Over-skilling and job satisfaction in the Australian labour force

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About the research

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Over-skilling and job satisfaction in the Australian labour force

Kostas Mavromaras, Seamus McGuinness, Sue Richardson, Peter Sloane and Zhang Wei

In a not-too-uncommon scenario individuals may find themselves in a job where they feel their qualifications (over-educated) or skills (over-skilled) or both are greater than are required to do the work. Previous research has found that people who work in jobs which do not make full use of their education and training earn lower wages than those in jobs that provide a good match to the education and training.

Using data from the Household Income and Labour Dynamics in Australia (HILDA) survey, the work of Mavromaras and colleagues extends previous research on the effect of over-skilling on wages in two ways: by expanding the categories of mismatch to also include over-education; and by looking at the effect of mismatch on job satisfaction as well as wages. Further, this study distinguishes between 'genuine' mismatch—where wages and job satisfaction are both low—and 'apparent' mismatch—where a job may pay less but is accepted because it has some other redeeming attribute, such as greater flexibility in work hours.

Key messages

- Irrespective of the type of post-school qualification, becoming mismatched in a job almost always results in lower job satisfaction, especially with the actual work that is done. This is particularly the case for those with vocational qualifications.
- Mismatch is more detrimental for those with intermediate vocational qualifications (certificate III/IV). However, over-skilling is less likely to occur amongst this group and, if it does, will not last long. The same does not hold true for university graduates.
- Being over-skilled as opposed to over-educated is the greater driver of the adverse consequences of lower wages and job satisfaction.
- Gender matters when it comes to experiencing mismatch—compared with their well-matched peers, women who are either over-skilled or over-educated suffer wage penalties and lower job satisfaction. Such differences between well-matched and mismatched males are not as apparent.

Tom Karmel
Managing Director, NCVER

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Executive summary

The purpose of this research is to examine the effects of employee over-skilling and over-education on two major labour market outcomes, namely, wages and job satisfaction. Using data from the Household Income and Labour Dynamics in Australia (HILDA) survey, the research focuses on full-time employees in Australia between the years 2001 and 2008. This phenomenon has been shown in the literature to be associated with lower pay and job satisfaction, both of which indicate reduced productivity in Australian workplaces.

We extend the definition that has been used to date in Australian research to include three main categories of mismatch: *over-skilled-only*, *over-educated-only* and *over-skilled and over-educated*. *Over-skilled only* employees report their skills to be under-used in their job but are well matched in their qualifications. *Over-educated-only* employees have qualifications that are above the norm in their occupational group but they report that their skills are appropriately used in their job, and *over-skilled and over-educated* are both. The analysis uses reported job satisfaction as a measure of employee dissatisfaction with mismatch. The analysis is carried out by gender and by education pathway.

This work confirms previous results on the negative effect of mismatch on wages. It further extends previous work through the application of the three-way, more focused definition of mismatch described above and by using panel estimation, which controls for unobservable differences between employees, such as ability and motivation. We examine in detail whether mismatch influences job satisfaction and find that it does, particularly among those with post-school education. We find that in most cases over-education and over-skilling appear to produce adverse labour market outcomes, but there were few patterns in the results.

We carry out multivariate regression analysis using the panel element of the Household Income and Labour Dynamics in Australia survey data to estimate the causal effect of becoming mismatched on wages and job satisfaction. Our analysis finds extensive education level and gender differences in the effects of mismatch on wages and job satisfaction. We compare cross-section and panel evidence on mismatch wage penalties and find that cross-section estimates are considerably higher. This confirms the presence of unobserved heterogeneity in the data. That is, people who have personal characteristics that are not recorded in the data but are associated with wages are also more likely to be in a mismatched job: the relationship between mismatch and low wages is more complex than the data reveal.

The research looks at the facets of job satisfaction reported by employees and finds differences by type of mismatch, education pathway, gender and age. The possible impact of cohort (age) differences in the sample is also examined, with strong, but not always clearly interpretable, differences found. This may be an artifact of small sample sizes, in particular for those with diplomas or advanced diplomas, where there are too few over-skilled employees.

To measure the quality of new matches through the way in which mismatched and well-matched employees may differ systematically, wages (as an indicator of the productivity of a new job match) are combined with job satisfaction (an indicator of the perceived success of a new match). We use the estimated effect of mismatch on wages and job satisfaction to categorise the nature of the onset of a mismatch as being: a genuine mismatch (both wages and job satisfaction reduced); a weak mismatch (only job satisfaction reduced); no evidence of a mismatch (neither wages nor job

satisfaction reduced); or evidence of compensating differentials (wages not reduced and job satisfaction increased). Reported mismatches are more likely to be genuine mismatches among those having post-school education qualifications and for females in full-time work. The findings have potential policy implications, as they help us to identify the origin of mismatches (either from 'informal' under-utilisation of self-reported skills, or from 'formal' under-utilisation of qualifications, or from both) and the consequences of mismatches (either in the form of reduced satisfaction from the job or wages). The research indicates that, on balance, some combinations are less likely to be harmful than others.

In addition to these specific results, this research has made important advances in the knowledge of how mismatches may be measured and evaluated. First, the research confirms that job satisfaction is important in distinguishing genuine from apparent mismatch. Second, it highlights that average wages at a given point in time provide a limited understanding of the effect of mismatch on labour market outcomes: longer-term measures should be used. The research also highlights the importance of splitting the analysis by age cohorts, as educational achievement and related labour market outcomes can be heavily age cohort-dependent. Finally, it adds the first extensive set of panel estimations of the causal effect of the onset of mismatch on wages and job satisfaction as an additional measure of the general association of mismatch with labour market outcomes.

In many cases becoming mismatched has a direct effect on wages. It does not matter for those who are not paid well and these are typically those without post-school qualifications. But for those with post-school qualifications there is a wage penalty. For the over-educated-only, the penalty affects mostly females. There is no pattern for the over-skilled-only. For the over-skilled and over-educated (the strongest form of mismatch) the wage penalty is stronger and affects both genders.

Becoming mismatched is particularly harmful for vocational education and training (VET) graduates with certificates III/IV. Offsetting this, over-skilling is less common among VET certificates III/IV graduates and it is not self-perpetuating, which means that VET graduates do not get trapped in the state of over-skilling. By contrast, university graduates do.

Overall, job dissatisfaction rises almost universally for those with post-school qualifications when they move to a mismatched job. The facet of the job that is most diminished by mismatch is satisfaction with the actual work done in the job. Here mismatch shows clearly that the content of mismatched jobs is less appealing for VET graduates than it is for university graduates.

The picture of university graduates offers some surprises. While anecdotal evidence focuses on the story of females who are over-educated and underpaid out of choice, we find this is not supported by our data and analyses: over-educated female university graduates are underpaid and they do not like it. By contrast, over-educated male university graduates do not seem to suffer any discernible losses as a consequence of being over-educated. This gender difference is also present among the over-skilled university graduates. Both males and females dislike being over-skilled, but it is the females who suffer an over-skilling wage penalty. When it comes to those who are both over-skilled and over-educated, the most severe type of mismatch, gender differences disappear and both males and females report lower wages and higher dissatisfaction.

Introduction

Earlier studies have looked at the extent of over-skilling in Australia, its impact on wage levels and on job mobility, as well as its persistence over time, using the Household, Income and Labour Dynamics in Australia (HILDA) survey data (see Mavromaras, McGuinness & Fok 2009a, 2009b, 2009c; Mavromaras et al. 2010a, 2010b). This study extends the analysis by differentiating between various manifestations of skills mismatch and examining their impact on levels of job satisfaction among individual employees. Job satisfaction has been used in previous studies as an indicator of the quality of job matches, especially in those cases where the qualifications (over-education) or the skills (over-skilling) possessed by the worker appear to be in excess of those required to do the job. The idea is simple: where conventional mismatch indicators such as over-education and over-skilling suggest the presence of a mismatch and the worker reports a low level of job satisfaction, we can interpret the conventional measures of over-education and over-skilling as true indicators of job-employee mismatch. Where, however, the worker does not report a below-average level of job satisfaction in the presence of over-education or over-skilling, the evidence for a true mismatch becomes less convincing and alternative explanations may be sought.

Chevalier (2003) used job satisfaction to estimate the extent to which workers and jobs were well matched. He defines a genuine mismatch as a case where the worker possesses more qualifications than are necessary for the job and is at the same time dissatisfied with that job. He defines an apparent mismatch as a case where the worker possesses more qualifications than necessary for the job, but is at the same time satisfied with that job. Workers may be over-qualified but still satisfied with their work if, for example, the job accommodates important family demands, or enables them to pursue other major interests, or has a short commute, or has particularly congenial social relations among co-workers, or offers unusual levels of security.

Following a similar line of thinking, Green and Zhu (2010), in an attempt to unify the literature on over-education and over-skilling, distinguish between 'real' and 'formal' over-education according to whether or not it is accompanied by (self-reported) skills under-utilisation. Green and Zhu find that those in the 'real' over-education category suffer from higher wage penalties than those in the 'formal' over-education group, and that only the former exhibits significantly lower job satisfaction. The work of Chevalier (2003) and Green and Zhu (2010) has been extended by Mavromaras et al. (2010b), who, using the first seven waves of the survey data, estimate the level of job satisfaction for university graduates according to education and skill matching in Australia; they conclude that there is, indeed, some evidence that job satisfaction is a useful addition to the empirical literature.

The present research follows Chevalier (2003), Green and Zhu (2010), and Mavromaras et al. (2010b) in the definition of different types of mismatch based on combinations of over-education and over-skilling. This research advances our understanding of skills mismatch in two major ways.

First, it examines the level of job satisfaction and the wages of under-utilised workers and the degree to which any observed skill under-utilisation may be counted as genuine mismatch or as apparent mismatch. Following strong indications in the literature of the influence of education pathways on mismatch and resulting labour market outcomes, all analyses are performed separately for each education pathway. The research pays particular attention to the ways in which workers with VET qualifications differ from those with university qualifications, and from those with no post-school qualifications. This is particularly in relation to the extent to which skills are well matched to jobs or not and to the labour market outcomes of the level of (mis)match. The Household Income and Labour Dynamics in Australia survey data provide us with rich information on job satisfaction, in particular by including questions on a number of facets of job satisfaction. The investigation of these facets allows us to test for possible gender differences, as well as for more detailed education pathway differences, in the effects of job mismatch.

Second, the research uses the unique panel information on over-skilling contained in the first eight waves of the survey data to test again the hypotheses put forward in the earlier literature, and to compare the results by education pathway after controlling for unobserved individual heterogeneity.

Over-education as a type of mismatch

To introduce over-education as an explicit type of mismatch in the analysis we need to explain how it relates to over-skilling and how the two strands of research on job mismatch (namely over-education and over-skilling) can be placed within a unified framework. The bulk of the literature to date has been on over-education, beginning with Freeman's seminal book in 1976 on over-educated graduates in the United States. Although some of the very negative possibilities predicted from Freeman's work did not materialise (especially that of an over-supply of graduates), the persistence of over-education as an economic phenomenon continues to fascinate both labour economists and those who are in charge of education and labour market policy design. By contrast, little has been written on over-skilling, the prime reason for this being the lack of appropriate data for its investigation. This research deficit has begun to be rectified with the emergence of datasets such as the Household Income and Labour Dynamics in Australia survey for Australia and the UK Workplace Employment Relations Survey, both of which contain over-skilling questions. In particular the repeated observations of the Australian survey allow the study of over-skilling using panel econometric methodologies which come as close as possible to making causal inferences using survey data.

The most comprehensive attempt to categorise over-education mismatch has been that of Sicherman (1991), who suggests that over-educated workers are paid *less* than their well-matched counterparts (that is, other workers with the same education level, but working in different jobs which match that education level), but *more* than their well-matched colleagues (that is, workers with less education working in jobs that match their—lower—education level). He also investigates the opposite type of mismatch; that is, under-education where a worker is working in a job that requires higher levels of education than those that they possess. He suggests that under-educated workers are paid *more* than their matched counterparts (that is, workers with the same education level who work in different jobs with lower education requirements), but *less* than their matched colleagues (that is, workers with more education who work for a job that requires this level of education). There has been a lot of empirical confirmation of Sicherman's predictions, albeit using cross-section data and estimation methods over a number of countries (see Sloane 2003). The main disadvantage of using cross-section data and estimation methods is that we cannot identify any causal relationships, as we are in effect estimating net associations. Hence the interpretation of such results should be treated with caution.

Recent research by Bauer (2002) and Tsai (2010) using panel data finds that caution is, indeed, required. Bauer finds that the over-education wage penalty can be attributed to unobserved individual (worker) heterogeneity and Tsai finds that it can be attributed to the non-random assignment of workers to jobs.[1] Although these two results point to the same deficiency in cross-

1 Bauer (2002) uses the German Socio-Economic panel and Tsai (2010) uses the US Panel Survey of Income Dynamics. They both find that the effect of over-education on wages disappears when controlling for unobserved heterogeneity and non-random assignment to jobs respectively.

sectional analysis, they also highlight another crucial factor in the context of mismatch, by suggesting that a mismatch wage penalty can be due to either labour supply factors (Bauer) or labour demand factors (Tsai). This is an important finding that must be borne in mind in interpreting our results. The implication is that, to the degree that any data do not represent adequately the labour demand side of the way in which workers are matched with jobs, there will always be the possibility of bias in the estimation due to omitted variables. Previous analyses have shown that the use of industry and (or) occupation indicators in estimation controls for a substantial amount of over-education (CEDEFOP 2010) and over-skilling (Mavromaras, McGuinness & Fok 2009b), so that these variables can be interpreted as valid approximations of labour demand factors in the estimations that follow.

Combining over-education and over-skilling mismatch

A more recent development in the empirical labour economics literature has been the recognition that over-education on its own is not always a sufficiently informative measure of mismatch. Other measures have been emerging in the literature, some closer to over-education than others. Over-skilling is one such measure where the under-utilisation of skills is considered to be a form of mismatch.[2] Job satisfaction is another measure of possible mismatch and lower levels of job satisfaction have been treated as a direct or indirect measure of mismatch. This research uses both of these measures in an attempt to create a broader understanding of how jobs and workers may be mismatched in the workplace.

This research first combines education qualifications and skills mismatch in recognition of the possibility that the two types of mismatch may be related, both in their causes as well as in their effects on labour market outcomes. We follow the definition of mismatch categories first suggested by Green and Zhu (2010), which uses information on both over-education and over-skilling. The following categories are defined:

- *well-matched*: matched in both qualifications and skills
- *only over-educated*: mismatched in qualifications and matched in skills
- *only over-skilled*: mismatched only in skills and matched in qualifications
- *both over-educated and over-skilled*: mismatched in both qualifications and skills.

We do not follow the definition proposed by Chevalier (2003), who uses job satisfaction as a direct measure of a mismatched job. Instead we estimate the degree to which the four mismatch categories defined above may themselves be the cause for higher or lower job satisfaction.

2 Mavromaras, McGuinness and Fok (2009a) contains an up-to-date account of how over-skilling can be treated as a measure of mismatch in the workplace. Mavromaras et al. (2010b) gives a basic account of how over-skilling and over-education contain different information regarding mismatch and how the profiles of the over-educated and the over-skilled differ considerably, supporting the view that the two phenomena are empirically distinct.

