Horizontal and Vertical Educational Mismatch and Wages

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Abstract:

This paper utilises the panel element of the HILDA survey to examine the effect of horizontal and vertical educational mismatch on wages in Australia. Our key finding is that for men horizontal mismatch itself does not lower hourly wages while vertical mismatch on its own does. It is horizontal mismatch jointly with vertical mismatch that leads to the largest wage penalty at least for males. Horizontal mismatch does, however, by itself significantly reduce earnings for women according to the fixed effects estimates. The estimated effects in the fixed effects and random effects with a mundlak correction models are much weaker than the pooled OLS model for men in relation to vertical mismatch and vertical and horizontal mismatch combined, suggesting the relationship between mismatch and labour market outcomes is strongly influenced by unobserved heterogeneity in this case.

JEL classification: I2, J24, J31

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1. INTRODUCTION

An educational mismatch is defined in a broad manner as the situation where the education qualifications of an employee do not match the qualifications required for the job they do. A mismatch can be *vertical* where the level of the employee's qualification is not the one required by the job. A typical example would be a graduate employee who works in a job that is typically considered to be a non-graduate job, in which case the graduate is over-educated. A mismatch can also be *horizontal* where the level of the employee's qualification is of the correct level for the job, but the type of the qualification is not. A typical example would be a person with a degree in engineering working in a job that requires no engineering knowledge at all. A mismatch can be both horizontal and vertical, where someone may have a qualification at the wrong level and of the wrong type for the job they are hired to do.

An important distinction between the two types of mismatch is that a vertical mismatch can preserve some of the specific human capital that is encompassed within a type of qualification. For example, an employee with an ICT qualification who happens to be over-educated (e.g. with an ICT university degree in a job that requires an advanced vocational ICT qualification), will be of clear use to the job they are hired to do, as they know more than their job requires about ICT. Indeed, it may be in the interest of either the employer or the employee to form an over-educated mismatch, the employer with a long-run hiring strategy in mind and the employee as a form of probation or queuing within the company for a better job. Similarly, an employee with an ICT qualification who happens to be under-educated will be of clear use to the job they are hired to do, as it will be much easier for them to develop their knowledge through on-the-job training and experience, which may be the only viable hiring option for an employer in a shortage situation.

In contrast, a horizontal mismatch may find it harder to preserve any specific human capital that is encompassed within a type of qualification, though general human capital may have a role to play here.. Clearly, different qualifications contain some common elements, for example a degree in engineering, or finance, or economics, contains specific elements of mathematical modelling that can be useful to a financial sector expert, but differences are often more obvious than similarities between qualifications. In some circumstances, similarities are much harder to define and often are not there at all. For example, a degree in Linguistics can have little direct application in an engineering design section of a manufacturing unit. These considerations make the definition of horizontal mismatch less straightforward than the conventional vertical mismatch case.

Given the difficulties in the definition of horizontal mismatch, most existing studies of mismatch have focussed on the vertical dimension in which the level of education in a particular occupation does not match the job requirements, in the sense that the worker is over- or under- qualified for the job in question. However, it is worth noting that in many cases where the literature defines an overeducation mismatch, the data used to identify this mismatch contains elements of both vertical and horizontal mismatch. For example, an overeducated university graduate may not only be working in a non-graduate job, but also in a job where their degree is of little relevance. A common result in the literature is that over-education is associated with negative labour market outcomes. Employees who do not utilise fully their education qualifications earn lower wages, have lower job satisfaction and experience higher voluntary and involuntary labour mobility.

Among the limited studies of horizontal mismatch, some surveys ask workers directly whether their particular qualification is appropriate for the work that they do. In the absence of this type of self-reported definition of mismatch, one has to rely on the types of qualification that are found in particular occupations and compare the actual qualification of an individual with the modal type of qualification in that occupation. We would expect that all or most doctors would have a medical degree or most or all lawyers a legal qualification. But in other cases there may be a range of particular qualifications that are held by current employees within an occupation, the reason for having been hired not being the specific topic of their degree, but the signal their degree conveys in terms of their ability to learn fast and well. Graduates may be employed because they can pick up new tasks quickly.

