[15] The main differences in overskilling incidence probabilities arise between those without any post-school qualification and those with post-school education (the categories of VET and diploma/degree graduates).

Pooled results suggest that those with certificates I or II are not all that different from the reference category who have no post-school qualifications. But, interestingly, the panel results suggest that there may be a temporary reduction in severe overskilling immediately after (and possibly because of) obtaining a certificate I or II, of about 2.5%. However, if the estimation of this temporary reduction is accurate, then why is the estimated overskilling reduction not traced in the pooled estimation? Given the small sample size caveat we have already mentioned regarding this group, we will have to leave this question open until a longer HILDA sample is available.

Diploma/degree graduates offer a clear picture of lower incidence of overskilling. Panel results suggest that obtaining a diploma/degree results in a reduction of overskilling, and pooled results suggest that this advantage remains with diploma/degree graduates in the longer run. The pooled estimation results suggest that, on average, those with certificates III or IV are far less likely to be overskilled than the reference category. However, when we look at the panel results we see that those who have just completed a certificate III or IV have not at the same time moved to a less overskilled job. Clearly, whichever way certificates III and IV work to reduce overskilling, there is a long-run process at play that results in reducing overskilling. Further research would be useful to establish exactly how this type of result is occurring.

In conclusion, overskilling incidence estimation by education pathway suggests a pronounced difference between those who obtain post-school qualifications and those who do not. Post-school education reduces the probability of mismatch in the workplace. Although post-school education clearly reduces overskilling mismatch, we find differences between VET certificates on the one hand and diplomas and degrees on the other hand. Our estimations suggest that the timing of the effect of the two different pathways is different, and the need for further examination of these differences is noted.

[15] Additional data will be necessary for looking at this question in satisfactory detail. This type of investigation would be best made using one of the data sets that oversample young people at school leaving age such as LSAY, especially if/when LSAY data increase the observation frame to follow respondents to an older age.

Assessing the relative demand for skills in vocational markets

We now extend the analysis further to assess the extent to which the incidence of overskilling among workers holding vocational qualifications varies by occupation. Although it is widely believed that VET leads to high proportions of vocationally trained workers taking up posts relevant to their education and training, evidence suggests that this is only the case for some courses (for example, trades and some community health services jobs) (NCVER 2009). As it turns out, a large proportion of VET graduates work in occupations other than those in the area they trained for. This indicates that VET contains useful elements of general human capital and gives rise to the question of whether occupation could provide a useful indicator of the relative demand for particular skills and for the resulting mismatches in the labour market. To examine this we estimate the same type of panel model (a random effects probit) that we used in the previous section, but this time (i) we restrict the sample to contain only level III and IV certificate holders, and (ii) we include a detailed set of occupation variables and examine their estimates. Results are presented in table 3.

Table 3 Incidence of overskilling and occupational categories (certificates III/IV)

Explanatory variable	Severely overskilled		Moderately overskilled	
	M.E.	Std error	M.E.	Std error
Occupation: managers	-0.018	0.006	-0.094	0.037
Occupation: professionals	-0.021	0.005	-0.093	0.034
Occupation: associate professionals	-0.020	0.006	-0.071	0.031
Occupation: mechanical & fabrication engineering tradespersons	-0.019	0.007	-0.074	0.048
Occupation: automotive tradespersons	-0.023	0.005	-0.129	0.044
Occupation: electrical and electronics tradespersons	-0.024	0.005	-0.040	0.056
Occupation: construction tradespersons	-0.025	0.005	-0.020	0.061
Occupation: other tradespersons	-0.018	0.006	-0.075	0.040
Occupation: clerk	-0.016	0.006	-0.051	0.038
Occupation: intermediate clerk and workers	-0.004	0.008	-0.030	0.032
Observations	6411		7929	
Restricted log likelihood	-2064.35		-4455.58	
Unrestricted log likelihood	-1975.33		-4434.23	

Note: Reference category occupations by ASCO 2-digit code and name: 81 Elementary clerks; 82 Elementary sales workers; 83 Elementary service workers; 90 Labourers and related workers; 91 Cleaners; 92 Factory labourers; 99 Other labourers and related workers. Full estimation results are in appendix table A4.

We focus on certificates III and IV as they constitute the clear majority of vocationally qualified workers. Small sample size problems raised doubts over the potential reliability and robustness of a model estimated using a sample consisting only of VET graduates with certificates I and II. As occupation and sector are often highly correlated, the sector variables have been omitted from these estimations. The occupational groupings are constructed to provide a relatively disaggregated view of the demand for craft workers relative to other, more broadly defined groups such as managers and associate professionals. The reference category contains occupations of an elementary nature. Concentrating on the occupation marginal effects, we see that, in the case of severe overskilling, with the exception of the 'intermediate clerks and workers' category, VET graduates who work in all other areas are practically indistinguishable from one another. What the severely overskilled column says is that in terms of occupations and overskilling VET graduates are split in two very distinct parts. Interestingly, a different pattern prevails regarding moderate overskilling. It suggests that 'automotive tradespersons', 'managers', 'professionals' and 'other tradespersons' are considerably less likely to be moderately overskilled than the remaining occupational categories. Hence, the second message that comes out of table 3 is that the spread of overskilling is uneven. It is worth remembering at this point that moderate overskilling has nowhere near as serious repercussions as severe overskilling, so the moderate overskilling occupational differences should not be overinterpreted. The intuition behind these marginal effects suggests a number of possibilities. It could be that, in terms of the vocational labour market, demand is highest for electricians, construction workers, and mechanics and that this higher demand works towards these VET graduates being placed more in accordance with their skills and training than is the case in other occupations. It could also be that the training provided is more relevant to the occupation and better tailored to the needs of industry. Alternatively, and especially for the rather clear-cut split in the case of severe overskilling, the differences may be caused by the fact that some occupations offer more low-level menial jobs than others.