Data and estimation methodology

Preparing the data

Education

The data for this research come from the first eight waves of the Household, Income and Labour Dynamics in Australia survey, which began in 2001 (wave 1) with a large national probability sample of Australian households and their members.[3] We use an unbalanced panel of all working-age employees (16–64 years for males and 16–59 years for females) in full-time employment, who provided complete information on the variables of interest. The sample size we retain is approximately 4500 observations per wave. This varies for different estimations, but not by much.

We split the data into the following five educational categories based on the highest education level achieved at time of interview:

- university degrees (including bachelor degrees, graduate certificates, graduate diplomas and higher degrees)
- advanced diplomas and diplomas
- certificates III and IV
- only completed school (Year 12)
- did not complete school (Below Year 12).[4]

Table 1 reports the distribution of education by gender. The data here are pooled person-year observations across all eight waves of the survey. The sample sizes in each education category are clearly sufficient to run regressions split by gender and educational category, with some reservations relating to the 'Advanced diplomas and diplomas' category when performing panel regressions. We also note that the sample contains far fewer females than males in the categories 'Did not complete school' and 'Certificates III/IV'. One reason for this is that the sample is restricted to full-time employees only, and less-educated females are more likely to be either not working or working part-time, in both cases being excluded from our sample. By contrast, the proportion of females among the non-VET graduates reflects the decrease in gender participation differences among those graduates.

[3] See Watson and Wooden (2004) for a detailed description of the HILDA data.

[4] Certificates I and II have been subsumed in the category 'Did not complete school', depending on their highest year of schooling completed.

Table 1 The distribution of highest education levels of full-time employees, by gender

	Highest education					
	Did not complete school	Only completed school	Certificates III/IV	Diplomas	Degrees	**Total**
Males	5 088	3 389	6 478	1 937	5 537	**22 429**
Females	2 867	2 404	1 962	1 523	4 889	**13 645**
Total	**7 955**	**5 793**	**8 440**	**3 460**	**10 426**	**36 074**

Notes: The sample is person years of working-age full-time employees from HILDA 2001–08.

Over-skilling

The over-skilling variable used in this research is derived from the self-completed questionnaire of the survey. Interviewees are asked to respond on a seven-point scale to the statement 'I use many of my skills and abilities in my current job', with a response of 1 corresponding to strongly disagree up to 7 strongly agree. Individuals selecting 1, 2, 3, or 4 on the scale are classified as over-skilled and those selecting 5 or higher as skill-matched.[5]

Table 2 The distribution of skill utilisation by gender

		Question: 'I use many of my skills and abilities in my current job'							
		1	2	3	4	5	6	7	**Total**
Males	Cases	409	666	924	1 875	3 991	7 446	4 421	**19 732**
	%	2	3	5	10	20	38	22	**100**
Females	Cases	246	399	518	1 049	2 285	4 527	3 215	**12 239**
	%	2	3	4	9	19	37	26	**100**
Total	**Cases**	**655**	**1 065**	**1 442**	**2 924**	**6 276**	**11 973**	**7 636**	**31 971**
	%	**2**	**3**	**5**	**9**	**20**	**37**	**24**	**100**

Notes: The sample is person years of working-age full-time employees from HILDA 2001–08. 1 stands for strongly disagree (strongest mismatch) and 7 for strongly agree (strongest match).

Table 2 reports the distribution of skill use by gender. No significant gender difference is found in the degree of over-skilling, and the cut-off point we select to define over-skilling (4 or less) gives sufficient observations to support regression analysis. The way the over-skilling question is asked in the HILDA survey does not allow the researcher to examine the phenomenon of under-skilling and so we do not address this further here. Therefore, all comparisons and results in the following analysis look only at the under-utilisation side of potential skills mismatch.

Over-education

The HILDA survey does not contain any direct questions on over-education. To generate an over-education measure, we use the 'empirical method', which defines a person to be over-educated if he or she has a higher qualification than some chosen norm for employees in the same occupation (see Sloane 2003). Different norms have been used in the literature. Here we choose the mode, as it is the measure least affected by the shape of the distribution of education. We categorise the whole

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5 In previous research we have categorised over-skilling as 'Well-matched', 'Moderately over-skilled' and 'Severely over-skilled' (for example, Mavromaras, McGuinness & Fok. 2009a). For the purposes of this research it would have been too complicated to retain this three-way split of over-skilling. Extensive experimentation has revealed that reducing the variable to a two-way one does not alter the core results of the analysis. The same holds for the choice of cut-off point. The application of different cut-off points makes no qualitative difference, with lower cut-off points reducing the number of those categorised as over-skilled but obviously picking from the sample the more over-skilled people, thus increasing the size of the effects of over-skilling, but applying it to a smaller part of the sample.

survey sample of employees by their years of education and their two-digit occupational classification, and then compare their education level with the mode of education for their occupation group.[6] A person is said to be over-educated if his or her educational achievement is above the mode of their occupational group.[7] Mavromaras et al. (2010b) considered using an 'objective method' similar to the one used by Kler (2005) to define over-education. The Australian and New Zealand Standard Classification of Occupations (ANZSCO) provides a detailed list of the minimum required qualifications for each two-digit occupation, which could be used as an objective method for determining the threshold to define over-education. But these minimum required qualifications are sometimes ambiguous, especially for occupations with lower skill levels. Using the occupation of protective service workers as an example, the requirements are:

> AQF Associate Degree, Advanced Diploma, or Diploma, or at least three years of relevant experience (ANZSCO Skill Level 2); or AQF Certificate III including at least two years of on-the-job training, or AQF Certificate IV, or at least three years of relevant experience (ANZSCO Skill Level 3); or AQF Certificate II or III, or at least one year of relevant experience (ANZSCO Skill Level 4); or AQF Certificate I, or compulsory secondary education (ANZSCO Skill Level 5).

This example indicates that different sub-occupations under a two-digit occupation may have different qualification requirements. Thus, a more detailed classification of occupations may allow the objective method to be used, but the information available would not allow its use here.[8] Following this logic, this research simply uses the empirical method.

Table 3 reports the incidence of over-education by gender and highest education level. The data show that the incidence of over-education varies significantly across educational category and gender. Over-education is the most severe among VET graduates, particularly for those with diplomas. In addition, the greatest gender difference occurs among those who have certificate III or IV.

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6 In accordance with the literature, we use all employees to identify the modal level of education in an occupation, not just full-time employees.

7 The mean and median could be too dependent on the shape of the distribution, and hence we follow the majority of the recent literature and use the mode. We do not use the rule of one standard deviation above the mode to define over-education for the following reasons. First, years of education in our data are not continuous and do not follow a normal distribution, so using the one standard deviation rule excludes many observations with higher education than the mode from the over-educated group. For instance, we find zero observations for over-education in the category of 'Did not complete school'. A better definition of occupation and education would allow the one standard deviation rule to be used, but this is not feasible here. Also, a standard deviation may not have the same meaning for every level of education.

8 It is always possible that the data on occupations are not sufficiently detailed to allow for a precise definition of over-education. In this research there is little that can be done to address this issue, as we are standing between a rock and a hard place. On the one hand a more detailed occupational classification would be beneficial, if it were available to us. On the other hand, observation of the cells would suggest that a more detailed classification would lead to statistical problems due to small cell sizes.

Table 3 The distribution of over-educated full-time employees

	Males	Females	Total over-educated
Did not complete school			
Cases	262	122	384
%	5	4	5
Only completed school			
Cases	341	290	631
%	10	12	11
Certificates III/IV			
Cases	1579	843	2422
%	24	43	29
Diplomas			
Cases	1119	805	1924
%	58	53	56
Degrees			
Cases	1109	853	1962
%	20	17	19
Total			
Cases	**4410**	**2913**	**7323**
%	**20**	**21**	**20**

Note: The sample is working-age full-time employees from HILDA 2001–08.

A definition of mismatch that combines over-education and over-skilling

Table 4 presents the four different matching categories by education and gender.[9] Although the proportions of those who are over-educated are similar to those who are over-skilled, the two groups do not contain the same people. This is evident by observing that the category 'both over-educated and over-skilled' is the least populated one in table 4. The correlation between over-education and over-skilling is generally low at 0.096 for men, 0.117 for women, and 0.103 for both genders combined. Table 4 confirms the intuition suggested earlier, namely, that over-skilling and over-education are two different measures that reflect different aspects of worker−job mismatch.

Table 4 provides a clear but complex picture of the incidence of both educational and skill mismatches. It is not surprising that over-education is rarely encountered among those in the lowest education group.

[9] This research focuses on the different ways in which mismatch influences labour market outcomes by education level and gender. Allen and van der Velder (2001) and Green and Zhu (2010) have examined this relationship in its aggregate forms, which this paper clearly shows to be incomplete.

Table 4 Job mismatches by gender and educational category: full-time employees

			Well matched	Over-educated only	Over-skilled only	Over-skilled and over-educated	Total
Did not complete school	Males	Cases	3 029	151	1 090	71	4 341
		%	70	3	25	2	100
	Females	Cases	1 862	75	590	31	2 558
		%	73	3	23	1	100
	Total	Cases	4 891	226	1 680	102	6 899
		%	71	3	24	1	100
Only completed school	Males	Cases	1 977	158	604	120	2 859
		%	69	6	21	4	100
	Females	Cases	1 422	164	408	88	2 082
		%	68	8	20	4	100
	Total	Cases	3 399	322	1 012	208	4 941
		%	69	7	20	4	100
Certificates III/IV	Males	Cases	3 755	1 005	597	369	5 726
		%	66	18	10	6	100
	Females	Cases	839	557	140	197	1 733
		%	48	32	8	11	100
	Total	Cases	4 594	1 562	737	566	7 459
		%	62	21	10	8	100
Diplomas	Males	Cases	637	799	89	224	1 749
		%	36	46	5	13	100
	Females	Cases	589	566	69	153	1 377
		%	43	41	5	11	100
	Total	Cases	1 226	1 365	158	377	3 126
		%	39	44	5	12	100
Degrees	Males	Cases	3 615	723	427	279	5 044
		%	72	14	8	6	100
	Females	Cases	3 408	545	308	228	4 489
		%	76	12	7	5	100
	Total	Cases	7 023	1 268	735	507	9 533
		%	74	13	8	5	100
Total	**Males**	**Cases**	**13 013**	**2 836**	**2 807**	**1 063**	**19 719**
		%	**66**	**14**	**14**	**5**	**100**
	Females	**Cases**	**8 120**	**1 907**	**1 515**	**697**	**12 239**
		%	**66**	**16**	**12**	**6**	**100**
	Total	**Cases**	**21 133**	**4 743**	**4 322**	**1 760**	**31 958**
		%	**66**	**15**	**14**	**6**	**100**

Note: The sample is working-age full-time employees from HILDA 2001–08.

Without post-school qualifications

The extent of over-education among those with less than Year 12 is limited. The meaning of over-education in this context is also limited, as it refers to differences between people who have school education levels between Year 9 and Year 11. By contrast, over-skilling is very prevalent as the previous research of the authors has established. There are no gender differences in this education group. The prevalence of over-education is still limited among those who have completed Year 12. The meaning of over-education for this group too remains somewhat limited. Over-skilling is also prevalent in the Year 12 group. The category of being both over-skilled and over-educated is not well populated for those without post-school qualifications. It is worth noting that a large proportion of those who are over-educated are also over-skilled, but not the other way around. For those without Year 12 completion, 31% of the over-educated are also over-skilled, while for those with Year 12 completion but no post-school qualifications, 39% of the over-educated are over-skilled.

With post-school qualifications

The proportion of over-educated employees increases substantially for the post-school education groups, while that of over-skilled workers decreases. Over-education is at its highest among those with VET diplomas and at its lowest among those with university degrees. For VET graduates with a diploma, this result occurs presumably because they are predominantly employed in occupations with many other VET graduates with certificates III/IV, which means that the majority of their occupational comparators are not as well qualified. The same comparison does not work in that way for university graduates who work in graduate jobs. Certificate III/IV graduates are somewhere in the middle in relation to their prevalence of over-education. The pattern where those who are over-educated are also very likely to be over-skilled is repeated among those with post-school education, but with slightly lower proportions.

Job satisfaction

The self-completion questionnaire of the survey asks all employed respondents a number of questions on how satisfied or dissatisfied they are with different aspects of their *main* job using a scale between 0 (least satisfied) and 10 (most satisfied). These are:

- total pay
- job security
- the nature of work
- hours of work
- flexibility
- overall job satisfaction.

Tables A1−A6 in appendix A summarise the answers of all respondents.[10] It is noteworthy that most answers are at the higher end of the satisfaction scale, with some 70–80% of respondents giving a score of 7 or more. This bunching is common in surveys that ask for measures of wellbeing that include satisfaction and health. It is best that the job satisfaction index is regarded as an ordinal variable; we have little information to quantify in a precise manner the meaning of each score level in job satisfaction variables.

Workers at all levels of education have high levels of overall job satisfaction (table A1). No more than 13% rank their jobs below 6. Also notable is that people with the lowest levels of education tend to have higher levels of job satisfaction. While only 4−5% of graduates give a score of 10 to their jobs, the figure for those who did not complete school is 16−18%.

There is more dissatisfaction with pay than with the job overall (table A2). But it is remarkable that the pay satisfaction variable scores as high as it does for those with the lowest education qualifications. One (speculative) explanation could be that the question is answered with the work

[10] The important information in tables A1 −A6 is to see how the percentages of people with different levels of satisfaction change. It is worth noting that there are considerable differences at the moderate levels of satisfaction by education level. For example, in table A1 there are 20% (6+14%) females at levels of 6 and 7 (moderate satisfaction) among those who did not complete school and 32% (9+23%) among those with degrees. Similarly, there are 40% (22+18%) at the 9 and 10 levels (highest satisfaction) for females at the lowest education against 24% for those with degrees. The reader is encouraged to take their time and examine this information in detail, noting that it would be lost if mere averages are presented.

colleagues as the comparators. If pay dissatisfaction can arise due to relative pay comparisons, the relative pay equality among the least-educated employees (with few of them being highly paid) may then generate higher pay satisfaction.

There are no noteworthy differences in the distribution of job security satisfaction by education level (table A3). There is some propensity for men to be less satisfied with their job security than women, especially among the more highly educated.

There are no noteworthy differences in the distribution of work satisfaction by education level (table A4). Levels of dissatisfaction are low, and the less educated tend more often to report the highest levels of satisfaction.

There is more dissatisfaction with hours than with the previous elements of work (table A5). Satisfaction with hours is lower for both males and females with VET diplomas and university degrees: about a quarter of graduates report dissatisfaction with their hours. This suggests that higher-level jobs are more likely to involve overtime that is not liked by the employee, probably because overtime is more likely to be unpaid in that group of employees.

Satisfaction with job flexibility is lower among those with more education, more so for females with VET diplomas and university degrees (table A6). It is remarkable that 40% of women who did not finish school rate their satisfaction with job flexibility as a 9 or 10. This compares with 26% of women graduates. Recall that the women in question are all employed full-time, so the flexibility is not coming from casual part-time work.

Overall, full-time employees with the lowest levels of education tend to have higher levels of job satisfaction, in aggregate and on each separate dimension, than do those with the highest education. This research is not a study of job satisfaction per se, but nonetheless, this is a most interesting finding.