Our basic proposition is that horizontal mismatch, like vertical mismatch, is likely to have harmful consequences. Three main questions were put by Robst (2007a). First, what proportion of graduates are working in jobs unrelated to their field of study, second, which degree fields lead to greater mismatch and third, what is the effect on earnings of working outside one's degree field. It may be hypothesised that education mismatch is more likely among those graduates in degree fields that provide more general skills and less likely among those from degree fields providing more occupation specific skills, though the wage effects may be greater in the latter case for those who fail to find a match. What is crucial, however, is the degree of transferability of skills. Individuals who face discrimination on account of gender, race, or disability, or who have lower ability are more likely to be mismatched due to demand side reasons and the wage effects may be greater here than where the mismatch occurs for supply side reasons. Demand–related horizontal mismatch can be regarded as involuntary whereas supply-related horizontal mismatch can be regarded as voluntary and initiated by the individual, although differences in the wage levels of the occupations that typically employ specific degrees may make this distinction empirically hard to identify: how would we classify the mismatch of a worker who gets a better wage doing a (mismatched) job in a shortage occupation, than a (matched) job in an occupation with high unemployment. There may be gender differences in the extent to which supply side reasons are important. The wage effects may also be more severe when graduates are mismatched both horizontally and vertically.

2 LITERATURE

The number of empirical studies of horizontal mismatch is limited. For the US Robst (2007b), uses the 1993 National Survey of College Graduates, to find that 20% of graduates report that their work is not related to their degree field and the reasons for this differ by gender. Robst (2007a) confirms that graduates with degrees that emphasise general skills have a higher likelihood of mismatch, but face relatively low costs from being mismatched. In their study of US employment of Science and Social Science PhDs Bender and Heywood (2009) find that 7.3% of their sample report that education and job are not related at all and an additional 23.4% that their education and job are only somewhat related. The probability of mismatch increases with age. Every measure of mismatch is associated with lower earnings, reduced job satisfaction and greater turnover, even after controlling for a wide range of explanatory variables and even given the relative homogeneity of their sample. Controlling for fixed effects reduces the size of the coefficients, though statistical significance remains.

Sweden appears to experience more horizontal mismatch, and with stronger wage effects than the US. Thus, according to Nordin, Persson and Rooth (2010) 23% of men and 17% of women are horizontally mismatched in Sweden and a further 18% of men and 8% of women only weakly matched. The wage penalty is large for both sexes, and for men twice as large as for men in the US, though for women it is about the same as for US women. A Spanish study using REFLEX data (Kucel and Vilalta-Bufi, 2010) finds that 8% of workers are horizontally mismatched and there is a wage penalty for being in this state. This study takes into account the likelihood that wages and mismatch will be simultaneously determined. Another factor to take into account is that in choosing jobs individuals may be concerned not only with the level of wages but also the variance of potential wages, particularly if they have a strong risk aversion. Domademik, Farcnik and Pastore (2013) find that mismatch of graduates on entry into the Slovenian labour market is influenced by both institutional quality and the duration of their study. Using the UK data from the Longitudinal Destination of Leavers of Higher Education, 2003, Chevalier (2011) shows that while the gap in mean salaries between subjects (ignoring medics) is around 0.25 log points, the gap within subjects in the 10/90 range is about three times larger.

Finally, there are two sector based models. First, Sgobbi and Suleman (2013) take both horizontal and vertical mismatch into account in their study of Portuguese retail bankers. They argue that traditional measures of mismatch cannot capture fully the multi-dimensional and job specific nature of skill mismatch. There is a difference in core and supplementary skills between customer-focussed and back-office employees. Second, Estache and Foucart (2012) use a monopsony argument involving young and old workers and young and old sectors. High bargaining power of employers in the young sector pushes wages down in such a way that even those with low search costs suffer from mismatches. However, this seems to neglect the possibility that labour shortages are likely to force up wages in the new sector. There is clearly a need to develop the theory of mismatch if we are to have a fuller understanding of these issues.

In the current paper we utilise the panel element of the Household Income and Labour Dynamics in Australia (HILDA) survey to examine the effect of educational mismatch on wages, distinguishing between horizontal and vertical mismatch. The use of panel estimation, distinguishes our paper from earlier studies and brings major benefits to the way we can analyse the data at hand, especially where it enables us to control for certain forms of unobserved heterogeneity and inform our understanding of causal relationships. In the twelfth wave for the first time a question was included on the field of study of graduates. However, the survey does not contain an appropriate question on educational mismatch. We thus derive estimates using a variant of the (so-called) empirical method. Since the analysis is limited to graduates, the group with the highest level of education, under-education is not possible and vertical mismatch has the same meaning as over-education in this context. The analysis of horizontal mismatch is not straightforward in the absence of a question asking repondents whether their field of study is relevant to the job they do. We have to examine the distribution of fields of study across occupations. We have two alternative approaches; first we assume that an individual is matched if they are in the modal group for a particular occupation. Second, we take the three highest modal groups as indicating a match as sensitivity tests. We cannot be certain that those in an occupation which is not in the top modal groups for their particular field is in fact horizontally mismatched, so that we measure horizontal mismatch with a degree of error. However, we can examine whether there is a pay penalty from being employed in occupations with relatively few employees from a particular field of study. Hence, the possible categories of worker-job matching are limited to:

(a) *Well-matched*: the individual is matched in education both horizontally and vertically.