Is overskilling a 'sticky' labour market state?

A major area of empirical research in modern labour economics aims to answer the question of whether there is state dependence in some of the key labour market processes or not (for example, unemployment, wages etc.) after we have controlled for observed and unobserved individual heterogeneity. The presence of state dependence is pertinent in the context of overskilling. Overskilling state dependence can be defined as the situation where past and/or present overskilling may influence the probability of future overskilling. The presence of state dependence has important implications regarding the effectiveness of policy. Often the term 'sticky' is used to describe the state dependence of a labour market outcome. Labour market states that are sticky will also be much harder for policy interventions to influence in a clean, direct, and quick way. Given that it is not possible to influence the past values of overskilling, if there is state dependence, policy has to work on current causal relationships and wait for the effect of state dependence to be reduced with time. In some economic processes this can take time, which can only be afforded with difficulty.

In this section we use results from Mavromaras, McGuinness and King (2009b) and build them into the general picture of overskilling research developed in this monograph. We measure the presence and the extent of state dependence by estimating a 'random effects' dynamic panel model along the lines described in earlier 'data and definitions' section.[16] After considering the evidence that moderate overskilling cannot be shown to generate any major costs (substantial wage penalties are shown in Mavromaras et al. [2007] and Mavromaras, McGuinness and King [2009a] to be present only for the severely overskilled workers), we concentrate on the dynamic persistence of severe overskilling. Since the route we follow in this section involves the estimation of several interrelated models, it pays to outline their underlying logic before we present their results. The first question we address is whether or not there is state dependence. To do this we estimate several models using the full sample in table 4, to see if they all give a similar result. We find that they do. A secondary objective of table 4 estimations is to determine whether education pathways remain statistically significant after state dependence has been controlled for. We find that they stay significant, but we recognise that this is a very crude and restrictive way to estimate the effect of education pathways. We therefore split the sample into three parts and estimate separately. These estimations are given in table 5 and they show how state dependence is very different by education pathway.

We begin with the presentation of the models used to estimate the 'stickiness' (state dependence) of severe overskilling in table 4. Two findings arise from this analysis. First, the prime finding is about the presence or not of state dependence, while the secondary finding is that education levels still influence overskilling after state dependence has been controlled for. Regarding the presence of state dependence of overskilling, we find that, even after we have applied a number of econometric corrections that are known to remove spurious state dependence, there remains considerable true state dependence of overskilling. Table 4 shows that the first lag of overskilling (that is, overskilling in the previous year) is statistically highly significant, demonstrating that severe overskilling is a self-

[16] This is a model that that controls for both the initial conditions problem and the potential correlation between the error term and contemporaneous covariates. For details see the appendix.

perpetuating state. This implies that an individual falling into severe overskilling is likely to maintain that labour market state in the following year. Considering their size (standard errors), state dependence estimates appear to be robust to the specification of the model, ranging from 0.77 (0.08) to 0.84 (0.08).

Table 4 Dynamic random effects probit estimations for severe overskilling

Variable	Model 1 Coefficient (std error)	Model 2 Coefficient (std error)	Model 3 Coefficient (std error)	Model 4 Coefficient (std error)
Overskilling at t-1	0.78 (0.08)	0.81 (0.08)	0.84 (0.08)	0.77 (0.08)
Certificates III or IV	-0.28 (0.32)	-0.30 (0.31)	-0.30 (0.32)	-0.15 (0.32)
Diploma/degree	-1.45 (0.43)	-1.23 (0.38)	-1.23 (0.37)	-1.10 (0.41)
Gender (female=1)	0.17 (0.08)	0.07 (0.07)	0.07 (0.07)	-0.24 (0.09)
Occupational tenure	-	0.01 (0.005)	0.003 (0.12)	-
Occupational tenure squared	-	-	0.01 (0.035)	-
Hours worked	-	-	-	-0.01(0.004)
Means over time (Mundlak effects)				
Certificates III or IV	-0.20 (0.34)	-0.18 (0.34)	-0.16 (0.34)	-0.25 (0.34)
Diploma/degree	0.62 (0.43)	0.49 (0.39)	0.50 (0.38)	0.36 (0.42)
Occupational tenure	-	-0.06 (0.008)	-0.08 (0.13)	-
Occupational tenure squared	-	-	0.83 (0.33)	-
Hours worked	-	-	-	-0.03 (0.006)
Constant	-1.91 (0.09)	-1.25 (0.09)	-1.12 (0.097)	-0.27 (0.16)
ρ^1	0.72 (0.02)	0.67 (0.03)	0.65 (0.26)	0.70 (0.024)
θ^2	0.83 (0.08)	0.93 (0.11)	0.95 (0.11)	0.88 (0.09)
Log likelihood	-4130.72	-4023.22	-4016.17	-4019.35
Sample size	24 057			

Notes: 1 ρ is an estimate of the cross-period correlation of the composite error term $\varepsilon_i + \mu_{it}$.
2 θ is the statistic used to test if the initial conditions are exogenous. A clearly positive value of θ rejects the hypothesis that the initial conditions are exogenous, thus lending support to the adoption of the Heckman method. We do not report here full results.[17] Education reference category is all below certificate III/IV.

Regarding the effect of education on overskilling, we find that, even after we have controlled for state dependence, the direction and significance of the education coefficients in table 4 remain consistent with those in table 2. The estimates of both certificates III/IV and diploma/degrees remain negative and only the diploma/degree estimate is statistically significant. This confirms the picture that overskilling incidence is concentrated where the probability of doing menial or low-level jobs is high and that these jobs are clearly less likely to be present for diploma/degree holders and possibly less likely to be present for certificate III/IV holders.

State dependence results in table 4 would tend to contradict the temporary mismatches predictions of matching theory. If, for example, overskilling mismatches were simply due to asymmetric information, one would expect that overskilled workers would have achieved more suitable matches within a year. A further interpretation of our state dependence results is that they do not lend support to theories that present job mobility as an explanation of mismatch, as it may not be as likely that individuals seeking core experience would require a period in excess of one year to grasp the basic elements of their chosen occupation and cease to report themselves overskilled.