The use of the job satisfaction question is crucial for the development of this research. Survey respondents are asked 'all things considered, how satisfied are you with your job' and they are instructed to respond with clear reference to their main job. The use of the job satisfaction information allows the research to estimate a specific hypothesis in relation to mismatches and their economic meaning. On the one hand, over-education and over-skilling could be the manifestation of true mismatch (that is, a disadvantageous labour market state that individuals would wish to avoid). On the other hand, over-skilling and especially over-education could be the manifestation of an apparent mismatch (that is, the result of a compensating differential that may not be captured by the data). The hypothesis is that where we observe reduced wages to follow a mismatch, this is a true mismatch if it is also followed by a reduction in job satisfaction and an apparent mismatch if it is not followed by reduced job satisfaction. These hypotheses are tested below.

Wages

Table 5 reports the unadjusted average gross weekly wage levels for each combination of mismatch by gender and by educational category. The relationship between over-skilling and over-education with wages varies by education level. For well-matched employees, earnings rise with the level of education. Irrespective of gender, workers who were either over-educated and (or) over-skilled earned substantially less than well-matched employees. In most cases being over-educated and over-skilled is associated with the lowest wages, but this is not so for all education levels.

Not surprisingly, we observe that earnings are higher for males for each category of mismatch. This is a well-established regularity in the data which can be only partly explained by the observed differences in the personal and employment characteristics of the employees. The male–female wage gap is a serious issue in the Australian labour market, and it is clear from the data in table 5 that the wage gap varies by education level (chiefly between those with and without post-school qualifications) and by mismatch type (chiefly between all mismatch categories and the well-matched). The wage gap is lower for those without post-school qualifications and lower for those who are mismatched in one of the three ways defined in our data. It would appear that the wage penalty associated with mismatch is greater amongst males than amongst females and greater amongst those with, than those without, post-school education. Although these differentials are of interest, it is not advisable that one derives any strong conclusions about gender pay inequality based on this statistic, and without the use of multivariate regression and the appropriate decomposition analysis.

Table 5 Wages by gender and education pathway for full-time employees: $ per week

		Well-matched	Over-educated only	Over-skilled only	Over-skilled and over-educated
Did not complete school	Males	871.4	773.8	770.2	769.9
	Females	721.8	684.8	623.0	686.2
Only completed school	Males	926.0	794.0	822.4	754.7
	Females	759.4	740.9	644.1	628.0
Certificates III/IV	Males	1 078.7	865.3	1 011.8	849.9
	Females	762.5	668.9	674.3	661.3
Diplomas	Males	1 417.4	1 128.9	1 074.9	852.5
	Females	1 074.5	757.2	932.5	767.8
Degrees	Males	1 577.4	1 180.4	1 357.0	917.9
	Females	1 132.6	909.7	1 039.4	725.3

Notes: The sample is working-age full-time employees from HILDA 2001–08. Wages are measured as nominal gross weekly wages and salary from main job in Australian dollars.

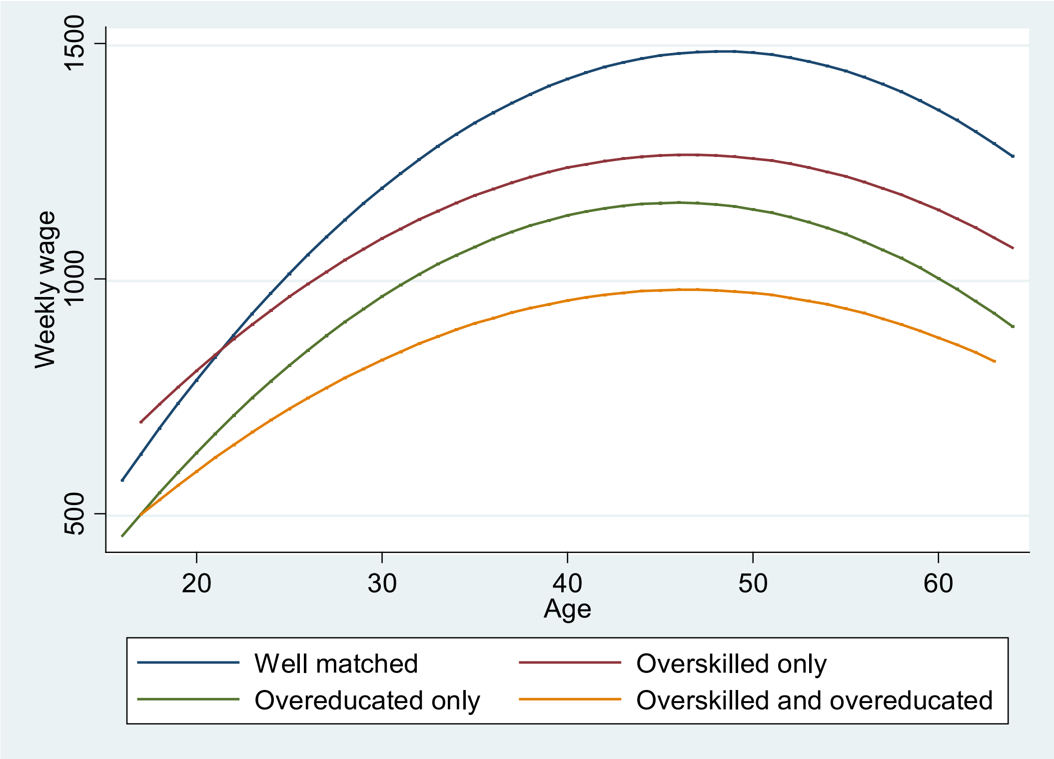
Wages and age

The data at hand are representative of the Australian population between the years 2001 and 2008. As expected, the association between age and wages is strong, but varies a lot by mismatch and by education category. By way of example, this association between age and wages is presented in figures 1 and 2 for those with post-school education only.[11] The data contain two pieces of information. First, remembering that this is a panel dataset with repeated individual observations, the data consist of many eight-year long histories of lifecycle incomes for the survey respondents. That is, they show the way incomes develop in the eight years that they are observed. Second, the data contain information on all cohorts of the Australian population, as they are representative of this population. Put simply, for a person who is 25 years old in 2000, the data contain their wage progression between the ages of 25 and 33, while for a person who is 35 years old in 2000, the data contain their wage progression between the ages of 35 and 43. When we look at the data in figures 1 and 2, we can see that both these types of information have been put together to show an overall picture between age and wages by level of mismatch.[12]

[11] The relationship between mismatch and age is complex. Mismatch is more likely to be a temporary phenomenon at younger ages where younger workers may be searching for the right job or career, or when they may be accepting a job that appears to be a mismatch but is in fact a long-term investment towards a better lifetime income. A common case of a period with lower wages and less attractive job attributes could be a probation period or a training position. This type of information is not often recorded in large datasets and can thus be misinterpreted as a mismatched job. The crucial difference is that it is temporary in nature and it can end up as an investment in human capital. Although this is beyond the scope of this research, it is important that the different age–wage profiles by types of mismatch are noted.

[12] To produce these figures we regressed wages on age and age square for each of the mismatch categories and for those with post-school education. We then derived the predicted age–wage profiles to construct figures 1 and 2.

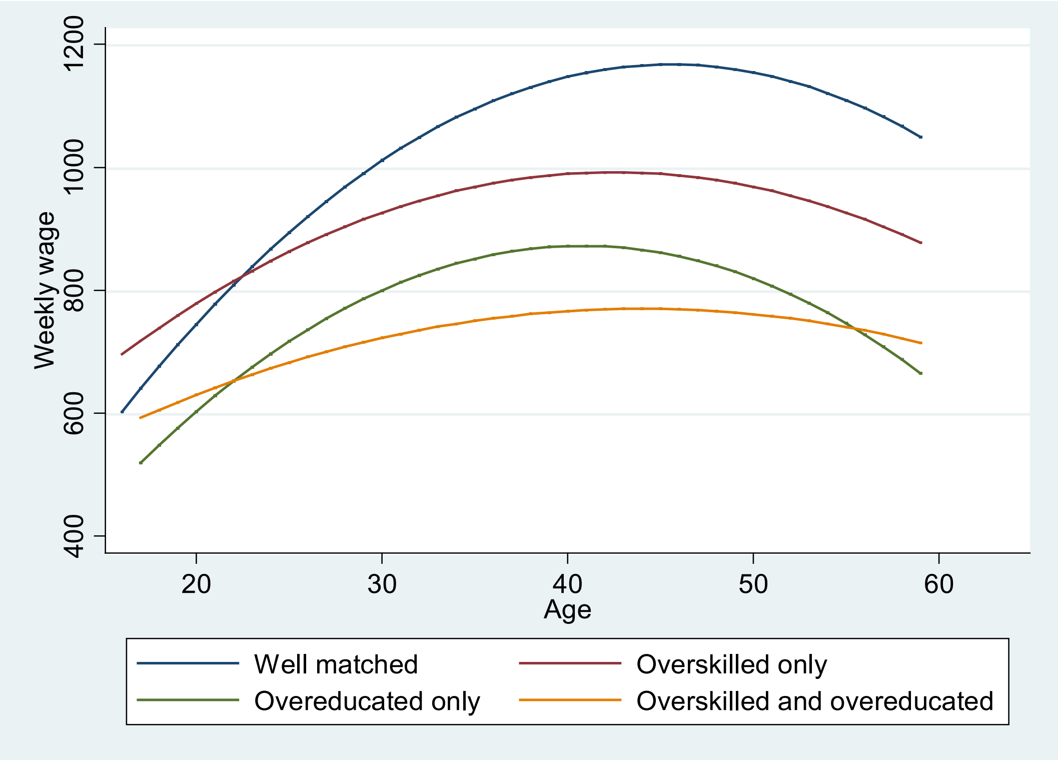
Figure 1 Wage−age profiles by mismatch type for males with a post-school qualification



The overall picture presented in figures 1 and 2 accords with human capital theory and the considerable validating research that accompanies it: wages rise with age at a decreasing rate and at some point, usually well past the middle of the working life, wages peak and start to decline all the way until retirement. Two main differences by type of mismatch arise, starting wages and wage progression, and both differences are informative. First, well-matched and over-skilled-only males have higher starting wages than over-educated-only or over-educated and over-skilled employees.

Over-education seems to be the main difference for the starting wages of younger males. A similar, but not as clear-cut result appears for the starting wages of younger females. Second, well-matched male and female employees experience a steeper wage progression than all mismatched employees. The wage progression profiles of males and females who are either over-skilled or over-educated are flatter and the progression of those who are both over-educated and over-skilled is the flattest of all four groups. Indeed the progression of females who are both over-skilled and over-educated is hardly noticeable in the data. The income of males peaks for all groups in their late 40s, while that of females peaks in their early 40s, with well-matched females being the highest paid ones, peaking just above age 45. Figures 1 and 2 suggest strongly that mismatch plays a very significant role in the development of lifetime incomes for both males and females, but it is clear that the precise nature of this relationship cannot be established by this initial depiction and that more detailed multivariate analysis would be necessary to achieve this.

Figure 2 Wage−age profiles by mismatch type for females with a post-school qualification



Estimation methodology

When complex data are used for econometric analysis the estimation methodology must be chosen to optimise the match between the specific way the research question is asked and the capability of the data to answer that specific question. This brief section explains some of the principles and the choices made in this analysis. There is no single criterion for choosing the most appropriate estimation method, as many objectives must be considered jointly, and the criteria for a good choice do not always pull in the same direction. For example, on the one hand it is sensible for us to hope that our estimation results are as informative as possible, both in their detail and their 'big picture', which calls for more complex estimation structures to reflect real-life complexities. On the other hand, it is also sensible for us to hope that our estimation results are as robust as possible, which calls for simpler estimation structures with reduced detail and a lower probability of making mistakes. There are many such conflicts and trade-offs in the application of econometric analysis and the final choice of estimation is a balancing act, after judicious joint consideration of the research question and the data at hand. Although the final choice of estimation may not be always easy to decide, there are some main principles that we can use to make that choice.

First, we wish to have an estimation method that will allow us to use our sample to produce results representative of the population in which we are interested. The choice of sample and estimation method should be determined by the population to which our estimation results need to be generalised. For example, in this research the sample has been restricted to those who are of working age and all inference refers only to those of that age. As we are only interested in employment issues, this is uncontroversial, but it must always be remembered that all statistical results say nothing at all about those who are aged below 15 or above 65 years for men and 59 years for women. Researchers must often make some harder decisions in their choice of samples. For example, in this research, we chose to exclude those who are not employed full-time. This choice was made primarily because of the strong, unobserved heterogeneity between the not-employed, the part-time employed, and the full-time employed and the complexity that this would introduce. Simply put, trying to apply the same estimation methods to all persons of working age would introduce a complexity which would make the analysis too complex for useful interpretation.[13] The trade-off is that the representativeness of the analysis only extends to a sub-group of the labour force, but the estimation method and the data are better matched and the results are more trustworthy.

In this research we deal with two labour market outcomes: wages and job satisfaction. These two outcomes need different forms of estimation, as the wage is a continuous variable, while job satisfaction is an ordered variable. Different forms of regression have been applied: linear regression for wages and non-linear for job satisfaction.[14] We examine two types of relationships. First, we wish to know who gets the better wages and who is more satisfied at work and, second, we wish to examine if mismatch has a direct and causal impact on wages and job satisfaction and for whom. These two questions need different types of estimation and data. The estimation of associations can be best performed using ordinary least squares (OLS) regression and pooling the data, perhaps the simplest and most robust form of estimation, but one that contains less information. The estimation of a causal relationship can be best performed using panel regression with longitudinal data, a more complex form of estimation, but one that conveys considerably more information. Note the trade-off: OLS is simpler, more trustworthy, and less informative; panel regression is more complex, less trustworthy, and more informative. It is always a good guide to keep this distinction in mind.

Wage effects of mismatch

To investigate the effect of job mismatch on the wage, we estimate a conventional Mincer earnings function. The dependent variable is the log of weekly earnings. Independent variables contain three job mismatch dummy variables as defined earlier, namely *over-educated-only*, *over-skilled-only* and *both over-skilled and over-educated,* the reference category being the *well-matched*. We use other relevant personal and workplace characteristics as control variables in the estimation, including age, marital status, number of children, socioeconomic background, unemployment history, country of origin, employment and occupational tenure, union membership, firm size, and industry.[15] Like all panel data sets, the Household Income and Labour Dynamics in Australia survey contains two major types of information on individuals: the cross-section information (that is, how different the behaviour and circumstances of different individuals may be, called the *between* variation) and the longitudinal information (that is, how each individual's circumstances and behaviour may have changed over time, called the *within* variation). Both types of information can be valuable for answering different questions, but they should not be confused with one another. More often than not, this is a difficult task for empirical research. By applying different estimations and comparing

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[13] As expected, there are no data on mismatch for those who are not at work. The wage determination and job satisfaction of part-time employees are sufficiently different from those of full-time employees to suggest that the two categories should be examined separately. The possibility of modelling selection is always open in such cases, but more often the data do not help in providing variables that clearly influence selection but not wages and (or) job satisfaction and vice versa.