(b) *Horizontally mismatched only*: the individual is matched vertically but mismatched horizontally.

(c) *Vertically mismatched only*: the individual is matched horizontally, but mismatched vertically.

(d) *Both horizontally and vertically mismatched*: the individual is mismatched in education both horizontally and vertically.

This paper is structured as follows. Section 2 describes the data and Section 3 provides an overview of the estimation methods we use. Section 4 presents estimation results on the relationship between mismatches and wages. Section 5 concludes. Appendix I contains descriptive statistics. An extended Appendix II, which is available upon request, contains the complete estimation results.

3. DATA

This paper uses the first twelve waves of the HILDA survey. Modelled on household panel surveys undertaken in other countries, the HILDA survey began in 2001 with a large national probability sample of Australian households and their members.[1] The sample used in this paper is restricted to an unbalanced panel of all working-age employees (16-64 for males and 16-59 for females) holding a university degree or equivalent qualification who provide complete information on the variables of interest. Self-employed, full-time students and the Top-Up sample in wave 11 are excluded. The sample size we retain is approximately 1,500 observations per wave.[2]

As mentioned earlier, the HILDA survey does not contain any direct question on educational mismatch. To overcome this, we generate measures of mismatch using the ‘empirical method’, where an individual is classified as vertically mismatched if his education level is

[1] See Watson and Wooden (2004) for a detailed description of the HILDA data.
[2] The Swedish study is limited to those aged28 to 39, excludes migrants and those holding PhDs and ignores vertical mismatch.

above the mode level for his occupation using the ANZSCO 4-digit occupational classification. Similarly, an individual is defined as horizontally mismatched if her field of education is different from the mode field for her occupation. We present the incidence of horizontal and vertical mismatch by gender in Table 1. We observe from our sample that using our first definition of horizontal mismatch, the occurrence of horizontal mismatch is much more likely than the vertical one, with approximately a quarter of workers in our sample being classified as horizontally mismatched compared to about ten percent being vertically mismatched. Also, men are more prone to mismatch than women both horizontally and vertically. However, under the second definition the situation is reversed with vertical mismatch being more common than horizontal mismatch.

Table 1: Horizontal and vertical educational mismatch of graduates by gender

	Males		Females		Total	
Definition 1	*Cases*	*Per cent*	*Cases*	*Per cent*	*Cases*	*Per cent*
Well-matched	3,905	50.6	5,538	57.6	9,443	54.5
Horizontal mismatch only	2,324	30.1	2,440	25.4	4,764	27.5
Vertical mismatch only	791	10.3	693	7.2	1,484	8.6
Both horizontal and vertical mismatch	690	8.9	938	9.8	1,628	9.4
Definition 2						
Well-matched	5,396	70.0	7,092	73.8	12,488	72.1
Horizontal mismatch only	833	10.8	886	9.2	1,719	9.9
Vertical mismatch only	1,251	16.2	1,202	12.5	2,453	14.2
Both horizontal and vertical mismatch	230	3.0	429	4.5	659	3.8
Total	7,710	100.0	9,609	100.0	17,319	100.0

Notes: HILDA waves 2001-2012. Unit of observation is person-years.

Table 2 shows mean nominal hourly earnings for each mismatch category by gender. Consistent with findings in the literature, females have much lower earnings than males. Also, irrespective of gender, workers who were *vertically mismatched only* are paid substantially less than *well-matched* employees. In contrast, the hourly wage of *horizontally mismatched only* workers is slightly higher than those who are well-matched. In addition, the wage is the lowest for graduates who are *both horizontally and vertically mismatched*, the wage penalty is about 30 percent for men and 25 percent for women.

Table 2: Hourly wages of graduates by type of job match by gender

	Definition 1		Definition 2	
	Males	Females	Males	Females
Well-matched	38.3	31.1	38.4	31.3
Horizontal mismatch only	38.9	31.7	39.4	31.3
Vertical mismatch only	30.7	24.2	30.4	23.5
Both horizontal and vertical mismatch	28.7	22.9	25.8	23.4

Notes: HILDA waves 2001-2012. Wages are nominal measured in Australian dollars.

As is to be expected the use of definition 2 reduces the percentage horizontally mismatched (from 27.5% to 9.9%) compared to definition 1. It also results in an increase in the percentage recorded as vertically mismatched compensated by a reduction in the percentage both horizontally and vertically mismatched from 9.4% to 3.8%. Focusing on definition 2 the percentage matched ranges from10.3 in food, hospitality and personal services (a disparate occupation where 46% are recorded as both horizontally and vertically mismatched) to 86.9% in both nursing and education, where there are clearly defined career paths. Thus, field of study is an important factor in determining the degree of horizontal and vertical mismatch.