[17] The variables used for both initial conditions and main equation are gender, occupational tenure, occupational tenure squared, hours worked, four firm size dummies and 16 sector dummies. The Mundlak corrections include all time-variant variables amongst these. The following historical variables were used to identify the initial conditions equation, country of birth distinguishing between English and non-English speaking countries and the professional status of each of the parents independently. A full account can be found in Mavromaras, McGuinness and King (2009b).

Note that, after controlling for state dependence in overskilling, the higher education variable remained strong and statistically significant, while the vocational education variable remained insignificant. These results are the same in all four specifications we present here, but have also been observed in a large number of additional regressions, which we carried out in order to test the sensitivity and robustness of our model and which we do not report here for reasons of space. The results in table 4 demonstrate that the effectiveness of diploma/degree qualifications as a guard against severe overskilling remains unaffected by the presence of persistent dynamic effects. However, regressions in table 4 do not examine whether overskilling persistence may vary across vocational and tertiary labour markets.[18]

To gain this further insight we estimate the same model separately for each of the three main education groupings. We present the results in table 5 and concentrate on the coefficients of lagged overskilling (overskilling at t-1) that represent state persistence. State persistence clearly varies by level of education. The coefficient on lagged overskilling for VET graduates is the lowest amongst all education groups and is not significantly different from zero. This implies that VET graduates who find they are presently overskilled are clearly no more likely to be overskilled in the future than their presently well-matched counterparts. Put simply, we find no evidence of mismatch state dependence, or 'stickiness', amongst VET graduates in employment. By contrast, there appears to be overskilling state dependence for both the 'up to Year 12' category and even more so for the diploma/degree category. Workers with a diploma/degree who are presently severely overskilled are more likely to find themselves severely overskilled in the future than their counterparts who are presently well matched. The same applies but not as strongly to severely overskilled workers with up to Year 12 education, that is, the workers with no post-school qualifications at all. The strong overskilling state persistence for diploma/degree holders, combined with their already well-established strong overskilling wage penalty paints an interesting picture for the labour market position of higher education graduates. On average, they do better. However, those who do worse are far worse off than their average graduate counterparts. This is bad news for those who get it wrong. It is worth remembering, however, that the comparisons in these regressions are made within each education group; hence, the reference point will also differ by education.

Table 5 Dynamic random effects probit estimations of severe overskilling by education

	All school including Year 12	Certificates III & IV	Diploma/degree
Overskilling at t-1	0.63*** (0.13)	0.28 (0.22)	1.11*** (0.17)
Observations	9607	5205	9245
Restricted log likelihood	-1883.94	-828.62	-1091.84
Unrestricted log likelihood	-1781.01	-733.23	-984.19
ρ[1]	0.704 (0.044)	0.818 (0.043)	0.565 (0.064)
θ[2]	0.789 (0.130)	1.855 (0.430)	1.818 (0.584)

Notes: 1 ρ is an estimate of the cross-period correlation of the composite error term $\varepsilon_i + \mu_{it}$.
2 θ is the statistic used to test if the initial conditions are exogenous. A clearly positive value of θ rejects the hypothesis that the initial conditions are exogenous, thus lending support to the adoption of the Heckman method. The same control variables as in table 4 are used in these regressions. The estimation of the certificates III/IV category was difficult to converge, but then produced sensible results.

Source: Mavromaras, McGuinness and King (2009b).

The evidence in table 5 supports the view that in the case of VET graduates any severe overskilling state dependence that may be present tends to be a short-term phenomenon that dissipates quickly

[18] Regressions in table 4 force all estimates except for the education dummies themselves to represent a person with average education. Thus all the differences between education levels are represented by the one estimate of the relevant education dummy. While statistically correct, this assumption is too restrictive in our case where we want to know how other estimates may vary by education. We thus split the sample by education level and estimate separately, allowing all estimates to be education-level-specific.

enough for it to not be present a year later, when the next HILDA interview takes place. Considering the long-term costs that severe overskilling imposes on workers, VET graduates score very well with the lowest costs. The opposite is true for workers qualifying by more conventional academic routes. It is worth noting at this stage that the absence of state dependence for VET graduates, but not for other education pathways, ties in well with the different incidence estimates between the pooled and panel estimates in table 2. Remember that the pooled estimates showed that, as a whole group, certificates III or IV are generally less overskilled, while at the same time the panel estimates showed that those who just obtained their certificate III or IV qualification did not enjoy an immediate reduction in their overskilling. The implication here is that the beneficial effect of certificates III and IV in terms of helping improved matching happens over a longer time span, which is, in terms of long-run matching outcomes, the story that the dynamic estimates are also suggesting.

Having established that true state dependence is present (in the form of a significant lagged overskilling variable in the right-hand side of our overskilling incidence estimation), it would be useful to know how far back into the past (or equivalently and more usefully, how far into the future) this effect may stretch. A number of additional regressions were estimated to try to answer this question. This was achieved by including further lags of the overskilling variable in the overskilling estimations. We do not present these estimation results here because we do not believe that they are sufficiently reliable. Our reading of these results is that, once further lags are introduced, the data available for estimation become too short for detailed and robust estimation. In all the attempts we made, the second lag of overskilling was significant and, as one would expect, had a weaker effect than the first lag. The majority of the remaining coefficients, however, lost significance and a small number of them assumed values that could not be reconciled with other existing evidence. Adding a third lag in the right-hand side did not result in a significant coefficient, indicating that the lagged effects do not carry back further than two periods. Although we could be tempted to argue that this is evidence of short-lived state persistence of overskilling, we believe that we should not make this argument and that we should simply acknowledge that our data are not sufficient for testing longer-lags hypotheses. Nevertheless, if we look at our persistence results as a whole, we can argue that once an individual becomes severely overskilled they have a pretty good chance of remaining so for one more year and possibly for two years. There is therefore some evidence that casts doubt on the presence of empirical support for job mobility and matching theories in the labour market, and the ability of labour markets to clear in the context of allocating skills efficiently, but only for some educational pathways. Given that by international standards the Australian labour market can be considered as a relatively de-regulated market with considerable flexibility, this is a noteworthy result.