[14] Linear and log-linear regression assumes that the difference between any two levels of wage can be compared with that between two other levels of wage (e.g. in the log-linear model the difference between $30 and $33 is the same as that between $40 and $44—about 10%). By contrast, in the ordered case of a 1 to 10 job satisfaction scale, the 'distance' between answers 2 and 4 and between answers 6 and 8, or between 5 and 7, cannot be assumed to be comparable in a direct manner. Estimation only needs to assume that answer 2 declares lower satisfaction than answer 3, which in turn declares lower satisfaction than answer 4, but nowhere does it assume the size of the difference between the levels in the scale. The way this is done is by assuming an underlying (unobserved) continuous relationship which is approximated by the ordered function which we estimate. The maths is complex, but it can prove that this estimation is almost as good as the conventional linear estimation at producing the right estimates. The ordered nature of the data simply means that estimation is not as 'efficient', which means that we need larger samples to obtain statistical significance. As we see below, where the sample sizes are small, this limitation shows up.

[15] Variables are listed and explained in detail in appendix B.

them, we offer novel insights into the problem of mismatch. Cross-section estimation allows us to examine overall *associations* between variables, and panel estimation allows us to examine possible *causal relationships* between labour market outcomes and mismatch. As mentioned above, while panel estimation can be clearly more informative (it addresses the 'why' questions), it requires more complex methodology, which puts intense demands and constraints on the quality and type of data that must be used. As we show below, when both estimations are performed, the comparison of their outcomes can be highly informative.

Job satisfaction effects of mismatch

We remind the reader that in the survey all job satisfaction variables are measured on a scale from 0 to 10 (lowest to highest). For simplicity of estimation, methodology, and clarity of interpretation we have converted the ordered job satisfaction variables into binary variables. We use a binary variable which is zero (not satisfied) for values between 0 and 6, and is one (satisfied) for values between 7 and 10. Extensive sensitivity analyses to find the most appropriate cut-off point to use were carried out, suggesting that estimation results are not sensitive to the exact cut-off point selected. The same conversion to a binary variable and sensitivity analyses were applied to each of the job satisfaction facet measures. Since job satisfaction is not a continuous measure, the conventional pooled OLS and fixed-effects models are not appropriate. We use a pooled probit model for the cross-section estimation of associations between mismatch and job satisfaction and a random-effects probit model with a Mundlak correction to estimate the causal effect of job mismatch on job satisfaction. To allow for further comparisons, we leave the explanatory variables to be exactly the same as those used in the wage effects estimation.[16]

[16] It is worth noting that, since the information contained in the data is the same for both estimations, the major difference in the estimates is that the panel estimation controls for unobserved heterogeneity, while the pooled estimation does not. However, the panel estimates also have their limitations as they cannot handle well the cases where there is little variation over time. We discuss these issues below when we contrast and interpret pooled cross-section with random and fixed-effects panel results.

Regression results

Wage effects of job mismatch

A critical and well-researched consequence of mismatch has been the effect it can have on wages. A common result in the literature, as noted earlier, is that mismatches are associated with lower pay, which reflects the lower productivity of a sub-optimal worker−job match, although it must be noted that over-educated workers do receive higher pay than their educationally appropriately matched co-workers, suggestive of some productivity advantage to being over-educated (see Sicherman 1991). Tables 6a to 6f present the relationship between the various forms of job mismatch and wages by gender and by educational category. We estimated our equations using three methods: first, OLS using all survey waves as a large cross-section dataset; second, using the survey in its longitudinal form with a random-effects model with Mundlak corrections; and third, a fixed-effects model. Of the two panel regressions we do not report the fixed-effects estimates as they have only been carried out as an additional check.[17] The reader must be reminded that the OLS results estimate the overall association between wages and the mismatch variable, while the random-effects panel model provides the closest estimate we may obtain of the one-way (causal) effect of mismatch on wages. The difference in the estimates between the two methods has an important and relevant message about the way we interpret results and the way we understand their policy implications.

Table 6 results show that OLS estimation in general produces highly significant and negative coefficients for all types of mismatch. The strongest associations are usually found for those who are both over-educated and over-skilled, but there are also sizeable associations for the over-educated-only and over-skilled-only mismatch categories. This implies that where we meet mismatch we can also expect to meet lower wages. The question that arises from this result is: are the lower wages that are associated with mismatch due to some unobserved differences between those with and those without a mismatched job, or does mismatch cause lower wages? OLS estimation using cross-section data cannot answer this question. Note that OLS-estimated association between mismatch and wages has already accounted for all observed factors included in the multivariate regression. To examine the possibility of a causal relationship we use panel regression. The main difference between OLS regression using cross-section data and random effects regression (with Mundlak corrections) using panel data is that the random-effects panel model controls for unobserved heterogeneity (that is, differences between individuals that are not captured by the data) in the sample. Table 6 shows that in most cases random-effects estimation produces much weaker estimates than the OLS model, an indication of the presence of considerable unobserved heterogeneity in the data. We also note that results differ considerably across educational category and by gender.

17 Fixed-effects estimates were also obtained but are only presented in the appendix. They are almost identical to the random effects ones with Mundlak corrections, as they should be, but not identical as numerical solutions of the probit model can create very small differences.

With post-school qualifications

University graduates

Table 6a presents wage estimations for university graduates. OLS results are very strongly negative for both genders and they accord with what is found in the literature. The over-skilled-only estimates for both genders are somewhat lower than those typically found in the literature, which could be attributed to the inclusion of the category 'both over-skilled and over-educated', which shows the strongest wage penalty.

Table 6a Wage effects of job mismatch (university graduates)

	Relative to well matched:		
	Over-educated only	Over-skilled only	Over-skilled and over-educated
Full-time males			
OLS	**-0.213 (-11.98)**	**-0.092 (-4.29)**	**-0.324 (-11.59)**
RE with Mundlak corrections	-0.017 (-0.94)	-0.003 (-0.19)	**-0.073 (-2.88)**
Observations in mismatch category	723	427	279
Total observations	5044	5044	5044
Full-time females			
OLS	**-0.213 (-12.31)**	**-0.038 (-1.86)**	**-0.326 (-12.83)**
RE with Mundlak corrections	**-0.054 (-2.83)**	**-0.054 (-3.80)**	**-0.091 (-4.24)**
Observations in mismatch category	545	308	228
Total observations	4489	4489	4489

Note: This table uses HILDA waves 1 to 8 and presents OLS and random effects (with Mundlak corrections) estimations. The dependent variable is the log of current weekly gross wages and salary from the main job. A number of control variables have been used but are not presented here. Full results for all estimations are in the support document. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

Panel estimates differ from OLS, indicating that there is considerable unobserved heterogeneity within the sample that affects the relationship between wages and mismatch, which is not picked up by OLS regression. Over-skilled-only or over-educated-only male university graduates do not appear to suffer a wage penalty upon switching from a well-matched job. This result is at odds with the over-skilling literature to date and needs further examination. Male university graduates who become both over-skilled and over-educated suffer a significant wage penalty.

Unlike the OLS estimates, panel estimation reveals some gender differences. To begin with, female full-time employees who became mismatched suffer a wage penalty which is statistically significant for all mismatch categories, albeit generally much lower than that estimated using OLS. This result implies that, although estimation still reveals the presence of unobserved heterogeneity in the data, it is less influential among females.

Finally, it is clear from table 6a that university graduates who are both over-skilled and over-educated suffer the strongest wage penalty and that this effect is revealed both as a strong association between wages and mismatch as well as a causal effect of entering mismatch on wages. The penalty is about 7% for males and 9% for females.

Advanced diplomas and diplomas

Although this category of education attainment presented us with some practical estimation problems, we have included estimation results in the report for reasons of completeness and because some of the results are worth consideration. We have been faced with the problem of a small sample, in that there are too few persons in the over-skilled-only category. This makes the panel estimation results for that mismatch category statistically untrustworthy. By contrast, there are enough over-educated people to support estimation for the other two mismatch categories and clearly enough of all types of mismatch and for both genders to support OLS estimation.[18]

Table 6b Wage effects of job mismatch (diplomas and advanced diplomas)

	Relative to well matched:		
	Over-educated only	Over-skilled only	Over-skilled and over-educated
Full-time males			
OLS	**-0.113 (-4.68)**	**-0.168 (-3.58)**	**-0.242 (-7.07)**
RE probit with Mundlak corrections	-0.002 (-0.06)	**-0.047 (-1.64)**	-0.023 (-0.73)
Observations in mismatch category	799	89	224
Total observations	1749	1749	1749
Full-time females			
OLS	**-0.207 (-9.34)**	**-0.110 (-2.63)**	**-0.188 (-5.72)**
RE probit with Mundlak corrections	**-0.053 (-2.61)**	-0.033 (-0.99)	-0.046 (-1.55)
Observations in mismatch category	566	69	153
Total observations	1377	1377	1377

Note: This table uses HILDA waves 1 to 8 and presents OLS and random effects (with Mundlak corrections) estimations. The dependent variable is the log of current weekly gross wages and salary from the main job. A number of control variables have been used but are not presented here. Full results for all estimations are in support document. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

We note that the signs of estimates agree with our intuition and that there is evidence that unobserved heterogeneity plays a role for this education pathway too. We also note that estimates do not appear to resemble either the university graduates or the VET certificates graduates, which supports the view that this group should be estimated by itself, or at least should not be included with any of the other two groups, even if that leads to some inconclusive estimates.

VET certificates III/IV

Table 6c presents the VET certificates III/IV education pathway. OLS results show a negative association between wages and mismatch. The estimated wage penalties are not as strong as those for university graduates, but are all statistically significant. The presence of unobserved heterogeneity is manifested through the differences between OLS and panel estimates of the wage penalties. Its effect works in opposite directions by gender for over-skilled-only males and females, a result that was also present for university graduates.

The panel estimates show clearly that starting a job where VET graduates are mismatched results in a reduction in their wages, less so for males than for females. As with the other two post-school education categories, the strongest mismatch results are found among those who are over-skilled and over-educated, with a similar wage penalty caused by the mismatch as is found for graduates.

[18] This is an example of the extra demands that are put on estimation when we use panel methods rather than cross-section methods.

Table 6c Wage effects of job mismatch (certificates III/IV)

	Relative to well matched:		
	Over-educated only	Over-skilled only	Over-skilled and over-educated
Full-time males			
OLS	**-0.161 (-12.12)**	**-0.043 (-2.91)**	**-0.173 (-8.90)**
RE probit with Mundlak corrections	**-0.042 (-3.50)**	**-0.026 (-2.09)**	**-0.063 (-3.42)**
Observations in mismatch category	1005	597	369
Total observations	5726	5726	5726
Full-time females			
OLS	**-0.116 (-5.25)**	**-0.064 (-1.94)**	**-0.087 (-2.80)**
RE probit with Mundlak corrections	**-0.063 (-2.38)**	**-0.083 (-2.21)**	**-0.096 (-2.85)**
Observations in mismatch category	557	140	197
Total observations	1733	1733	1733

Note: This table uses HILDA waves 1 to 8 and presents OLS and random effects (with Mundlak corrections) estimations. The dependent variable is the log of current weekly gross wages and salary from the main job. A number of control variables have been used but are not presented here. Full results for all estimations are in support document. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

Without any post-school qualifications

Completed school Year 12

As we move down the educational attainment ladder among the full-time employees, we see a lower proportion of over-education and a higher proportion of over-skilling. Tables 6d and 6e present, respectively, the estimation results for those who completed school Year 12 and those who have only completed Years 9, 10, and 11, but who have not gained any further qualification after doing that. Employees without post-school qualifications are typically paid lower wages than those with qualifications. Given the presence of a national minimum wage, this implies that the wage distribution of these two groups will have a more compressed shape than that of employees with post school qualifications. This is more so for those without school Year 12 completion.

Table 6d Wage effects of job mismatch (completed Year 12)

	Relative to well matched:		
	Over-educated only	Over-skilled only	Over-skilled and over-educated
Full-time males			
OLS	-0.054 (-1.44)	-0.020 (-1.05)	**-0.070 (-1.71)**
RE probit with Mundlak corrections	-0.008 (-0.22)	-0.003 (-0.19)	**-0.107 (-2.83)**
Observations in mismatch category	158	604	120
Total observations	2859	2859	2859
Full-time females			
OLS	0.019 (0.64)	**-0.038 (-1.87)**	**-0.095 (-2.40)**
RE probit with Mundlak corrections	0.030 (1.06)	**-0.046 (-2.06)**	-0.019 (-0.53)
Observations in mismatch category	164	408	88
Total observations	2082	2082	2082

Note: This table uses HILDA waves 1 to 8 and presents OLS and random effects (with Mundlak corrections) estimations. The dependent variable is the log of current weekly gross wages and salary from the main job. A number of control variables have been used but are not presented here. Full results for all estimations are in appendix B. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

The evidence that those who are in mismatched jobs are also being paid less than their well-matched counterparts is not strong for this group. This is reflected in the small size of the estimates and their general lack of statistical significance. Panel estimation confirms this result as well.

Completed school years 9, 10 or 11

This category contains a small number of full-time employees who are over-educated and this is reflected in the size and significance of the estimates. These are employees who completed Year 11 and are in an environment with a modal education level Year 10 or below. Estimation is not trustworthy for the mismatch categories over-educated-only and over-skilled and over-educated. However, results for the over-skilled-only category and their differences with the corresponding over-skilled-only results for those with Year 12 completion are informative and justify the separate estimation for the two groups of employees without post-school qualifications. This group contains the most vulnerable and least well-paid part of all full-time employees.

Table 6e Wage effects of job mismatch (completed school up to Year 11)

	Relative to well matched:		
	Over-educated only	Over-skilled only	Over-skilled and over-educated
Full-time males			
OLS	**-0.065 (-1.97)**	**-0.031 (-2.19)**	0.032 (0.68)
RE probit with Mundlak corrections	-0.038 (-1.34)	0.009 (0.76)	-0.008 (-0.22)
Observations in mismatch category	151	1 090	71
Total observations	4341	4341	4341
Full-time females			
OLS	0.003 (0.07)	**-0.067 (-3.69)**	-0.021 (-0.29)
RE probit with Mundlak corrections	0.027 (0.69)	-0.007 (-0.52)	0.037 (0.81)
Observations in mismatch category	75	590	31
Total observations	2558	2558	2558

Note: This table uses HILDA waves 1 to 8 and presents OLS and random effects (with Mundlak corrections) estimations. The dependent variable is the log of current weekly gross wages and salary from the main job. A number of control variables have been used but are not presented here. Full results for all estimations are in support document. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

For these least well-paid full-time employees in the sample who have only completed up to Year 11 formal education, it is noteworthy that the negative association between wages and mismatch loses its significance when panel estimation is applied, indicating that there are unobservable characteristics that are associated both with more mismatch *and* lower wages. For this group of people, mismatch has a specific and additional meaning, in that they are in all likelihood doing the most menial jobs in the labour market; they feel that they have skills to do more, but their jobs do not allow them to. Their wages confirm their predicament and the association appears to be stronger for full-time female employees.

The question that arises is what is the nature of the skills and abilities they are not using, and why this may be the case. Their low wages and the presence of some statistically significant negative associations between wages and different types of mismatch in table 6e suggest there may be a problem. We note that one would need additional data and statistical analysis in order to begin to understand exactly where the problem lies and what its implications are.

Our data do not contain much information on the workplace, so we cannot examine why there are so many full-time employees who feel they could contribute more but end up not doing so. It could be a matter of ability, or it could also be a matter of job design. As these are people who have obviously not taken advantage of the opportunities offered by the education system, or been well served by it, there is an obvious question about the circumstances and factors that contributed to their present position in the labour market. There are some individual characteristics that are worth noting.