Table 3: Horizontal and vertical educational mismatch of graduates by field of study

Field of study	Well-matched	Horizontal mismatch only	Vertical mismatch only	horizontal and vertical mismatch	Total
	Per cent	*Per cent*	*Per cent*	*Per cent*	*cases*
			Definition 1		
Natural and physical sciences	22.5	58.9	3.5	15.1	1,077
Information technology	67.0	19.7	4.1	9.2	857
Engineering and related technologies	37.9	36.5	15.9	9.6	1,099
Architecture and building	50.7	22.9	17.0	9.4	341
Agriculture, environment and related studies	14.4	54.3	13.1	18.2	374
Medicine	42.3	44.6	0.0	13.1	350
Nursing	85.6	6.1	2.5	5.7	1,496
Other health-related	44.1	41.6	4.2	10.1	1,058
Education	77.9	13.3	4.3	4.5	3,699
Management and commerce	50.7	24.1	17.8	7.5	3,464
Law	55.6	29.9	1.4	13.1	581
Society and culture	44.4	34.8	9.8	11.0	2,360
Creative arts	16.8	50.2	5.5	27.5	476
Food, hospitality and personal services	0.0	34.5	6.9	58.6	87

Total	54.5	27.5	8.6	9.4	17,319
			Definition 2		
Natural and physical sciences	57.1	24.2	11.0	7.7	1,077
Information technology	70.7	16.0	7.8	5.5	857
Engineering and related technologies	61.2	13.2	22.4	3.2	1,099
Architecture and building	58.9	14.7	21.1	5.3	341
Agriculture, environment and related studies	37.2	31.6	16.6	14.7	374
Medicine	65.4	21.4	2.9	10.3	350
Nursing	86.9	4.9	4.7	3.5	1,496
Other health-related	69.7	16.1	8.0	6.2	1,058
Education	86.9	4.4	7.4	1.4	3,699
Management and commerce	71.5	3.3	24.4	0.8	3,464
Law	69.5	16.0	6.7	7.7	581
Society and culture	73.9	5.3	19.5	1.3	2,360
Creative arts	30.0	37.0	18.3	14.7	476
Food, hospitality and personal services	10.3	24.1	19.5	46.0	87
Total	72.1	9.9	14.2	3.8	17,319

Notes: HILDA waves 2001-2012. Unit of observation is person-years. Percentages are of the total in each row.

4 ESTIMATION METHODOLOGY

To investigate the effect of educational mismatch on wage, we estimate the following earnings function:

$$\ln Y_{it} = \alpha_0 + \alpha M_{it} + \beta X_{it} + \varepsilon_{it} \qquad (1)$$

where $\ln Y_{it}$ is the log of hourly earnings and M_{it} contains three mismatch dummy variables as defined earlier, namely *horizontally mismatched only*, *vertically mismatched only* and *both horizontal and vertically mismatched* for individual i at time t. X is a matrix of other relevant personal and workplace characteristics that are used as control variables in the estimation, including age, country of birth, ATSI status, disability status, marital status, number of children, residential location, field of study, hours of work, type of contract, unemployment history, employment and occupational tenure, firm size and industry.[2] ε is the conventional iid error term. We start to estimate equation (1) using a pooled OLS model on a sample of working age graduate employees, separately for males and females. The use of a pooled regression is a good starting point and benchmark for the analysis that follows. It provides us with an overview of the most prevalent associations in the data as a whole without making any distinction between the different types of variation it encompasses, such as over time or cross section at the population level and over time at the individual level. In the context of the present paper the OLS pooled regression provides us with a useful descriptive picture of how much vertical and horizontal mismatch there is in the data and how wages may be associated with each type of mismatch. However, since this paper primarily focuses on the way in which mismatch may influence wages, we are only able to elicit this information which is contained in the causal relationship between mismatch and wages. To this purpose we will use panel

[2] Variables are listed and explained in detail in Appendix I.