Wage effects of overskilling?

Having completed the examination of the incidence and persistence of overskilling, we update the Australian evidence on the wage consequences of overskilling by incorporating a total of six waves of the HILDA data in the analysis. We begin this section with a concise explanation of how the wage effects of overskilling have been measured in the literature. We know that typically, when all levels of qualifications are well matched, wages improve. We also know that higher qualifications typically improve wages. The reader must note the comparison we make when we talk in the remainder of this section about the 'wage penalty' that results from overskilling. Put simply, we compare the wages of two people who are in all aspects identical, including that they do the same job and have the same qualifications. Their only difference is that one reports to be overskilled and the other reports to be well matched in their job. Our research asks whether the overskilled person may be paid lower than the well-matched person and the answer to this question is clearly yes. In this two-person comparison, where the percentage of the pay of the overskilled person is lower, we call the 'overskilling wage penalty'. We generalise this example by comparing the average overskilled person with the average well-matched person and we use multivariate regression to estimate the average wage penalty. There are, of course, other valid and relevant comparisons to be made, depending on the question to be answered; for example, a comparison between the pay of an overskilled degree holder and that of a well-matched school leaver doing the same job. Typically, research suggests that the degree holder will be paid something above the pay of the well-matched school leaver, which will still be below the pay of a well-matched degree holder, but this is not the comparison that these estimations were set up to make.

We follow Mavromaras, McGuinness and King (2009a) by estimating the wage impacts using both standard ordinary least squares (OLS) and the more robust approach of propensity score (PSM) matching as described earlier.[19] For further details on this methodology see the appendix.

The results from both the ordinary least squares and propensity score matching models are presented in table 6. The first thing that becomes apparent is that the ordinary least squares estimates are generally similar to the propensity score matching estimates, confirming the finding of Mavromaras, McGuinness and King (2009a) that, on this occasion, the ordinary least squares estimates are not subject to a high degree of bias. Table 6 presents the wage impact of moderate and severe overskilling within each educational grouping.[20] Looking at the complete sample, the majority of our estimates suggest that individuals who are severely overskilled earn between 10 and 13.5% less than their well-matched counterparts.

In line with Mavromaras, McGuinness and King (2009a), the present analysis does not find wholly consistent evidence of a pay penalty to be a consequence of moderate overskilling. Splitting the sample by education level, the penalty from severe overskilling was highest among graduates, ranging from 13.8 to 18.9%. The severe overskilling wage penalty among vocationally qualified workers was lower at between 11.6 and 14.4%.

There is no evidence for the presence of an overskilling pay penalty among the Year 11 and 12 grouping, but there is evidence of a wage penalty (of between 6.0 and 10.2%) among the completely unqualified workers (that is, highest education attainment to school Year 10 or less) who deem themselves to be severely overskilled. This final result could lend support to the view that those individuals at the very bottom of the labour market and the education distributions are not only undertaking the most menial of tasks, but they are also doing this for lower wages. This is particularly so, given that the wage distribution of this group is more compressed than other parts of the labour market.

[19] Studies by McGuinness (2007) and Mavromaras, McGuinness and King (2009a) have demonstrated that the principal determinant of present mismatch is an individual's history of mismatch. Therefore, we again harness the panel characteristics of our sample to include a measure of overskilling in the previous wave as a covariate in the propensity score estimates. In doing this we effectively compare the wages of individuals who are overskilled with those with the same characteristics who were previously overskilled but are now matched. Thus, to the extent that lower levels of ability may be evident in the treatment group, they will also be present in the control group by nature of their previous overskilling. Given that no lagged information exists for wave 1, the models are estimated on pooled waves 2 to 6.

[20] Reliable propensity score matching estimates could not be generated for the certificate I and II grouping due to their small sample size.

Table 6 OLS *versus* PSM estimates for the effect of overskilling on wages (waves 2–6)

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

Notes: Sample sizes in the category certificates I and II were too small to allow for the necessary matching for PSM estimation. The following control variables were included in the estimation: gender, country of birth, proportion of past year in unemployment, education level, father's professional status, urban region, marital status, occupational experience, tenure, hours worked, employment related training in last year, four age dummies, union membership, children below 5, children between 5 and 14, four firm size dummies. In the balancing equation for the PSM estimation, previous overskilling was also used as a means of matching based partially on individual unobserved heterogeneity.
Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1/5/10 per cent level.

Discussion

Incidence

Our research has shown that overskilling incidence varies by education level even after we have controlled for the differences in the composition of labour market participants by education level. Estimation results confirm the result that people with more education are less likely to be overskilled in their job. It looks as though the incidence of bad matches in the workplace are the problem of lower education levels. The best way to guard against a worker ending up overskilled in their workplace appears to be post-school education. The overall message is clear: employed people with higher education levels are less likely to be mismatched in their workplace.

Our results go further than just showing that the pertinent delineation of the effect of education is between those with and those without post-school qualifications. It is notable that we find no statistically significant differences in overskilling outcomes between Years 10, 11 and 12 school graduates. In an era where considerable emphasis is given to the importance of earlier stages of education (often for good reasons), this research would suggest (i) that post-school education plays an important role in allowing workers to realise their potential in the workplace and firms to find and match the right skills to the right jobs, and (ii) that the completion or not of the last few school years does not make a lot of difference in terms of eventual mismatch in the labour market. We believe that there is scope for further research in this area, especially using data with complete information on the education pathway to employment, as opposed to the HILDA set, which reports only highest attained level of education. Research that distinguishes explicitly the differences between Years 10, 11 and 12 and their interaction with vocational education that may have been obtained in place of some of these school years would benefit our understanding of mismatch in the workplace and some of the resulting consequences of educational pathway choices. Further, although we control for some cohort differences, our results may in part reflect the differences in education composition between the younger and older cohorts of Australian workers.