Figure 3a Age distribution of males and females with only Year 9 to 11 school completion

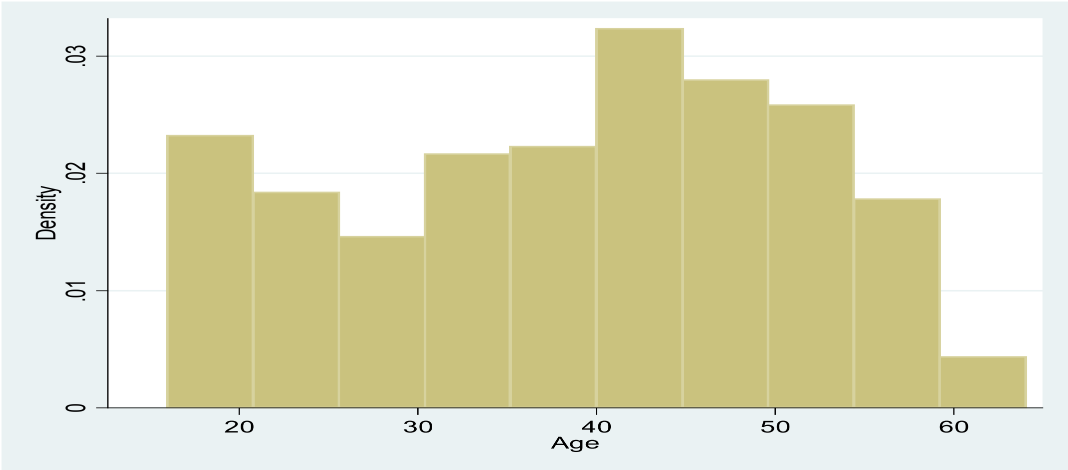
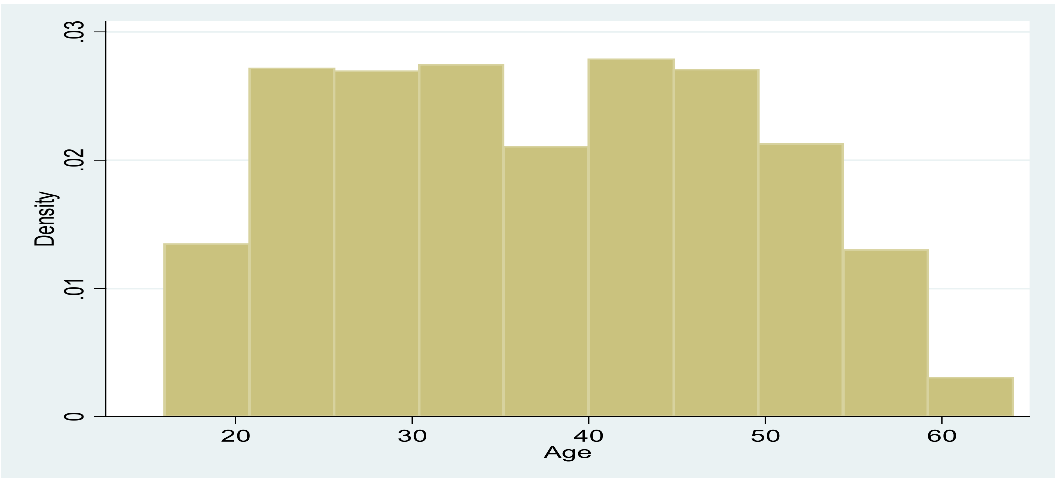


Figure 3a presents the age distribution of those with minimum qualifications and figure 3b presents the same for all full-time employees. Those with these minimal qualifications appear to be in the main older than the overall full-time employed labour force. Figure 3a shows that there are considerably more low-qualified full-time employees among the youngest group (age below 21), as well as among the prime age group (40−54).

Figure 3b Age distribution of all males and females in the sample



It is possible that the 16–20 age group could be less qualified, because some of the youngest employees among them have yet to complete their education. One would still wonder why they have interrupted their schooling at that early age to work full-time. Looking at the two distributions more closely, one sees that the desired difference (that is, to have fewer less-qualified employees) appears at its strongest between the ages of 21 and 35, which implies that the demographics will take a long time to close the gap and that it is not just the very old who occupy that space of very low qualifications.

The sectors that employ disproportionately more low-qualified employees are: agriculture, manufacturing, construction, wholesale trade, retail trade, and transport and postal. The sectors that employ fewer are: information media, financial and insurance, professional, scientific, public administration, and education and training. Looking at job stability, we note that the job mobility rates of the least qualified are very similar to those of the whole labour force, possibly with marginally higher layoffs and lower quits, as one would expect.

Job satisfaction and job mismatch

This section presents the estimation results for overall job satisfaction and for a number of facets of job satisfaction. Job satisfaction is an important indicator in understanding data on labour market outcomes. It is particularly useful in the context of this research for the following reason. When we observe a mismatch such as an employee being either over-educated or over-skilled, we are faced with two possibilities. Either there is a genuine mismatch, in that an employee is in a job where they are involuntarily under-utilised, or there is an apparent mismatch, in that an employee is in a job where they are voluntarily under-utilised. Job satisfaction information has been used in the literature to distinguish between voluntary and involuntary under-utilisation, a simple and clear, if somewhat limited, example is Chevalier (2003), who assumed that over-educated employees who are not satisfied with their jobs are genuinely mismatched and over-educated employees who are satisfied with their jobs are only apparently mismatched. Although Chevalier's idea is sound in principle, it has the limitation that it does not allow for the fact that job satisfaction is not only dependent on mismatch, but also on other factors.

In the following analysis we use multivariate regression to estimate the direct effect of mismatch on overall job satisfaction and on its various facets. We then combine the results on wage effects with job satisfaction for the different education categories to address the question of whether the observed wage effects reflect genuine or apparent mismatch. An estimated wage penalty caused by genuine mismatch can be considered as a negative economic outcome, while the same cannot be said about a wage penalty in the context of an apparent mismatch.

The intuition of what we do runs as follows. Where mismatch appears to reduce job satisfaction it is more likely that this mismatch reflects involuntary under-utilisation of skills or qualifications and the wage penalty is real. This type of mismatch represents lower productivity and an economic and welfare loss which could be improved if the employee were offered better opportunities. By contrast, a mismatch that does not reduce job satisfaction is more likely to reflect voluntary under-utilisation (or, at least if not voluntary, not harmful according to the employee's perception), in which case there may well be no economic loss that could be improved, as such employees report that they are happy in their position. Tables 7a to 7e present the estimation of the effect of the three categories of mismatch (with the well-matched as the reference category) on overall job satisfaction and on the five facets of job satisfaction. Estimation uses a random-effects (panel) probit with Mundlak corrections. We report results on mismatch for males and females and different educational categories, separately and include the full results in support document.

The gender differences suggest that males and females not only do different jobs, but also appear to value different aspects of these different jobs—after we control for their personal and job differences. It should be noted, however, that these tables do not provide formally comparable male−female estimates, as the male estimates compare a mismatched male with a well-matched male, and the female estimates compare a mismatched female with a well-matched female.

With post-school qualifications

University graduates

Table 7a estimates job satisfaction for university graduates. The main source of job dissatisfaction for male university graduates is when they become over-skilled-only, and more so when they become both over-skilled and over-educated. The overall dissatisfaction of being over-skilled-only is accompanied by work and hours dissatisfaction. By contrast, over-educated-only male graduates show no significant dissatisfaction effect of any type; they only show positive satisfaction with their job security. Results appear to suggest that over-education-only in the case of male university graduates is not perceived by those affected in a negative manner, a suggestion supported by the lack of significance of the panel mismatch effect on wages for that type of mismatch in table 6a.

Table 7a Impact of mismatch on job satisfaction and its facets (university degrees)

	Relative to well-matched		
	Over-educated only	Over-skilled only	Over-skilled and over-educated
Full-time male employees			
Overall job satisfaction	-0.099 (-0.82)	**-0.357 (-3.34)**	**-0.694 (-4.32)**
Pay satisfaction	0.056 (0.50)	0.120 (1.09)	-0.124 (-0.80)
Job security satisfaction	**0.230 (1.89)**	-0.082 (-0.67)	0.055 (0.32)
Work satisfaction	0.029 (0.24)	**-0.592 (-5.64)**	**-0.692 (-4.44)**
Hours satisfaction	-0.152 (-1.35)	**-0.178 (-1.65)**	**-0.512 (-3.10)**
Flexibility satisfaction	0.058 (0.50)	-0.039 (-0.35)	-0.143 (-0.87)
Full-time female employees			
Overall job satisfaction	**-0.301 (-2.15)**	**-0.660 (-5.32)**	**-0.598 (-2.95)**
Pay satisfaction	-0.091 (-0.72)	**-0.243 (-1.97)**	-0.178 (-0.93)
Job security satisfaction	-0.136 (-0.91)	-0.096 (-0.63)	-0.216 (-0.96)
Work satisfaction	-0.231 (-1.61)	**-0.866 (-6.95)**	**-1.19 (-5.99)**
Hours satisfaction	0.032 (0.24)	0.083 (0.66)	-0.211 (-1.05)
Flexibility satisfaction	0.012 (0.09)	-0.066 (-0.52)	0.010 (0.05)

Note: Random effects panel probit estimation with Mundlak corrections. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level. Full results are in support document.

When we combine the panel results of tables 6a (on wages) and 7a (on job satisfaction) we see that for males the over-educated-only are enjoying better job security without an associated wage or job satisfaction penalty. The over-skilled-only do not suffer a wage penalty either, but they report overall job dissatisfaction, which is broken down to dissatisfaction with the type of work they do and the hours they work. The over-skilled and over-educated suffer a wage penalty and also report high levels of overall job dissatisfaction, which is broken down into dissatisfaction with the type of work they do and the hours they work.

Female graduates are different. The over-educated-only report significant overall job dissatisfaction, but they do not report this in any of the facets asked by the Household Income and Labour Dynamics in Australia survey. We note from table 6a that the wage penalty of these female graduates is significant, but is not sufficiently large to generate significant pay dissatisfaction. The over-skilled-only female university graduates suffer a wage penalty and they report high overall job dissatisfaction, which is broken down into dissatisfaction with pay and with the type of work they do. The over-skilled and over-educated suffer a wage penalty almost double in size and report high levels of overall job dissatisfaction, which is expressed as intense dissatisfaction with the type of work they do.

Advanced diplomas and diplomas

Table 7b presents the job satisfaction estimation for those with diplomas and advanced diplomas. As mentioned in the previous section, the sample size for this group is too small for trustworthy statistical analysis. Although we note the presence of significant work dissatisfaction for both genders and the dissatisfaction of males with their job flexibility, we also note that job satisfaction estimation as a whole does not have a lot to add to the vague picture offered by wages estimation for this education group.

Table 7b Job satisfaction and its facets (advanced diplomas and diplomas)

	Relative to well-matched		
	Over-educated only	Over-skilled only	Over-skilled and over-educated
Full-time male employees			
Overall job satisfaction	0.045 (0.26)	**-0.430 (-1.71)**	**-0.460 (-2.11)**
Pay satisfaction	0.012 (0.08)	-0.036 (-0.15)	0.224 (1.07)
Job security satisfaction	-0.076 (-0.40)	0.081 (0.28)	-0.028 (-0.11)
Work satisfaction	-0.246 (-1.42)	**-0.626 (-2.50)**	**-0.946 (-4.41)**
Hours satisfaction	0.123 (0.78)	0.087 (0.35)	-0.035 (-0.16)
Flexibility satisfaction	-0.118 (-0.70)	0.226 (0.89)	**-0.560 (-2.54)**
Full-time female employees			
Overall job satisfaction	-0.042 (-0.20)	-0.381 (-1.26)	-0.280 (-1.08)
Pay satisfaction	0.040 (0.23)	0.075 (0.27)	-0.257 (-1.08)
Job security satisfaction	-0.216 (-0.90)	0.371 (0.96)	0.249 (0.84)
Work satisfaction	-0.143 (-0.70)	**-0.752 (-2.59)**	**-0.721 (-2.86)**
Hours satisfaction	0.151 (0.88)	0.063 (0.23)	0.108 (0.47)
Flexibility satisfaction	-0.011 (-0.06)	0.006 (0.02)	0.264 (1.08)

Note: Random effects panel probit estimation with Mundlak corrections. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level. Full results are in support document.

VET certificates III/IV

Estimation results for VET graduates with certificates III/IV in table 7c are very informative. To begin with, all types of mismatch produce overall job dissatisfaction for both genders, but more so for females. Male employees with certificates III/IV are dissatisfied with the content of their work, an effect found only for those females who are *over-skilled and over-educated*. There is a clear message that job flexibility is an issue for both genders of mismatched certificates III/IV graduates. The modest wage penalty from the panel wage regressions (table 6c) is reflected in significant pay dissatisfaction for both genders. Note that the lowest wage penalty estimate was for *over-skilled-only* males (table 6c, at -0.026), and this is shown to produce the lowest (and statistically not significant) pay job dissatisfaction estimate. There is significant hours dissatisfaction for *over-skilled-only* and *over-skilled and over-educated* males, but not for females. Finally, job security dissatisfaction appears to be significant only for females who are *over-skilled and over-educated*.

When we combine the panel results in tables 7c on job satisfaction and 6c on wages, we see a picture of a modest wage penalty for those who become mismatched, and a multifaceted job dissatisfaction that arises from the onset of mismatch. This picture is clearly suggesting that where mismatch is present, it is hurting VET certificates III/IV graduates both in the pay and the job satisfaction they derive from their employment. This picture must be augmented by adding that the incidence of over-skilling mismatch among VET graduates is amongst the lowest in the labour market and that its persistence (state-dependence) is the lowest in the labour market (Mavromaras, McGuinness & Fok 2009b). Simply put, a smaller proportion of VET graduates suffer from mismatch and they get out of their mismatch sooner than other mismatched full-time employees with other qualifications.

Table 7c Job satisfaction and its facets (certificates III/IV)

	Relative to well-matched		
	Over-educated only	Over-skilled only	Over-skilled and over-educated
Full-time male employees			
Overall job satisfaction	**-0.242 (-2.22)**	**-0.527 (-5.53)**	**-0.461 (-3.33)**
Pay satisfaction	**-0.236 (-2.46)**	-0.069 (-0.76)	**-0.330 (-2.54)**
Job security satisfaction	-0.112 (-0.97)	-0.084 (-0.82)	-0.230 (-1.55)
Work satisfaction	**-0.256 (-2.30)**	**-0.458 (-4.81)**	**-0.662 (-4.72)**
Hours satisfaction	-0.140 (-1.40)	**-0.206 (-2.23)**	**-0.436 (-3.24)**
Flexibility satisfaction	**-0.190 (-1.87)**	**-0.195 (-2.08)**	-0.158 (-1.16)
Full-time female employees			
Overall job satisfaction	**-0.471 (-2.23)**	**-0.789 (-3.46)**	**-0.842 (-3.15)**
Pay satisfaction	**-0.329 (-1.92)**	**-0.371 (-1.82)**	**-0.477 (-2.08)**
Job security satisfaction	-0.280 (-1.17)	-0.151 (-0.58)	**-0.659 (-2.17)**
Work satisfaction	-0.041 (-0.21)	-0.244 (-1.11)	**-0.682 (-2.74)**
Hours satisfaction	-0.123 (-0.70)	-0.107 (-0.51)	-0.308 (-1.31)
Flexibility satisfaction	**-0.287 (-1.65)**	-0.257 (-1.31)	**-0.454 (-1.98)**

Note: Random effects panel probit estimation with Mundlak corrections. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level. Full results are in support document.