estimation which controls for time invariant unobserved individual heterogeneity and will allow us to come closer to making a causal inference about the degree to which mismatch may cause wages to be different. Our first panel estimation method will be to use a fixed effects model (the within estimator), which is written as:

$$\ln Y_{it} = \alpha_0 + \alpha M_{it} + \beta X_{it} + a_i + u_{it} \tag{2}$$

where a_i is the individual fixed (and estimable) effect , and u_{it} is an idiosyncratic error term. An issue with such a fixed effects estimator, though, is that it is unable to identify time-invariant factors, although this is not a consideration in a random effects model. Mundlak (1978) has also demonstrated that the conventional random effects model can be adjusted to account for the (potential) correlation between unobserved heterogeneity and explanatory variables. Thus, the following random effects model is estimated – with the addition of the Mundlak correction – that also controls for unobserved time-invariant individual heterogeneity:

$$\ln Y_{it} = \alpha_0 + \alpha M_{it} + \beta X_{it} + \xi_1 \overline{M}_i + \xi_2 \overline{X}_i + v_{it} \tag{3}$$

where $\overline{M}_i$ and $\overline{X}_i$ are the time averages of M_{it} and X_{it} for individual *i* respectively, and v_{it} is a composite error term. In principle, the estimates of α and β in equation (3) approximate the fixed effects (within) estimators (see Wooldridge 2009). Unlike the fixed effects model in equation (2), the random effects with Mundlak correction model obtains explicit estimates on the variables with little or no over time variation within the observation period of the data, some of which, e.g. field of study, are of our particular interest. Again, estimation is carried out separately for males and females.

5. REGRESSION RESULTS

5.1 The effects of mismatch on wages

Possibly the most important and definitely the mostwell-researched consequence of mismatch is the effect it may have on wages. A common result in the literature is that mismatches are associated with lower pay, which reflects the lower productivity of a sub-optimal worker-job match.

Our main estimation results are presented in Table 4 below. The OLS estimation produces highly significant coefficients at the 1 percent level for vertical mismatch and vertical and horizontal mismatch combined,both for males and females, but is insignificant for horizontal mismatch on its own. Consistent with the existing international literature, it is found that relatively to those who are *well-matched* (the reference category), the hourly wages are estimated to be about 22 percent lower for men and 25 to 28 percent lower for women for those being *vertically mismatched only*. An even stronger wage penalty is found for those who are *both horizontally and vertically mismatched*. They earn up to 30 percent less than the well-matched employees. In contrast, we surprisingly find that employees who are *horizontally mismatched only* have wages that are little different than the reference category.

Table 4: Graduate wage effects of job mismatch by type of job match and gender

	Relative to well-matched:		
	Horizontal mismatch only	*Vertical mismatch only*	*Both horizontal and vertical mismatch*
Males		Definition 1	
OLS	-0.007	-0.232***	-0.204***
	(-0.57)	(-12.28)	(-10.31)
Fixed Effects	-0.024	-0.039*	-0.103***
	(-1.54)	(-1.86)	(-4.20)
Random Effects with Mundlak corrections	-0.024	-0.039*	-0.103***
	(-1.54)	(-1.85)	(-4.18)
		Definition 2	
OLS	-0.014	-0.212***	-0.260***
	(-0.80)	(-13.67)	(-8.38)
Fixed Effects	0.012	-0.053***	-0.070**
	(0.64)	(-3.00)	(-2.39)
Random Effects with Mundlak corrections	0.012	-0.053***	-0.070**
	(0.64)	(-2.99)	(-2.38)
No. of observations		7,412	
Females		Definition 1	
OLS	-0.023**	-0.261***	-0.311***
	(-2.04)	(-14.72)	(-18.09)
Fixed Effects	-0.038**	-0.135***	-0.132***
	(-2.05)	(-5.24)	(-5.69)
Random Effects with Mundlak corrections	-0.038**	-0.135***	-0.132***
	(-2.04)	(-5.23)	(-5.67)
		Definition 2	
OLS	-0.035**	-0.277***	-0.312***
	(-1.97)	(-19.20)	(-12.86)
Fixed Effects	-0.059**	-0.120***	-0.147***
	(-2.22)	(-5.72)	(-5.01)
Random Effects with Mundlak corrections	-0.059**	-0.120***	-0.147***
	(-2.22)	(-5.71)	(-5.00)
No. of observations		9,220	

Note: Estimated coefficients with t-statistics in brackets; */**/*** denotes significance at the 10%/5%/1% level; dependent variable is the log of gross hourly wages; the unit of analysis is person-wave.

The estimated effects in the Fixed Effects and Random Effects models are much weaker than the OLS pooled model. Such a difference suggests that unobserved systematic differences play a significant role in determining mismatch effects. Controlling for unobserved heterogeneity also substantially reduces the wage impact for other two mismatch categories. Graduate men who change status from a *well-matched* job to a *vertically mismatched only* job suffer a 4.0 percent wage penalty. *Well-matched* graduate men who change status to a job where they are *both horizontally and vertically mismatched* suffer an approximate ten per cent wage penalty.[4] In other words, horizontal mismatch itself does not lower hourly wages while vertical mismatch on its own does. It is horizontal mismatch jointly with vertical mismatch that leads to the largest wage penalty. The results for females present a somewhat different story. Horizontal mismatch by itself lowers female earnings by between 4 and 6 per cent. The wage penalty women suffer when they change status from a well-matched to a *vertically mismatched only* or *both horizontally and vertically mismatched* job is also higher than for men. The results show considerable overall statistical significance. The fixed and random effects results suggest very clearly that women who become mismatched lose a lot more than their male counterparts.