Our research has shown that there are clear differences between the two main streams of post-school education—VET versus diploma/degree. Although we highlighted these differences, we must caution the reader against overinterpreting them, as this research does not provide a framework of analysis that considers explicitly the impact of differences in the demand for labour between VET and diploma/degree graduates. We note that there is a general dearth of research in the area of labour demand by post-school educational pathway, and that international research does not provide a great deal of guidance either. Both holders of certificates III and IV and diploma/degree qualifications are less likely to be either moderately or severely overskilled, but they appear to be doing this in a different way. Our research has highlighted these differences (principally in terms of showing some short- versus long-term differences by education) but cannot provide more specific results about the timing of the reduction in mismatch by the two post-school educational pathways.

Certificates I/II provide an interesting picture, but sample size concerns would advise against overinterpreting these particular results before a longer panel can be used. Our research has raised the issue, but it has not provided an answer that can be statistically trustworthy.

Occupation

Different occupations are associated with different rates of overskilling. In general it looks as though elementary occupations are much more likely to be overskilled. This effect is present after factors such as age, education, experience and other equally important human capital and labour supply factors have been controlled for. This opens the possibility that it could be job attributes that are responsible for these differences. It could be that the lower/elementary occupations do not have the potential to adapt to individuals who may be able to do more than the original low specification of their job, so that they remain overskilled.

It should be noted that it is the lower/elementary occupations and the less-educated workers who suffer more by the presence of overskilling, but that the wage penalty of overskilling is less for Years 11 and 12 and rises again for Year 10 or below. This could be attributed in part but not wholly to the wage distribution being more compressed among those overskilled workers. It could also be that the lower education groups suffer different non-pecuniary penalties instead. These could be disadvantageous mobility and other job attributes. Further research examining the perceptions of these workers on their job attributes would help shed some light on this issue. Research on university graduates by the authors suggests that there are sizeable differences, but there is no such research for lower-level occupations and education. Further research on the perceptions of employers on job attributes and overskilling would also be valuable.

Persistence

We presented the results established by Mavromaras, McGuinness and King (2009b) showing that overskilling can be a persistent labour market phenomenon, in that once overskilled the probability to remain overskilled increases. Overskilling can be compared with other self-perpetuating adverse labour market states, such as long-term unemployment or welfare dependence, where empirical research finds evidence of scarring. We do not present any findings on reliable estimates on the presence and the impact of longer overskilling lags on present overskilling. We have presented findings indicating that persistence is at its maximum for diploma/degree graduates, reduces to about half for workers with no post-school qualifications, and becomes statistically not significant for VET graduates.

Wages

We have used the first six waves of HILDA to replicate and validate our previous results, which were based on only four waves. Estimations confirmed our past findings: the wage penalty associated with overskilling is higher for diploma/degree graduates and lowest for VET graduates. This was a useful confirmation and has produced a new set of up-to-date estimates using Australian evidence.

Concluding remarks

This research was motivated by the question of the attractiveness of VET participation to those who undertake it. It is one of a number of studies designed to increase our understanding of the pros and cons of different educational pathways in the Australian labour market in the 2000s and beyond. In this concluding section we sum up a number of practical and important points from the perspective of the person who is considering the hard job of upskilling. This may be at the start of a working life, it may be at an advanced stage of a career, or even during the last years before retirement. This being the year 2009, it will almost certainly be in a climate of considerable uncertainty regarding the state of the labour market in the near future. We offer three brief outlines addressed to (i) the school leaver, (ii) the VET student and (iii) the university student, indicating the essence of this research from a purely practical point of view. As this is an area of considerable ongoing research, with new data, new questions and new findings emerging continually, it will be prudent to treat these thoughts as our best reading of current research, but a reading that is both tentative and temporary. Further, the partial nature of our results should be borne in mind, in that we are not incorporating in our analysis the role of demand for labour, either in its level or its changes. The implicit assumption is that it is at the present level and roughly constant. This necessitates that results be interpreted in a judicious and careful manner.

The school leaver

This is the group faced with the largest number of possibilities. The first choice is whether the individual gets a job or continues with some post-school education. The answer is clear cut: continuing with post-school education is the way ahead. From past studies we knew that the pay would be better, although not for all, as some school leavers seem to be paid as well as VET graduates. So, it was the university route that seemed to confer most post-school benefits, but we know that universities are not the desired route for all school leavers for many reasons. Our research suggests that post-school education in the VET sector may not increase pay as much (although it does for all post-certificate IV qualifications) but it makes employment better in two other ways. First, it reduces the probability of being underutilised at work and, second, if bad luck strikes and a VET graduate ends up underutilised in the wrong job, getting out of this skills underutilisation is easiest for VET graduates. For the school leaver, going for the VET route seems to be a safer choice than staying with Year 12 as the highest qualification. The other route, getting a diploma or a degree, is clearly superior in terms of expected income. There are some caveats. First, a university degree takes a long time to complete, is a sizeable investment and may not suit everyone's plans and abilities. Second, although on average a university degree pays better than all other education routes, the differences by subject of study and subsequent occupational choice can be considerable. Some subjects can even result in negative net returns for those who studied them. Third, as research on mismatch shows, if one gets it wrong and ends up in an employment mismatch situation, the university graduate pays considerable penalties and getting out of mismatches can prove more difficult. The university route appears to be a higher return and higher-risk strategy by comparison.

The school leaver of today should be advised that a great deal of up-to-date research evidence has come from a long period of economic upturn, so that we cannot be sure that the relationships we have traced will continue to be true if the future turns out to be seriously recessionary.