Without any post-school qualifications

Completed school Year 12

Table 7d presents the job satisfaction estimation of employees who have only completed their school education. There is clearly much more job dissatisfaction among males, which is broken down into dissatisfaction with the type of work they do for all mismatches, with pay and hours for the over-skilled-only, with flexibility for the over-educated-only and with hours for the over-skilled and over-educated. Given the small sample size of the over-educated category, these results cannot be relied upon too much.

Table 7d Job satisfaction and its facets (only completed school)

	Relative to well-matched		
	Over-educated only	Over-skilled only	Over-skilled and Over-educated
Full-time male employees			
Overall job satisfaction	**-.540 (-2.07)**	**-.542 (-4.69)**	**-.613 (-2.30)**
Pay satisfaction	.151 (0.62)	**-.332 (-3.03)**	-.309 (-1.23)
Job security satisfaction	.264 (0.91)	-.124 (-1.00)	-.270 (-0.97)
Work satisfaction	**-.868 (-3.39)**	**-.504 (-4.44)**	**-.934 (-3.51)**
Hours satisfaction	-.256 (-1.05)	**-.191 (-1.74)**	**-.711 (-2.78)**
Flexibility satisfaction	**-.597 (-2.47)**	-.160 (-1.43)	-.375 (-1.46)
Full-time female employees			
Overall job satisfaction	-.071 (-0.30)	**-.288 (-1.98)**	-.180 (-0.63)
Pay satisfaction	-.089 (-0.41)	-.019 (-0.13)	.448 (1.58)
Job security satisfaction	-.097 (-0.35)	-.027 (-0.16)	.459 (1.34)
Work satisfaction	-.130 (-0.57)	**-.521 (-3.63)**	-.191 (-0.68)
Hours satisfaction	-.036 (-0.16)	-.178 (-1.30)	.246 (0.85)
Flexibility satisfaction	**.702 (2.83)**	.018 (0.13)	**.586 (1.95)**

Note: Random effects panel probit estimation with Mundlak corrections. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level. Full results are in support document.

Completed school Years 9, 10, or 11

This is the least informative set of estimations, as already explained, due to the very small sample size of the over-educated category of mismatch. Hence the main results to look at in table 7e are those of the over-skilled-only mismatch. Both males and females who are over-skilled-only are dissatisfied overall with their job, the effect being broken down for males into job security, type of work, and hours dissatisfaction; for females it is broken down into pay and work dissatisfaction. Note that the panel wage effects are not informative for this category, but this is not surprising, as the wage distribution is very compressed due to the generally low pay for this group.

Table 7e Job satisfaction and its facets (did not complete school)

	Relative to well-matched		
	Over-educated only	Over-skilled only	Over-skilled and Over-educated
Full-time male employees			
Overall job satisfaction	0.123 (0.51)	**-0.197 (-2.23)**	-0.084 (-0.28)
Pay satisfaction	0.216 (1.03)	0.035 (0.43)	-0.100 (-0.37)
Job security satisfaction	-0.148 (-0.57)	**-0.156 (-1.65)**	**-0.617 (-2.10)**
Work satisfaction	0.092 (0.36)	**-0.150 (-1.72)**	-0.288 (-0.92)
Hours satisfaction	-0.286 (-1.27)	**-0.230 (-2.73)**	0.073 (0.25)
Flexibility satisfaction	-0.037 (-0.17)	-0.115 (-1.39)	0.196 (0.70)
Full-time female employees			
Overall job satisfaction	0.412 (0.92)	**-0.419 (-3.14)**	-0.440 (-0.70)
Pay satisfaction	-0.408 (-1.11)	**-0.222 (-1.92)**	0.424 (0.86)
Job security satisfaction	-0.681 (-1.50)	-0.413 (-3.08)	-0.559 (-0.83)
Work satisfaction	0.098 (0.26)	**-0.512 (-4.11)**	-0.736 (-1.31)
Hours satisfaction	0.458 (1.19)	-0.084 (-0.69)	0.005 (0.01)
Flexibility satisfaction	-0.090 (-0.24)	-0.055 (-0.48)	-0.334 (-0.60)

Note: Random effects panel probit estimation with Mundlak corrections. Brackets adjacent to coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level. Full results are in support document.

Age cohort differences and mismatch wage penalties

The previous section implicitly assumes that the relationship between mismatch and skills and qualifications can be adequately represented by the inclusion of age as an explanatory variable in the wage and job satisfaction estimations. As we indicated through figures 1 and 2 in the data section earlier, the relationship between age and wage depends on qualifications in a way that is more complex than assuming that age only has a single and direct effect on wages. Figures 1 and 2 clearly suggest that education attainment influences the complete age–wage profiles with differences in starting wages; wage growth; and age at which the age–wage profile peaks, a picture that is too complex to model in the context of this present report.

There are two issues that need to be considered to come to grips with this problem. First, noting that the Household Income and Labour Dynamics in Australia survey provides us with only eight waves of data—the panel information—we can estimate partial lifecycle age–wage profiles, only up to eight years length each. The overall estimation will consist of many such lifecycle profiles, all of them beginning at a different starting age. These profiles put together represent the age distribution of all survey respondents in the year 2001 (wave 1). This brings us to the second issue. Let us, by way of example, compare two cohorts: a younger one consisting of those respondents who were between the age of 20 and 25 in 2001 and an older one consisting of those who were between the age of 45 and 50 in 2001. It would not be surprising to find that achievement in terms of qualifications will be different by age cohort. School education completion meant something different between 1968 and 1973—when the older cohort completed their school education—and 1993 and 1998—when the younger cohort completed their schooling. Similarly, post-school education opportunities have changed between these two dates. We could also expect that far more of the older workers will have achieved higher skill levels that are not represented by a formal qualification than their younger counterparts.

Notwithstanding these considerations, the remainder of this brief sub-section has estimated the wage and job satisfaction models by splitting the sample of full-time employees into two groups: those below 35 years of age (the 'young' cohort) and those above (the 'old' cohort). Table 8 sums up the relevant mismatch coefficients for males and females, respectively. A cursory view of results in table 8a for males and table 8b for females suggests that there are significant age-cohort-related differences, but that they do not appear to be clearly systematic, at least not using the present model specification, the present split of qualifications, and the rather simple age-cohort two-way split. Table 8a suggests that, for male workers with a university degree (compare with table 6a), the significant wage penalty obtained previously for those who are both over-skilled and over-educated is amplified among the older cohort and nearly disappears for the younger cohort, suggesting that it is the older men who suffer from this most intense mismatch. Similarly, the wage penalty suffered by those who are both over-skilled and over-educated with a certificate III/IV (compare with table 6c) is also driven by the older cohort, suggesting again that it is older men that suffer most. By contrast, the negative wage effect for males who are over-educated-only or over-skilled-only with a certificate III/IV, as well as for males who are both over-skilled and over-educated and who have only completed school, is largely driven by the younger cohort. Further, for males who did not complete school (compare with table 6e), over-education on its own, and jointly with over-skilling, leads to a wage penalty for the older group, while this effect was not observed in the previous estimation when we incorporated the two age groups.

Table 8a Wage effects of job mismatch for males by education level and age

	Relative to well-matched					
	Over-educated only		Over-skilled only		Over-skilled and over-educated	
	Young	*Old*	*Young*	*Old*	*Young*	*Old*
Did not complete school	-0.066 (-1.28)	**-0.060** **(-1.94)**	-0.002 (-0.12)	0.007 (0.50)	0.054 (0.89)	**-.105** **(-2.47)**
Only completed school	0.039 (0.93)	-0.084 (-0.96)	0.003 (0.16)	0.002 (0.07)	**-0.104** **(-2.30)**	-0.023 (-0.30)
Certificates III/IV	**-0.061** **(-2.79)**	**-0.030** **(-2.12)**	**-0.049** **(-2.31)**	-0.015 (-1.00)	-0.016 (-0.50)	**-0.077** **(-3.48)**
Diplomas	-0.069 (-1.28)	0.027 (0.78)	-0.039 (-0.85)	-0.045 (-1.25)	-0.014 (-0.25)	-0.006 (-0.17)
University degrees	-0.040 (-1.54)	0.004 (0.17)	0.002 (0.09)	-0.010 (-0.46)	-0.030 (-0.72)	**-0.069** **(-2.10)**

Note: This table replicates the random effects (with Mundlak corrections) estimations of table 7 for males. The same variables have been used, with the exception of age, which has been used here to split the sample. Brackets below coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

The opposite result arises for males who only completed school. This may suggest that the more general type of school education allowed them to adapt to a job with no wage penalty.

Table 8b shows age-cohort results for female full-time workers. For those with a university degree (compare with table 6a) the significant wage penalty obtained previously for the over-skilled-only category does not vary significantly by age cohort. For female university graduates who are over-educated-only or over-educated and over-skilled, wage penalties appear only among the younger cohort of full-time workers. Young female workers also drive the wage penalty from being both over-skilled and over-educated with a certificate III/IV (compare with table 6c) and from being over-skilled-only with a diploma (compare with table 6b). By contrast, the wage penalty from being over-educated-only or over-skilled-only with a certificate III/IV, as well as being over-skilled-only having only completed school, is driven by the older age cohort.

Table 8b Wage effects of job mismatch for females by education level and age

	Relative to well-matched					
	Over-educated only		Over-skilled only		Over-skilled and over-educated	
	Young	*Old*	*Young*	*Old*	*Young*	*Old*
Did not complete school	0.046 (0.44)	0.027 (0.68)	0.022 (0.74)	-0.015 (-0.99)	0.175 (1.51)	-0.030 (-0.53)
Only completed school	0.004 (0.11)	0.017 (0.47)	-0.007 (-0.29)	**-0.086** **(-2.00)**	-0.037 (-0.82)	0.047 (0.85)
Certificates III/IV	-0.044 (-1.36)	**-0.098** **(-2.35)**	0.001 (0.03)	**-0.128** **(-2.28)**	**-0.120** **(-2.81)**	-0.059 (-1.18)
Diplomas	-0.052 (-1.48)	-0.040 (-1.47)	-0.128 (-2.20)	0.006 (0.16)	-0.037 (-0.83)	-0.045 (-0.97)
University degrees	**-0.102** **(-3.46)**	-0.008 (-0.30)	**-0.049** **(-2.32)**	**-0.050** **(-2.47)**	**-0.109** **(-3.73)**	-0.047 (-1.45)

Note: This table replicates the random effects (with Mundlak corrections) estimations of table 7 for females. The same variables have been used, with the exception of age, which has been used here to split the sample. Brackets below coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

Clearly these results need further work and modelling to be trustworthy and generalised enough to inform policy. We have only used wage penalties as a mismatch outcome to measure the possible age-cohort differences. What this brief exploratory section clearly establishes is that: age cohort differences matter in the context of over-skilling and more general skills mismatch; that the differences are statistically significant; and that they are gender and level of qualifications sensitive.

Discussion

Summing up the estimation results

The analysis we presented offers a complex but informative picture. Tables 9 and 10 summarise the panel estimation results for ages and job satisfaction respectively and offer some estimation of their main points.

Table 9 shows that in many cases becoming mismatched has a direct effect on wages. It does not matter for those who are not paid well and these are typically those without post-school qualifications. We see that for those with post-school qualifications there is a wage penalty for becoming mismatched. For the over-educated-only, the penalty affects mostly females. There is no pattern for the over-skilled-only. For the over-skilled and over-educated (the strongest form of mismatch) the wage penalty is stronger and affects both genders. The lack of significance for diploma graduates is due to the small sample size and those estimates should be disregarded.

Table 9 Summing up wage effects of job mismatch estimation (random effects Mundlak)

	Relative to well-matched					
	Over-educated only		Over-skilled only		Over-skilled and over-educated	
	Males	*Females*	*Males*	*Females*	*Males*	*Females*
Did not complete school	-0.038 (-1.34)	0.027 (0.69)	0.009 (0.76)	-0.007 (-0.52)	-0.008 (-0.22)	0.037 (0.81)
Only completed school	-0.008 (-0.22)	0.030 (1.06)	-0.003 (-0.19)	**-0.046** **(-2.06)**	**-0.107** **(-2.83)**	-0.019 (-0.53)
Certificates III/IV	**-0.042** **(-3.50)**	**-0.063** **(-2.38)**	**-0.026** **(-2.09)**	**-0.083** **(-2.21)**	**-0.063** **(-3.42)**	**-0.096** **(-2.85)**
Diplomas	-0.002 (-0.06)	**-0.053** **(-2.61)**	**-0.047** **(-1.64)**	-0.033 (-0.99)	-0.023 (-0.73)	-0.046 (-1.55)
University degrees	-0.017 (-0.94)	**-0.054** **(-2.83)**	-0.003 (-0.19)	**-0.054** **(-3.80)**	**-0.073** **(-2.88)**	**-0.091** **(-4.24)**

Note: Brackets below coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

The picture we see suggests that becoming mismatched is particularly harmful for VET graduates with certificates III/IV. We recall recent results on two aspects which suggest otherwise, but do not cover the complete definition of mismatch in this research, as they refer to over-skilling on its own as a form of mismatch. First, we know that over-skilling is less common among VET certificates III/IV graduates (Mavromaras, McGuinness & Fok 2009a). Second, where over-skilling is encountered, it is not self-perpetuating among VET certificates III/IV graduates, which means that VET graduates do not get trapped in the state of over-skilling. By contrast, university graduates do. We do not have sufficient sample sizes to test this hypothesis for diploma graduates and the analysis of incidence and self-perpetuation has not been carried out for the more general definition of mismatch used in this research. To the degree that the results on incidence and self-perpetuation of over-skilling also apply to over-education, the position of VET graduates will not be as unfavourable as table 9 suggests.

Tables 10a and 10b summarise the effect of becoming mismatched on overall job satisfaction and on job satisfaction with the work itself. These two types of job satisfaction appear to be the most consistently damaged by mismatch. Overall job dissatisfaction rises almost universally for those with post-school qualifications when they move to a mismatched job. This dissatisfaction is shown to depend on a number of different facets of job satisfaction. There is no discernible pattern regarding the facets estimates, but when they are looked at on a case-by-case basis most of them make sense, and in most cases the job satisfaction results tie up well with the wage penalty results, but not always.