5.2 The effects of field of study on wages

There are significant differences in earnings among the various fields of study. Thus, for men compared to the reference group of management and commerce, graduates in medicine earn between 18 and 21% more and engineers between 7 and 8% more, while those in nursing earn between 19 and 20% less (more than double the penalty for women).In the case of women the gains to medicine are somewhat lower than for men and those to engineering somewhat higher, while women earn significantly less (compared to female graduates in management and commerce) in natural and physical sciences, architecture and building, nursing, education, society and culture, creative arts and food, hospitality and personal

[4] Underlying the estimation of our models is the movement between mismatch states between waves. Such figures are set out in Appendix Table A2.

services. Thus, there are some important gender differences in the returns to particular fields of study.

Table 5: The effects of field of study on hourly wages

Field of study	Definition 1		Definition 2	
The reference category is Management and commerce	*Coef.*	*t-statistics*	*Coef.*	*t-statistics*
Males				
Natural and physical sciences	-0.032	(-0.69)	-0.019	(-0.43)
Information technology	0.028	(0.76)	0.041	(1.13)
Engineering and related technologies	0.070**	(2.13)	0.075**	(2.27)
Architecture and building	-0.019	(-0.31)	-0.008	(-0.14)
Agriculture, environment and related studies	-0.011	(-0.17)	0.004	(0.07)
Medicine	0.188**	(2.10)	0.207**	(2.33)
Nursing	-0.203***	(-2.80)	-0.187***	(-2.66)
Other health-related	0.034	(0.43)	0.049	(0.66)
Education	-0.112**	(-2.41)	-0.103**	(-2.28)
Law	0.020	(0.42)	0.034	(0.71)
Society and culture	-0.028	(-0.75)	-0.026	(-0.73)
Creative arts	-0.122**	(-2.22)	-0.106*	(-1.88)
Food, hospitality and personal services	0.047	(0.65)	0.077	(0.95)
No. of observations		7412		
Females				
Natural and physical sciences	-0.123***	(-2.81)	-0.124***	(-2.73)
Information technology	0.052	(0.88)	0.054	(0.90)
Engineering and related technologies	0.110**	(1.96)	0.111*	(1.94)
Architecture and building	-0.106**	(-2.04)	-0.101*	(-1.94)
Agriculture, environment and related studies	-0.084	(-1.53)	-0.083	(-1.43)
Medicine	0.133**	(2.28)	0.131**	(2.19)
Nursing	-0.090***	(-2.67)	-0.087***	(-2.62)
Other health-related	-0.026	(-0.74)	-0.026	(-0.76)
Education	-0.097***	(-2.82)	-0.093***	(-2.79)
Law	0.057	(1.13)	0.059	(1.14)
Society and culture	-0.103***	(-3.75)	-0.104***	(-3.82)
Creative arts	-0.101**	(-2.43)	-0.105**	(-2.38)
Food, hospitality and personal services	-0.117**	(-2.32)	-0.105*	(-1.90)
No. of observations		9220		

Note: Random effects linear model with Mundlak corrections is used for estimation;
Estimated coefficients with t-statistics in brackets;
$^{*}/^{**}/^{***}$ denotes significance at the 10%/5%/1% level;
dependent variable is the log of gross hourly wages;
the unit of analysis is person-wave.

5. CONCLUSIONS

This paper introduces the possibility that horizontal and vertical mismatch may be inter-related phenomena. It highlights the measurement of horizontal mismatch in a specific way which resembles the empirical method by which vertical mismatch is estimated. Although it is clear that the two cases are not analogous, the results suggest that there is a clear relationship between horizontal and vertical mismatch, which has not been examined before in the literature. Notwithstanding the data caveats that we present, we use two definitions of horizontal mismatch within the panel element of the HILDA survey to estimate the association of horizontal and vertical mismatch with wages in the broader employed population using OLS for a pooled regression. OLS estimation, confirms the evidence in the existing literature of a negative association between vertical mismatch (over-education) and hourly wages. Moreover, those who are *both horizontally and vertically mismatched* suffer a much stronger wage penalty than those who are *vertically mismatched only*.