Notwithstanding this caveat about predictions, our research appears to be in line with the view that the principal route that Australian youth should be following regarding education and skills is upwards, as most indicators in this research suggest better average outcomes for those with post-school education.

The VET student

The question is whether the individaul stays with their certificate I or II, or goes for the higher certificate III or IV, or for the higher diploma/degree type of education. Staying with a certificate I or II seems to be making little difference in the medium or long run. It seems clear that the individual should be opting for a certificate III or IV at least. The question is whether an individual should be going for a diploma/degree type of upskilling. The arguments concerning school leavers presented in the previous paragraph regarding the differences between VET and higher education remain the same. One possible further consideration would be that these findings suggest that the employment benefits from certificates III or IV may take some time to materialise. This would suggest that, although certificates III or IV may not result in instant pay rises and better job–worker matches, they are a good avenue for achieving this type of improvement in the longer run. There is one caveat the reader should consider. We have not had the chance to look into the differences between starting and completing VET courses and the extent to which non-completions as a consequence of beginning a new job may confer any advantages that span beyond the very first job that induced the non-completion of the VET qualification. We have not had the chance to look into the various combinations of school Years 10, 11 and 12 and VET certificates in terms of their longer-term labour market outcomes. Furthermore, we have not had the chance to look at those VET graduates who may have continued onto university education, using their VET qualification as an education stepping stone. Further research should examine these contingencies.

The university student

University graduates have seen the returns to their degrees continue to hold well in most Western economies for many decades, despite the sizeable increase in numbers of graduates. A university degree continues to be the best predictor for increased lifetime earnings and the predictions are that this will continue. All indicators of the future needs in production suggest that upskilling to the university level remains a sound investment in human capital. However, our research suggests that workplace-mismatched university graduates are the group most adversely affected by their mismatch. This group suffers the highest wage penalty (admittedly, they fall from a higher level) and the highest persistence of mismatch, in that they receive the most severe scarring from being in a mismatched job. This cautionary note should be read with a caveat. There may well be a long-run story which these data cannot tell. This implies that, although we know that overskilling is a bad trap for the university graduate, in that it reduces pay and is difficult to get out of, we do not know how long these effects may last. If there are any similarities with long-term unemployment, the news will not be good. Furthermore, we do not know the degree to which lower pay and apparent mismatch may be the result of a choice to take the easy employment option and accept lower pay for less responsibilities and more flexibility. Our ongoing research may shed light on this question in the near future.

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Appendix

Descriptive statistics

Table A1-1 Overskilling by employment status and by age (pooled data)

Highest education level	Extent of overskilling (%)			%
	Well matched	Moderately overskilled	Severely overskilled	
All employed				
Year 10 and below	50.99	30.68	18.32	18.69
Year 11–12	47.39	32.25	20.36	25.79
Certificates I and II and below	45.19	35.88	18.92	1.73
Certificates III and IV and apprenticeship	62.13	27.88	9.99	21.02
Advanced diploma and tertiary	62.46	26.33	11.21	32.78
All qualifications	56.06	29.16	14.78	100.00
No. of observations	23 688	12 322	6 245	42 255
Full-time				
Year 10 and below	55.93	30.15	13.92	16.47
Year 11–12	55.17	31.22	13.61	21.60
Certificates I and II and below	44.65	34.96	20.39	1.68
Certificates III and IV and apprenticeship	64.13	27.74	8.13	24.80
Advanced diploma and tertiary	65.32	26.2	8.47	35.45
All qualifications	60.94	28.47	10.59	100.00
No. of observations				28 766
Part time				
Year 10 and below	43.35	31.51	25.14	23.60
Year 11–12	36.77	33.65	29.59	35.09
Certificates I and II and below	46.3	37.79	15.91	1.82
Certificates III and IV and apprenticeship	53.44	28.46	18.1	12.63
Advanced diploma and tertiary	54.07	26.7	19.23	26.86
All qualifications	45.25	30.7	24.06	100.00
No. of observations				13 489

The bottom two panels of table A1-1 separate the data according to full-time and part-time employment status. The patterns observed in both the full-time and part-time data are very similar to those observed for all workers, that is, a higher incidence of matched employment among workers holding more advanced vocational and academic qualifications and a higher incidence of severe overskilling among workers in the bottom two educational categories. However, some differences are apparent between the part-time and full-time groupings. While the incidence of moderate mismatch is broadly comparable, the overall rate of severe overskilling among part-time workers is more than twice that of their full-time counterparts. The finding of higher levels of severe overskilling among part-time workers is, in itself, not totally surprising, given that many part-time workers tend to balance work with other commitments and, as a consequence, may put somewhat less emphasis on achieving a perfect labour market match. However, one might expect that any rebalancing of commitments would result in a higher incidence of moderate, as opposed to severe, overskilling.

Table A1-2 Overskilling in employment by age group

Highest education level	Extent of overskilling (%)			%
	Well matched	Moderately overskilled	Severely overskilled	
Age group: 16–24				
Year 10 and below	43.52	33.8	22.68	10.35
Year 11–12	36.98	35.2	27.82	57.98
Certificates I and II and below	42.17	33.09	24.74	1.39
Certificates III and IV and apprenticeship	55.47	30.84	13.69	14.33
Advanced diploma and tertiary	44.96	31.11	23.94	15.95
All qualifications	41.65	33.75	24.6	100.00
No. of observations				6 984
Age group: 25–39				
Year 10 and below	48.28	33.5	18.22	12.63
Year 11–12	49.38	32.87	17.75	23.06
Certificates I and II and below	47.6	44.23	8.16	1.23
Certificates III and IV and apprenticeship	61.95	27	11.05	22.00
Advanced diploma and tertiary	59.23	29.26	11.51	41.08
All qualifications	56.03	30.32	13.65	100.00
No. of observations				14 289
Age group: 40–54				
Year 10 and below	53.00	29.77	17.23	21.94
Year 11–12	56.67	29.11	14.22	17.24
Certificates I and II and below	40.47	33.97	25.56	2.20
Certificates III and IV and apprenticeship	62.61	29.08	8.31	24.51
Advanced diploma and tertiary	67.00	23.80	9.20	34.11
All qualifications	60.49	27.54	11.97	100.00
No. of observations				15 536
Age group: 55–retirement age				
Year 10 and below	57.99	26.59	15.42	31.29
Year 11–12	65.55	22.61	11.83	15.28
Certificates I and II and below	52.71	36.88	10.40	2.25
Certificates III and IV and apprenticeship	67.31	23.64	9.05	19.73
Advanced diploma and tertiary	71.90	20.58	7.52	31.45
All qualifications	65.24	23.74	11.02	100.00
No. of observations				4 029