Table 10a Overall job satisfaction effects of job mismatch

	Relative to well-matched					
	Over-educated only		Over-skilled only		Over-skilled and over-educated	
	Males	*Females*	*Males*	*Females*	*Males*	*Females*
Did not complete school	0.123 (0.51)	0.412 (0.92)	**-0.197** **(- 2.23)**	**-0.419** **(-3.14)**	-0.084 (-0.28)	-0.440 (-0.70)
Only completed school	**-0.540** **(-2.07)**	-0.071 (-0.30)	**-0.542** **(-4.69)**	**-0.288** **(-1.98)**	**-0.613** **(-2.30)**	-0.180 (-0.63)
Certificates III/IV	**-0.242** **(-2.22)**	**-0.471** **(-2.23)**	**-0.527** **(-5.53)**	**-0.789** **(-3.46)**	**-0.461** **(-3.33)**	**-0.842** **(-3.15)**
Diplomas	0.045 (0.26)	-0.042 (-0.20)	**-0.430** **(-1.71)**	-0.381 (-1.26)	**-0.460** **(-2.11)**	-0.280 (-1.08)
University degrees	-0.099 (-0.82)	**-0.301** **(-2.15)**	**-0.357** **(-3.34)**	**-0.660** **(-5.32)**	**-0.694** **(-4.32)**	**-0.598** **(-2.95)**

Note: Brackets below coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

The one facet of job dissatisfaction that is very prevalent is work satisfaction, which refers to the actual work done in the job. Here mismatch shows clearly that the content of mismatched jobs is less appealing for VET graduates than it is for university graduates. Well-matched university graduates typically have more discretion in their jobs, as graduate jobs offer typically more discretion. However, we do not know if this is also the case for (over-educated) university graduates who may be working in a non-graduate job or environment.

Table 10b Work satisfaction effects of job mismatch

	Relative to well-matched					
	Over-educated only		Over-skilled only		Over-skilled and over-educated	
	Males	*Females*	*Males*	*Females*	*Males*	*Females*
Did not complete school	0.092 (0.36)	0.098 (0.26)	**-0.150** **(-1.72)**	**-0.512** **(-4.11)**	-0.288 (-0.92)	-0.736 (-1.31)
Only completed school	**-0.868** **(-3.39)**	-0.130 (-0.57)	**-0.504** **(-4.44)**	**-0.521** **(-3.63)**	**-0.934** **(-3.51)**	-0.191 (-0.68)
Certificates III/IV	**-0.256** **(-2.30)**	-0.041 (-0.21)	**-0.458** **(-4.81)**	-0.244 (-1.11)	**-0.662** **(-4.72)**	**-0.682** **(-2.74)**
Diplomas	-0.246 (-1.42)	-0.143 (-0.70)	**-0.626** **(-2.50)**	**-.752** **(-2.59)**	**-0.946** **(-4.41)**	**-0.721** **(-2.86)**
University degrees	0.029 (0.24)	-0.231 (-1.61)	**-0.592** **(-5.64)**	**-0.866** **(-6.95)**	**-0.692** **(-4.44)**	**-1.19** **(-5.99)**

Note: Brackets below coefficients contain t-ratios. Coefficients in bold are statistically significant at least at the 10% level.

Finally, there have been other effects that have been shown to matter in the course of this research and which could warrant further investigation. First, we have looked into the possibility that age-cohort effects could be at play. Some preliminary work showed this to be the case, but not in a uniform way. Second, we find that there are strong gender differences. These are not necessarily due to behavioural differences; they may well be because of occupational and sectoral segregation, which would be able to produce strong gender differences in the data. For example, certificates III/IV probably mean different occupations and different sectors by gender. Just having an occupation and (or) a sector variable in the regressions will not necessarily capture the relevant gender variation.

The economic explanation of the consequences of mismatch

This research has shown that becoming mismatched affects the job satisfaction and the wages of employees. The panel analysis has enabled us to estimate two main outcomes: the wage penalty and the loss in job satisfaction that are caused by becoming mismatched. The economic interpretation of how these two outcomes may relate to each other offers useful and novel intuition on the consequences of mismatch. We explain this by way of example. Suppose we observe a mismatch that has caused a drop in the wage. How can additional information on job satisfaction increase our understanding of the consequences and the nature of that mismatch? If the mismatch and the wage drop are not followed by a drop in job satisfaction, we have to wonder if the new (mismatched) job has some other redeeming features that made the newly mismatched employee not feel worse off. Such a feature could be better working conditions, more flexibility, or some other factor.

Box 1 Wage penalty, job satisfaction and nature of mismatch

What happens to wages and job satisfaction after the onset of a mismatch:

Wage	Job satisfaction	Type of mismatch
Drop (Lower pay)	Drop (Higher dissatisfaction)	*Genuine mismatch with evidence of productivity drop: (GENMIS)* A drop in the wage suggests a drop in the value placed on the match output. Mismatched jobs can be expected to have lower productivity than the potential of the well-matched employee. A reduction in job satisfaction suggests that the employee does not like the change in circumstances, which implies that the net outcome of the onset of mismatch has made them worse off. That is, it is not likely that the new (mismatched) job has many compensating and redeeming features. We call this a genuine mismatch.
Drop (Lower pay)	No change	*Possible compensating differentials case: (POSCOMP)* The drop in wage is not followed by a commensurate drop in job satisfaction. This suggests that, although the employee is now mismatched and earning less than their well-matched colleagues, they do not mind it. This combination suggests that the new (mismatched) job may be offering some compensating benefits to the employee, so that on balance they do not feel worse off in their new (mismatched) job. We call this a possible compensating wage differential case, where employees sacrifice some wage for some non-pecuniary job benefits.
Drop (Lower pay)	Rise (Lower dissatisfaction)	*Compensating differential case: (COMDIF)* The same as the possible compensating differentials case, but stronger and unambiguous as the employee now feels better off despite the drop in wage.
No change	Drop (Higher dissatisfaction)	*Weak mismatch: (WEAKMIS)* The lack of a wage penalty suggests that the productivity of this match is as high as in the case of the well-matched counterparts. But the individual feels that they are worse off in their new (mismatched) job. We maintain that there is evidence of a weak mismatch. In the cases of the less well-paid parts of the labour market, this could also be an indication of genuine mismatch.
No change	No change	*No evidence of a mismatch (NOEV)* With no discernible change in outcome, we maintain that there is no evidence of a mismatch. This could be due to misreporting or due to weak statistical evidence.
No change	Rise (Lower dissatisfaction)	*No evidence of a mismatch (NOEV)* The evidence of an increase in job satisfaction suggests that there is no evidence of a mismatch.

By contrast, if the mismatch and the wage drop are followed by a drop in job satisfaction, then we should be inclined to believe that we have to deal with a case of genuine mismatch. There are a number of combinations of wage and job satisfaction outcomes, and each is given an interpretation in table 11.

We now combine the mismatch categorisations in box 1 with the combined results in tables 9 and 10a to derive an overview of matching by education pathway and gender in table 11. Where the estimation results were not statistically significant, we enter 'NS' (for not significant). Where the wage or job satisfaction dropped after the onset of a mismatch, we enter 'drop' and where it increased we enter 'rise'.

For the lowest education group (school Years 9 to 11) who report as mismatched there is evidence of a weak mismatch for the over-skilled-only. For those who only completed school (Year 12) the picture is mixed. There is no trace of compensating differentials.

VET graduates with certificates III/IV who report being mismatched, are clearly so, with all categories for both males and females being categorised as genuinely mismatched. Noting that this is the group with the lowest incidence of reporting mismatch, this research suggests that this reporting should be taken seriously.

Table 11 The nature of mismatch by gender and education pathway

Reported mismatch	Gender	Outcomes	Years 9–11	Year 12	Cert III/IV	Diplomas[1]	Univ degrees
OED	M	Wage	NS	NS	Drop	NS	NS
	M	Job Sat	NS	Drop	Drop	NS	NS
	M	Mismatch	NOEV	WEAKMIS	GENMIS	NOEV	NOEV
OED	F	Wage	NS	NS	Drop	Drop	Drop
	F	Job Sat	NS	NS	Drop	NS	Drop
	F	Mismatch	NOEV	NOEV	GENMIS	COMDIF	GENMIS
OSK	M	Wage	NS	NS	Drop	Drop	NS
	M	Job Sat	Drop	Drop	Drop	Drop	Drop
	M	Mismatch	WEAKMIS	WEAKMIS	GENMIS	GENMIS	WEAKMIS
OSK	F	Wage	NS	Drop	Drop	NS	Drop
	F	Job Sat	Drop	Drop	Drop	NS	Drop
	F	Mismatch	WEAKMIS	GENMIS	GENMIS	NOEV	GENMIS
OED+OSK	M	Wage	NS	Drop	Drop	NS	Drop
	M	Job Sat	NS	Drop	Drop	Drop	Drop
	M	Mismatch	NOEV	GENMIS	GENMIS	WEAKMIS	GENMIS
OED+OSK	F	Wage	NS	NS	Drop	NS	Drop
	F	Job Sat	NS	NS	Drop	NS	Drop
	F	Mismatch	NOEV	NOEV	GENMIS	NOEV	GENMIS

Note: OED denotes over-educated-only; OSK over-skilled-only; OED+OSK over-skilled and over-educated. M stands for male and F for female.
1 The statistical significance for this education category is low.

For those with diplomas the picture is too mixed and unreliable due to sample size problems. We only include it for the sake of completeness.

The picture of university graduates offers some surprises. Whereas anecdotal evidence focuses on the story of females who are over-educated and underpaid out of choice, we find this is not supported by our data and analyses: over-educated female university graduates are underpaid and they do not like it; that is, we cannot trace any compensating differentials. By contrast, over-educated male university graduates do not seem to suffer any discernible losses as a consequence of being over-educated. This gender difference is also present among the over-skilled university graduates. Both males and females dislike being over-skilled, but it is the females who suffer an over-skilling wage penalty. When it comes to those who are both over-skilled and over-educated, the most severe type of mismatch, gender differences disappear and both males and females report lower wages and higher dissatisfaction. Clearly, to the degree that lower wages and job satisfaction may be either associated or causing different levels of productivity, this research indicates some possible empirical links between mismatch and productivity. Our findings present a complex relationship between mismatch in the workplace and the resulting outcomes and highlight the need for further research on the relationship between mismatch and productivity.

Conclusions

This research examined the outcome of over-skilling and over-education on wages and job satisfaction on full-time employees in Australia between the years 2001 and 2008. Three main categories of mismatch were defined: *over-skilled-only*, *over-educated-only* and *over-skilled and over-educated*. The analysis was carried out by gender and by education pathway.

We examined in detail whether mismatch influences job satisfaction and found that it does, particularly among those with post-school education. Previous results on the negative effect of mismatch on wages were confirmed and further extended through the introduction of the three-way more focused definition of mismatch. We found that over-education and over-skilling appear to produce different adverse labour market outcomes, but there were few patterns in the results.

We carried out multivariate regression analysis using the panel element of the Household Income and Labour Dynamics in Australia survey data to estimate the causal effect of becoming mismatched on wages and job satisfaction. Our analysis found extensive education level and gender differences. We compared cross-section and panel evidence on mismatch wage penalties and found that cross-section estimates are considerably higher, indicating the presence of unobserved heterogeneity in the data.

We investigated in detail the different facets of job satisfaction offered in the survey and found differences by type of mismatch, education pathway, gender and age. We provided further detail on the possible impact of cohort (age) differences in the sample and found strong but not always clearly interpretable differences.

We combined wages as an indicator of the productivity of a new job match and job satisfaction as an indicator of the perceived success of a new match to measure the attractiveness of new matches by the way in which mismatched and well-matched employees may differ systematically. We categorised the nature of reported mismatches as *genuine mismatches*, *weak mismatches*, *no evidence of a mismatch,* and *evidence of compensating differentials*. We found weak evidence of compensating differentials and a number of occasions where reported mismatches cannot be confirmed as genuine mismatches according to our analysis of the resulting wages and job satisfaction outcomes.

We found that reported mismatches are more likely to be genuine mismatches among those with post-school education and for female full-time employees.

Results contain some novel findings regarding policy. First, mismatch is highly gendered in all the forms we have measured. Policy should reflect this, especially for female university graduates. Second, more of the mismatch evidence derives from the over-skilling measure than from the over-education measure, and the differences vary by gender and education level. Third, there are many instances where a mismatch is characterised by both a drop in wages and in job satisfaction, indicating that the eradication of mismatch would benefit both employers and employees.

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Appendix A

Table A1 Overall job satisfaction (%)

	Did not complete school		Only completed school		Certificates III/IV		Diplomas		Degrees	
	M	F	M	F	M	F	M	F	M	F
0	1	1	0	1	0	0	0	0	0	0
1	1	0	1	0	1	1	0	1	0	1
2	1	1	1	1	1	1	1	0	1	1
3	1	1	1	2	2	1	2	2	1	2
4	2	2	2	2	2	1	2	2	2	2
5	7	7	5	6	6	6	6	5	5	6
6	8	6	8	8	8	7	8	9	9	9
7	18	14	23	19	20	18	24	21	25	23
8	27	29	31	29	31	29	31	31	34	32
9	18	22	19	21	20	22	19	20	18	19
10	16	18	8	11	10	12	6	8	4	5
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Note: The sample is working age full-time employees from HILDA 2001–08.

Table A2 Pay satisfaction (%)

	Did not complete school		Only completed school		Certificates III/IV		Diplomas		Degrees	
	M	F	M	F	M	F	M	F	M	F
0	1	1	1	1	1	2	0	1	0	1
1	1	1	1	1	1	1	1	2	1	1
2	2	2	3	3	2	3	2	2	2	2
3	4	3	4	5	4	4	4	5	3	4
4	5	4	5	5	4	4	4	4	4	4
5	11	10	8	10	9	10	8	9	6	7
6	10	9	13	13	12	13	11	11	11	11
7	20	18	23	20	22	18	23	21	23	23
8	24	25	23	24	27	25	28	27	30	27
9	11	12	11	9	11	13	13	11	15	14
10	10	13	8	9	7	8	6	7	5	7
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Note: The sample is working age full-time employees from HILDA 2001–08.

Table A3 Job security satisfaction (%)

	Did not complete school		Only completed school		Certificates III/IV		Diplomas		Degrees	
	M	F	M	F	M	F	M	F	M	F
0	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
2	2	1	1	1	1	1	1	2	1	1
3	2	1	2	1	2	2	2	1	2	2
4	2	2	2	2	2	2	2	2	2	2
5	6	6	6	5	6	4	3	4	4	4
6	5	4	5	5	5	4	4	5	5	4
7	11	9	11	10	11	10	13	9	12	9
8	22	22	23	21	22	20	28	21	23	20
9	20	22	25	24	23	25	25	25	26	25
10	28	30	25	29	27	30	19	29	23	31
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Note: The sample is working age full-time employees from HILDA 2001–08.

Table A4 Work satisfaction (%)

	Did not complete school		Only completed school		Certificates III/IV		Diplomas		Degrees	
	M	F	M	F	M	F	M	F	M	F
0	0	1	0	0	0	1	0	1	0	0
1	1	0	1	0	0	1	0	0	0	0
2	1	1	1	2	1	1	1	1	1	1
3	2	2	2	2	2	2	2	2	2	2
4	2	2	3	3	2	3	3	2	3	2
5	8	9	7	7	6	7	6	6	5	6
6	7	6	9	10	8	7	10	9	10	8
7	17	14	20	17	18	16	20	18	20	19
8	27	27	28	27	30	25	26	29	30	30
9	16	19	17	18	19	20	20	21	20	20
10	19	19	13	15	14	16	11	11	8	11
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Note: The sample is working age full-time employees from HILDA 2001–08.