We then introduce fixed effects and random effects panel models to estimate the effect of becoming horizontally and vertically mismatched on the wages of a person who changes jobs. We find that becoming horizontally mismatched does not appear to influence male wages,though it does so for women, whilst becoming vertically mismatched or both horizontally and vertically does clearly lower wages, but more so for women than for men. These two findings are robust to the introduction of methods that control for unobserved individual heterogeneity, but estimates in the fixed effects and random effects models are much smaller than in the pooled OLS model. We believe that the weak result on horizontal mismatch may be the result of a weak definition, a data weakness which would not necessarily be picked up by the panel estimation.

This paper contributes to the existing literature on two aspects. First, previous studies of mismatch in Australia are concerned with the vertical dimension, focusing on whether the level of education matches the job requirement. We extend the analysis by distinguishing between horizontal and vertical mismatch. Second, due to data limitations, most existing studies of horizontal mismatch use cross-sectional analysis while the nature of the HILDA survey facilitates the application of panel data techniques which control for the influence of unobserved individual heterogeneity.

In summary, our key finding is that horizontal mismatch itself does not lower hourly wages for men while vertical mismatch on its own does. It is, however, horizontal mismatch jointly with vertical mismatch that leads to the largest wage penalty. The negative results are stronger for women and extend to horizontal mismatch also.This emphasizes the importance of ensuring that graduates find jobs at an appropriate level and ones in which the field of study is also appropriate.This in turn suggests that well informed careers guidance can play a critical role in ensuring that graduates maximize their returns to education, both by making appropriate judgements in choosing their fields of study and in selecting appropriate occupations after graduation.

REFERENCES

Bender K. and Heywood J. S., Educational Mismatch among PhDs: Determinants and Consequences, in Freeman R. B. and Goroff D. L., editors, *Science and Engineering Careers in the United States,* University of Chicago Press, 2009, 229-256.

Chevalier A., Subject Choice and Earnings of UK Graduates, *Economics of Education Review*, 30(6), 2011, 1187-1201.

Domademik P., Farcnik D. and Pastore F,, Horizontal Mismatch in the Labour Market of Graduates: the Role of Signalling, IZA Discussion Paper 7527, 2013.

Estache A. and Foucart R., Horizontal Skills Mismatch in the Labor Market: Protecting the Past vs. Protecting the Future, GRASP Working Paper 34, September, 2012.

Kucel A. and Vilalta-Bufi M. Is there a Wage Penalty for Horizontal and *Vertical* Mismatch? Demsoc Working Paper No. 2010-34, University Pompeu Fabra, Barcelona, March, 2010.

Nordin M., Persson I. and Rooth D-O, Education-Occupation Mismatch; Is there an Income Penalty? *Economics of Education Review*, 29, 2010, 1047-1059.

Robst J., Education and Job Mismatch: The Relatedness of College Major and Work, *Economics of Education Review,* 26, 2007a, 397-407.

Robst J., Education, College Major, and Job Match; Gender Differences in Reasons for Mismatch, *Education Economics*, 15(2), 2007b, 159-175.

Robst J., Over-education and College Major; Expanding the Definition of Mismatch between Schooling and Jobs, *The Manchester School*, 76(4), 2008, 349-368.

Sgobbi F. and Suleman F., A Methodological Contribution to Measuring Skill (Mis)Match, *The Manchester School, 81(3), 2013, 420-439.*

Watson N. and Wooden M., The HILDA Survey Four Years On, *Australian Economic Review*, 37(3), 2004, 343-349.

APPENDIX I

Definition of Variables:

<u>Wage</u>: Log of current hourly gross wages & salary from the main job.

<u>Mismatch variables</u>:

<u>Horizontally mismatched only:</u> Dummy variable, takes the value 1 if an individual is horizontally mismatched only, zero otherwise.

<u>Vertically mismatched only</u>: Dummy variable, takes the value 1 if an individual is vertically mismatched only, zero otherwise.

<u>Both horizontally and vertically mismatched</u>: Dummy variable, takes the value 1 if an individual is both horizontally and vertically mismatched, zero otherwise.

<u>Well matched</u> is the reference category.

<u>Age</u>: Continuous variable, expressed in years.

<u>Age Square/100</u>: Continuous variable, expressed in years.

<u>Country of birth:</u>

<u>Migrant (English speaking country)</u>: Dummy variable, takes the value 1 if migrant from an English speaking country, zero otherwise.

<u>Migrant (non-English speaking country)</u>: Dummy variable, takes the value 1 if migrant from a non English speaking country, zero otherwise.

<u>Aboriginal or Torres Strait Islander (ATSI)</u>: Dummy variable, takes the value 1 if and individual is Aboriginal or Torres Strait Islander, zero otherwise.

<u>Australian born non-ATSI</u> is the reference category.