Table A1-2 reports the incidence of overskilling by qualification level disaggregated by age group. A clear pattern emerges, in that the incidence of overskilling, both severe and moderate, falls as age increases. However, relative to those in other educational groupings, the rate of decline with age is much steeper for individuals with advanced vocational or tertiary qualifications.

Appendix table A1-3 presents the occupational distribution across education levels and gives a clear indication of the strongly vocational orientation of education, with individuals holding vocational certificates above level II more heavily represented in occupations such as mechanics, fabricators, electricians, construction workers, other tradespersons and intermediate clerical and service workers.

Table A1-3 Distribution of occupational employment by highest qualification level

Occupation	Highest education attainment				
	Year 10 and below	Year 11–12	Certificates I and II	Certificates III and IV	Adv. diploma & degree
Generalist managers	0.02	1.05	0.14	0.02	0.03
Specialist managers	0.82	2.66	0.43	1.76	2.05
Farmers and farm managers	1.27	2.00	3.01	2.65	9.01
Professionals nec		0.01		2.47	1.29
Science, building and engineering professionals	6.24	0.31	3.15	0.67	0.05
Business and information professionals	0.22	3.64	0.29	3.46	4.81
Health professionals	1.34	1.54	1.29	1.25	12.76
Education professionals	0.8	0.94	0.57	0.76	9.09
Social, arts and miscellaneous professionals	0.37	2.24	0.14	2.00	16.45
Science, engineering and related associate professionals	1.1	1.11	0.29	2.56	8.69
Business and administration associate professionals	0.66	4.95	0.86	3.72	1.94
Managing supervisors	2.93	4.95	3.15	5.23	6.10
Health and welfare associate professionals	4.42	0.32	4.87	2.02	2.92
Other associate professionals	0.34	1.65	0.29	0.91	1.12
Tradespersons and related workers		0.01		0.03	1.71
Mechanical and fabrication engineer tradespersons	0.65	1.24	0.14	6.35	0.31
Automotive tradespersons	1.12	0.57	2.72	3.16	0.06
Electrical and electronics tradespersons	0.61	1.15	0.43	5.99	0.67
Construction tradespersons	0.59	1.47	2.01	6.36	0.44
Food tradespersons	2.59	0.95	0.86	1.58	0.12
Skilled agriculture and horticulture	0.99	0.89	2.29	1.78	0.50
Other tradespersons and related workers	1.33	1.6	1.58	5.30	0.83
Secretaries and personal assistants	1.45	2.38	3.87	1.00	0.70
Other advanced clerical and service workers	2.6	2.54	0.57	1.25	1.59
Intermediate clerical workers	2.48	12.63	13.75	6.69	5.45
Intermediate sales and related workers	10.32	1.91	2.01	1.78	0.80
Intermediate service workers	1.76	9.18	9.31	8.66	3.97
Intermediate production and transport workers	6.53	0.01			
Intermediate plant operators	3.7	1.73	3.30	2.58	0.19
Intermediate machine operators	1.48	0.94	1.43	0.55	0.12
Road and rail transport drivers	6.03	2.13	5.16	3.35	0.48
Other intermediate production and transport workers	3.68	3.61	4.44	2.42	0.52
Elementary clerks	1.18	1.35	1.15	0.62	0.52
Elementary sales workers	10.96	14.64	8.02	3.45	2.18
Elementary service workers	2.39	1.57	4.73	0.86	0.34
Labourers and related nec	0.04	0.02			0.01
Cleaners	5.18	2.32	2.87	1.57	0.54
Factory labourers	3.92	2.16	4.30	1.64	0.45
Other labourers and related workers	7.93	5.65	6.59	3.58	1.18

Estimation results

Table A2 Probit estimations of severe and moderate overskilling (pooled data)