Table A5 Hours satisfaction (%)

	Did not complete school		Only completed school		Certificates III/IV		Diplomas		Degrees	
	M	F	M	F	M	F	M	F	M	F
0	0	1	1	0	1	1	0	0	0	1
1	1	1	1	1	1	1	1	1	1	1
2	2	1	2	2	2	2	2	2	2	2
3	3	3	3	2	3	2	4	4	4	4
4	4	3	4	5	4	3	6	3	5	5
5	10	11	8	10	10	8	10	11	9	10
6	9	9	10	10	10	9	10	14	13	12
7	17	16	20	17	19	18	20	20	22	19
8	24	24	27	24	26	25	26	22	25	24
9	15	16	14	16	14	16	15	14	14	14
10	16	16	11	13	11	14	7	10	6	7
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Note: The sample is working age full-time employees from HILDA 2001–08.

Table A6 Flexibility satisfaction (%)

	Did not complete school		Only completed school		Certificates III/IV		Diplomas		Degrees	
	M	F	M	F	M	F	M	F	M	F
0	2	2	1	1	2	2	1	2	1	1
1	2	2	2	1	2	2	2	2	1	2
2	4	3	3	2	4	3	3	3	2	4
3	4	3	3	4	4	3	4	4	4	5
4	4	4	4	4	4	4	5	5	4	6
5	10	10	9	10	9	9	9	9	7	10
6	7	7	7	7	8	9	9	10	10	10
7	13	12	14	13	13	14	15	15	17	16
8	20	20	22	21	21	19	21	21	23	20
9	14	16	17	16	17	18	17	14	18	15
10	21	24	19	21	17	18	13	15	13	11
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Note: The sample is working age full-time employees from HILDA 2001–08.

Appendix B

Definition of variables:

Wage: log of current weekly gross wages and salary from the main job.

Overall job satisfaction: dummy variable, takes the value 1 if overall job satisfaction is 7 or above, zero if 0 to 6.

Facets of job satisfaction: pay satisfaction, job security satisfaction, work satisfaction, hours satisfaction, and flexibility satisfaction are defined in the same way as overall job satisfaction.

Mismatch variables:

Over-educated-only: dummy variable, takes the value 1 if an individual is over-educated only, zero otherwise.

Over-skilled-only: dummy variable, takes the value 1 if an individual is over-skilled only, zero otherwise.

Over-skilled and over-educated: dummy variable, takes the value 1 if an individual is over-skilled and over-educated, zero otherwise.

Well-matched is the reference category.

Age: continuous variable, expressed in years.

Age square: continuous variable, expressed in years.

Married: dummy variable, takes the value 1 if an individual is married (or de facto), zero otherwise.

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

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

Country of birth:

Migrant (English-speaking country): dummy variable, takes the value 1 if migrant from an English-speaking country, zero otherwise.

Migrant (non-English-speaking country): dummy variable, takes the value 1 if migrant from a non-English-speaking country, zero otherwise.

Australian-born is the reference category.

Hours per week usually worked in main job: continuous variable, expressed in hours.

Tenure in the current occupation: continuous variable, expressed in years.

Firm size:

Less than 5 employees: dummy variable, takes the value 1 if working in a firm which has less than 5 employees, zero otherwise.

5 to 9 employees: dummy variable, takes the value 1 if working in a firm which has 5 to 9 employees, zero otherwise.

10 to 19 employees: dummy variable, takes the value 1 if working in a firm which has 10 to 19 employees, zero otherwise.

20 to 49 employees: dummy variable, takes the value 1 if working in a firm which has 20 to 49 employees, zero otherwise.

More than 49 employees is the reference category.

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

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

Per cent time spent unemployed in last financial year: continuous variable, value of which lies between 0 and 100.

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

Sector:

Agriculture, forestry and fishing: dummy variable, takes the value 1 if working in the industry of agriculture, forestry and fishing, zero otherwise.

Mining: dummy variable, takes the value 1 if working in the industry of mining, zero otherwise.

Electricity, gas, water, and waste services: dummy variable, takes the value 1 if working in the industry of electricity, gas, water and waste services, zero otherwise.

Construction: dummy variable, takes the value 1 if working in the industry of construction, zero otherwise.

Wholesale trade: dummy variable, takes the value 1 if working in the industry of wholesale trade, zero otherwise.

Retail trade: dummy variable, takes the value 1 if working in the industry of retail trade, zero otherwise.

Accommodation and food services: dummy variable, takes the value 1 if working in the industry of accommodation and food services, zero otherwise.

Transport, postal, and warehousing: dummy variable, takes the value 1 if working in the industry of transport, postal, and warehousing, zero otherwise.

Information media and telecommunications: dummy variable, takes the value 1 if working in the industry of information media and telecommunications, zero otherwise.

Financial and insurance services: dummy variable, takes the value 1 if working in the industry of financial and insurance services, zero otherwise.

Rental, hiring, and real estate services: dummy variable, takes the value 1 if working in the industry of rental, hiring and real estate services, zero otherwise.

Professional, scientific, and technical services: dummy variable, takes the value 1 if working in the industry of professional, scientific and technical services, zero otherwise.

Administrative and support services: dummy variable, takes the value 1 if working in the industry of administrative and support services, zero otherwise.

Public administration and safety: dummy variable, takes the value 1 if working in the industry of public administration and safety, zero otherwise.

Education and training: dummy variable, takes the value 1 if working in the industry of education and training, zero otherwise.

Health care and social assistance: dummy variable, takes the value 1 if working in the industry of health care and social assistance, zero otherwise.

Arts and recreation services: dummy variable, takes the value 1 if working in the industry of arts and recreation services, zero otherwise.

Other services: dummy variable, takes the value 1 if working in the industry of other services, zero otherwise.

Manufacturing is the reference category.

Table B1 Descriptive statistics (university degrees)

Explanatory variable	Males	Females
Age	39.59 (10.16)	37.57 (10.55)
Age square	1670.50 (827.6)	1522.70 (822.7)
Married	0.79	0.65
Urban	0.94	0.92
Father was a professional	0.28	0.27
Migrant (English speaking country)	0.13	0.10
Migrant (non-English speaking country)	0.15	0.14
Hours per week usually worked in main job	45.69 (8.60)	42.80 (8.03)
Tenure in the current occupation	9.46 (9.20)	8.78 (9.28)
Tenure with current employer	7.59 (8.42)	6.68 (7.67)
Firm has less than 5 employees	0.04	0.04
Firm has 5 to 9 employees	0.06	0.07
Firm has 10 to 19 employees	0.10	0.09
Firm has 20 to 49 employees	0.17	0.19
Have children aged between 5 and 14	0.28	0.19
Have children aged under 5	0.17	0.05
Per cent time spent unemployed in last financial year	0.84 (5.63)	1.13 (6.95)
Union member	0.31	0.45
Agriculture, forestry and fishing	0.02	0.01
Mining	0.02	0.00
Electricity, gas, water and waste services	0.02	0.01
Construction	0.03	0.01
Wholesale trade	0.03	0.01
Retail trade	0.04	0.02
Accommodation and food services	0.01	0.01
Transport, postal and warehousing	0.02	0.01
Information media and telecommunications	0.04	0.04
Financial and insurance services	0.08	0.04
Rental, hiring and real estate services	0.02	0.00
Professional, scientific and technical services	0.16	0.10
Administrative and support services	0.01	0.02
Public administration and safety	0.14	0.10
Education and training	0.19	0.32
Health care and social assistance	0.07	0.24
Arts and recreation services	0.02	0.01
Other services	0.02	0.01

Note: Mean (standard deviation). The sample consists of all working-age full-time graduate employees from HILDA 2001–08, and includes 5044 males and 4489 females.

Table B2 Descriptive statistics (diplomas)

Explanatory variable	Males	Females
Age	40.80 (10.42)	38.27 (10.57)
Age square	1773.20 (861.3)	1575.90 (819.3)
Married	0.76	0.60
Urban	0.90	0.90
Father was a professional	0.14	0.19
Migrant (English speaking country)	0.11	0.12
Migrant (non-English speaking country)	0.11	0.08
Hours per week usually worked in main job	44.57 (8.61)	41.63 (7.15)
Tenure in the current occupation	9.98 (9.15)	8.89 (9.28)
Tenure with current employer	8.84 (8.90)	6.86 (7.70)
Firm has less than 5 employees	0.06	0.06
Firm has 5 to 9 employees	0.09	0.11
Firm has 10 to 19 employees	0.15	0.16
Firm has 20 to 49 employees	0.17	0.24
Have children aged between 5 and 14	0.29	0.20
Have children aged under 5	0.14	0.06
Per cent time spent unemployed in last financial year	1.12 (7.51)	0.96 (6.63)
Union member	0.39	0.31
Agriculture, forestry and fishing	0.02	0.01
Mining	0.02	0.00
Electricity, gas, water and waste services	0.03	0.00
Construction	0.06	0.03
Wholesale trade	0.04	0.03
Retail trade	0.03	0.05
Accommodation and food services	0.02	0.04
Transport, postal and warehousing	0.07	0.01
Information media and telecommunications	0.05	0.03
Financial and insurance services	0.07	0.07
Rental, hiring and real estate services	0.02	0.03
Professional, scientific and technical services	0.07	0.08
Administrative and support services	0.01	0.04
Public administration and safety	0.18	0.09
Education and training	0.06	0.22
Health care and social assistance	0.06	0.17
Arts and recreation services	0.02	0.02
Other services	0.03	0.03

Note: Mean (standard deviation). The sample consists of all working age full-time graduate employees from HILDA 2001–08, and includes 1749 males and 1377 females.

Table B3 Descriptive statistics (certificates III/IV)

Explanatory variable	Males	Females
Age	39.16 (10.82)	35.89 (12.11)
Age square	1649.30 (866.0)	1434.40 (897.1)
Married	0.74	0.60
Urban	0.87	0.85
Father was a professional	0.09	0.10
Migrant (English speaking country)	0.10	0.09
Migrant (non-English speaking country)	0.07	0.09
Hours per week usually worked in main job	45.11 (8.97)	39.99 (6.89)
Tenure in the current occupation	11.18 (10.41)	6.69 (8.03)
Tenure with current employer	7.33 (8.29)	4.15 (4.88)
Firm has less than 5 employees	0.09	0.08
Firm has 5 to 9 employees	0.14	0.12
Firm has 10 to 19 employees	0.15	0.16
Firm has 20 to 49 employees	0.19	0.19
Have children aged between 5 and 14	0.29	0.18
Have children aged under 5	0.16	0.04
Per cent time spent unemployed in last financial year	1.29 (7.93)	2.29 (9.85)
Union member	0.36	0.26
Agriculture, forestry and fishing	0.03	0.01
Mining	0.06	0.01
Electricity, gas, water and waste services	0.03	0.01
Construction	0.13	0.01
Wholesale trade	0.05	0.04
Retail trade	0.07	0.10
Accommodation and food services	0.04	0.07
Transport, postal and warehousing	0.06	0.02
Information media and telecommunications	0.02	0.03
Financial and insurance services	0.01	0.06
Rental, hiring and real estate services	0.01	0.02
Professional, scientific and technical services	0.03	0.06
Administrative and support services	0.01	0.04
Public administration and safety	0.10	0.07
Education and training	0.01	0.07
Health care and social assistance	0.03	0.26
Arts and recreation services	0.02	0.01
Other services	0.07	0.05

Note: Mean (standard deviation). The sample consists of all working age full-time graduate employees from HILDA 2001–08, and includes 5726 males and 1733 females.

Table B4 Descriptive statistics (only completed school)

Explanatory variable	Males	Females
Age	31.74 (11.77)	32.58 (11.35)
Age square	1145.60 (866.1)	1190.40 (816.1)
Married	0.54	0.57
Urban	0.89	0.89
Father was a professional	0.18	0.14
Migrant (English speaking country)	0.09	0.10
Migrant (non-English speaking country)	0.09	0.12
Hours per week usually worked in main job	43.62 (8.11)	40.53 (6.85)
Tenure in the current occupation	6.20 (7.68)	5.67 (7.11)
Tenure with current employer	5.30 (6.89)	4.72 (6.14)
Firm has less than 5 employees	0.11	0.08
Firm has 5 to 9 employees	0.13	0.12
Firm has 10 to 19 employees	0.15	0.15
Firm has 20 to 49 employees	0.17	0.19
Have children aged between 5 and 14	0.15	0.16
Have children aged under 5	0.12	0.07
Per cent time spent unemployed in last financial year	1.99 (9.01)	1.93 (9.10)
Union member	0.25	0.19
Agriculture, forestry and fishing	0.03	0.01
Mining	0.02	0.01
Electricity, gas, water and waste services	0.02	0.01
Construction	0.10	0.02
Wholesale trade	0.06	0.03
Retail trade	0.10	0.11
Accommodation and food services	0.07	0.08
Transport, postal and warehousing	0.08	0.04
Information media and telecommunications	0.03	0.04
Financial and insurance services	0.04	0.09
Rental, hiring and real estate services	0.01	0.02
Professional, scientific and technical services	0.06	0.10
Administrative and support services	0.02	0.04
Public administration and safety	0.11	0.10
Education and training	0.01	0.04
Health care and social assistance	0.02	0.12
Arts and recreation services	0.02	0.01
Other services	0.05	0.03

Note: Mean (standard deviation). The sample consists of all working age full-time graduate employees from HILDA 2001–08, and includes 2859 males and 2082 females.

Table B5 Descriptive statistics (did not complete school)

Explanatory variable	Males	Females
Age	38.71 (12.52)	41.24 (11.58)
Age square	1655.30 (966.0)	1834.60 (890.8)
Married	0.67	0.64
Urban	0.84	0.86
Father was a professional	0.06	0.08
Migrant (English speaking country)	0.10	0.07
Migrant (non-English speaking country)	0.06	0.08
Hours per week usually worked in main job	44.62 (9.42)	40.25 (6.99)
Tenure in the current occupation	9.50 (9.84)	8.505 (8.84)
Tenure with current employer	7.08 (8.21)	6.835 (7.31)
Firm has less than 5 employees	0.13	0.09
Firm has 5 to 9 employees	0.14	0.14
Firm has 10 to 19 employees	0.16	0.16
Firm has 20 to 49 employees	0.18	0.18
Have children aged between 5 and 14	0.25	0.23
Have children aged under 5	0.11	0.04
Per cent time spent unemployed in last financial year	2.73 (12.11)	2.168 (10.97)
Union member	0.32	0.25
Agriculture, forestry and fishing	0.06	0.02
Mining	0.03	0.01
Electricity, gas, water and waste services	0.02	0.01
Construction	0.14	0.03
Wholesale trade	0.07	0.05
Retail trade	0.09	0.15
Accommodation and food services	0.03	0.06
Transport, postal and warehousing	0.12	0.04
Information media and telecommunications	0.02	0.02
Financial and insurance services	0.01	0.06
Rental, hiring and real estate services	0.01	0.03
Professional, scientific and technical services	0.01	0.06
Administrative and support services	0.02	0.03
Public administration and safety	0.06	0.09
Education and training	0.01	0.04
Health care and social assistance	0.03	0.17
Arts and recreation services	0.01	0.01
Other services	0.03	0.03

Note: Mean (standard deviation). The sample consists of all working age full-time graduate employees from HILDA 2001–08, and includes 4341 males and 2558 females.

Support document details

Additional information relating to this research is available in *Over-skilling and job satisfaction in the Australian labour force: support document*. It can be accessed from NCVER's website <http://www.ncver.edu.au/publications/2365.html> and contains estimation results.

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