Explanatory variable	Severely overskilled		Moderately overskilled	
	M.E	Std error	M.E	Std error
Female	-0.006	0.007	-0.003	0.008
Migrant from English speaking country	-0.017*	0.010	-0.002	0.012
Migrant from non-English speaking country	0.038***	0.011	0.025**	0.012
Education: Year 11–12	-0.004	0.009	0.005	0.011
Education: certificate I and II	-0.003	0.024	0.053**	0.026
Education: cert. III/IV, apprenticeships	-0.054***	0.008	-0.044***	0.010
Education: adv. dipl., degree or higher	-0.036***	0.009	-0.043***	0.010
Proportion of past year in unemployment	0.001***	0.000	0.0003	0.0003
Urban	0.010	0.009	0.018*	0.010
Occupational experience (years)	-0.004***	<0.001	-0.003***	0.000
Employment tenure (years)	-0.001	0.001	0.001*	0.001
Weekly hours worked	-0.005***	<0.001	-0.004***	0.000
Age: 25–39 years	-0.003	0.008	-0.007	0.010
Age: 40–54 years	0.001	0.009	-0.022**	0.010
Age: 55–64 years	-0.015	0.012	-0.058***	0.013
Union member	-0.002	0.007	-0.004	0.008
Have children aged between 5 and 14	-0.012*	0.007	0.013	0.008
Have children aged below 5	-0.018*	0.009	-0.015	0.010
Firm size less than 5 people	-0.034***	0.008	-0.032***	0.009
Firm size between 5 and 9 people	-0.042***	0.008	-0.030***	0.010
Firm size between 10 and 19 people	-0.031***	0.008	-0.023**	0.010
Firm size between 20 and 49 people	-0.020***	0.008	-0.013	0.009
Industry: agriculture, forestry and fishery	0.013	0.018	-0.008	0.020
Industry: mining	-0.042*	0.023	-0.027	0.027
Industry: electricity, gas and water	-0.034	0.035	-0.026	0.036
Industry: construction	-0.059***	0.010	-0.044***	0.015
Industry: wholesale	0.019	0.016	0.008	0.018
Industry: retail	0.012	0.012	-0.004	0.013
Industry: accom. cafes and restaurants	0.017	0.015	-0.012	0.017
Industry: transport	0.016	0.017	0.013	0.019
Industry: communication	0.031	0.026	0.011	0.027
Industry: finance	-0.071***	0.012	-0.056***	0.018
Industry: property & business services	-0.066***	0.009	-0.041***	0.013
Industry: defence	-0.098***	0.009	-0.053***	0.016
Industry: education	-0.138***	0.007	-0.155***	0.012
Industry: health	-0.117***	0.007	-0.127***	0.012
Industry: cultural & recr. services	-0.076***	0.012	-0.098***	0.018
Industry: personal & other services	-0.061***	0.011	-0.086***	0.017
Observations	29 978		36 198	
Pseudo R square	0.1435		0.0357	
Restricted log likelihood	-14504.94		-22900.13	
Unrestricted log likelihood	-12423.55		-22082.37	

Overskilling is negatively correlated with occupational experience, hours worked and employment in smaller firms. Furthermore, both moderate and severe overskilling are unevenly distributed amongst industries, with construction, finance, property, education, defence, health, cultural and personal services associated with lower overskilling. There are few estimates that differ by level of overskilling. For instance, relative to Australian natives, migrants from English speaking (non-English speaking countries) are less (more) likely to be severely overskilled. There is some evidence that moderate overskilling is lower among the 40-plus age group. Looking at the remainder of table A2 we see that the marginal effects of firm size become much less consistent and significant, while the marginal effects of sector become much more pronounced. Migrants from a non-English background are now more likely to be exposed to both severe and moderate overskilling. The influence of occupational tenure falls out of the model, while employment tenure becomes a significant determinant of moderate but not severe overskilling, and the small negative effect of weekly hours on overskilling remains significant. The changing nature of the marginal effects as we move from pooled to random effects estimation demonstrates that our earlier estimates were clearly affected by unobserved heterogeneity bias.

Table A3 Random effects probit estimations of severe and moderate overskilling

Explanatory variable	Severely overskilled		Moderately overskilled	
	M.E.	Std error	M.E.	Std error
Female	-0.007*	0.004	-0.005	0.010
Migrant from English speaking country	-0.006	0.006	0.0004	0.014
Migrant from non-English speaking country	0.025***	0.008	0.035**	0.015
Educational attainment: Year 11–12	0.013	0.013	-0.002	0.032
Education: certificate I and II	-0.025*	0.013	0.131*	0.079
Education: certificate III and IV and apprenticeship	-0.009	0.012	-0.002	0.037
Education: advanced diploma or degree or higher	-0.036***	0.013	-0.038	0.043
Proportion of past year in unemployment	<0.001	<0.001	<-0.001	<0.001
Urban	-0.015	0.011	-0.030	0.023
Occupational experience (years)	<0.001	<0.001	<0.001	0.001
Employment tenure (years)	0.001	<0.001	0.002**	0.001
Weekly hours worked	-0.002***	<0.001	-0.003***	<0.001
Age: 25–39 years	0.010	0.009	-0.005	0.021
Age: 40–54 years	0.006	0.010	0.006	0.025
Age: 55–64 years	0.002	0.012	0.038	0.029
Union member	-0.001	0.005	-0.007	0.013
Have children aged between 5 and 14	0.005	0.006	0.023*	0.012
Have children aged below 5	0.003	0.006	0.018	0.014
Firm size less than 5 people	-0.006	0.005	0.019	0.016
Firm size between 5 and 9 people	-0.011**	0.005	0.018	0.016
Firm size between 10 and 19 people	-0.004	0.005	-0.003	0.014
Firm size between 20 and 49 people	-0.001	0.005	-0.002	0.013
Industry: agriculture, forestry and fishery	0.028	0.020	0.035	0.037
Industry: mining	-0.006	0.017	-0.005	0.047
Industry: electricity, gas and water	-0.018	0.016	0.071	0.069
Industry: construction	-0.021***	0.006	0.013	0.027
Industry: wholesale	0.023*	0.014	0.064**	0.027
Industry: retail	0.021*	0.011	0.057**	0.024
Industry: accommodation, cafes and restaurants	0.007	0.012	0.019	0.032
Industry: transport	0.002	0.012	0.017	0.033
Industry: communication	-0.014	0.011	-0.024	0.042
Industry: finance	-0.018**	0.009	-0.043	0.034
Industry: property & business services	-0.026***	0.005	0.004	0.023
Industry: defence	-0.035***	0.004	-0.025	0.028
Industry: education	-0.041***	0.005	-0.092***	0.027
Industry: health	-0.042***	0.004	-0.069***	0.025
Industry: cultural & recreational services	-0.028***	0.005	-0.051	0.031
Industry: personal & other services	-0.022***	0.007	-0.043	0.031
Observations	29 978		36 198	
Restricted log likelihood	-11072.13		-20589.75	
Unrestricted log likelihood	-10630.14		-20496.34	

Table A4 Incidence of overskilling and occupational categories (certificates III–IV)

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

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