<u>Disability</u>: Dummy variable, takes the value 1 if an individual has a disability, zero otherwise.

<u>Casual employment</u>: Dummy variable, takes the value 1 if an individual is in casual employment, zero otherwise.

<u>Married</u>: Dummy variable, takes the value 1 if an individual is married (or de facto), zero otherwise.

<u>Urban</u>: Dummy variable, takes the value 1 if an individual domiciled within a major city, zero otherwise.

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

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

Tenure with current employer: 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.

Percent time spent unemployed in last financial year: Continuous variable, value of which lies between 0 and 100.

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.

Field of study:

Natural and physical sciences: Dummy variable, takes the value 1 if the field of study is natural and physical sciences, zero otherwise.

Information technology: Dummy variable, takes the value 1 if the field of study is information technology, zero otherwise.

Engineering and related technologies: Dummy variable, takes the value 1 if the field of study is engineering and related technologies, zero otherwise.

Architecture and building: Dummy variable, takes the value 1 if the field of study is architecture and building, zero otherwise.

Agriculture, environment and related studies: Dummy variable, takes the value 1 if the field of study is agriculture, environment and related studies, zero otherwise.

Medicine: Dummy variable, takes the value 1 if the field of study is medicine, zero otherwise.

Nursing: Dummy variable, takes the value 1 if the field of study is nursing, zero otherwise.

Other health-related: Dummy variable, takes the value 1 if the field of study is other health-related, zero otherwise.

Education: Dummy variable, takes the value 1 if the field of study is education, zero otherwise.

Law: Dummy variable, takes the value 1 if the field of study is law, zero otherwise.

Society and culture: Dummy variable, takes the value 1 if the field of study is society and culture, zero otherwise.

Creative arts: Dummy variable, takes the value 1 if the field of study is creative arts, zero otherwise.

Food, hospitality and personal services: Dummy variable, takes the value 1 if the field of study is food, hospitality and personal services, zero otherwise.

Management and commerce is the reference category.

Table A1: Descriptive statistics

Explanatory variable	*Males*		*Females*	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	40.40	10.77	38.91	10.23
Age Square/100	17.48	9.00	16.19	8.12
Migrant (English speaking country)	0.112	0.315	0.098	0.297
Migrant (non-English speaking country)	0.148	0.355	0.121	0.326
ATSI	0.006	0.080	0.012	0.108
Disability	0.125	0.330	0.142	0.349
Casual	0.087	0.281	0.122	0.327
Married	0.793	0.405	0.723	0.448
Urban	0.942	0.234	0.925	0.263
Hours per week usually worked in main job	43.34	10.83	35.40	13.10
Tenure in the current occupation	9.892	9.714	9.389	9.235
Tenure with current employer	7.590	8.503	6.812	7.316
Firm has less than 5 employees	0.039	0.193	0.040	0.196
Firm has 5 to 9 employees	0.059	0.236	0.070	0.256
Firm has 10 to 19 employees	0.102	0.302	0.095	0.294
Firm has 20 to 49 employees	0.165	0.371	0.185	0.388
Have children aged between 5 and 14	0.273	0.446	0.280	0.449
Have children aged under 5	0.167	0.373	0.135	0.342
Percent time spent unemployed in last financial year	1.094	6.933	1.299	7.641
Union member	0.320	0.467	0.437	0.496
Agriculture, forestry and fishing	0.011	0.103	0.002	0.048
Mining	0.018	0.134	0.005	0.067
Electricity, gas, water and waste services	0.013	0.115	0.004	0.066
Construction	0.034	0.181	0.005	0.069
Wholesale trade	0.026	0.158	0.014	0.116
Retail trade	0.034	0.182	0.027	0.162
Accommodation and food services	0.011	0.104	0.011	0.104
Transport, postal and warehousing	0.024	0.154	0.005	0.067
Information media and telecommunications	0.029	0.169	0.027	0.161
Financial and insurance services	0.078	0.268	0.038	0.192
Rental, hiring and real estate services	0.014	0.117	0.005	0.069
Professional, scientific and technical services	0.167	0.373	0.093	0.290
Administrative and support services	0.010	0.097	0.017	0.129
Public administration and safety	0.145	0.353	0.087	0.282
Education and training	0.193	0.395	0.329	0.470
Health care and social assistance	0.080	0.272	0.281	0.450
Arts and recreation services	0.019	0.136	0.013	0.111
Other services	0.016	0.124	0.015	0.121
Natural and physical sciences	0.084	0.278	0.044	0.205
Information technology	0.088	0.283	0.019	0.137

Engineering and related technologies	0.123	0.329	0.015	0.121
Architecture and building	0.028	0.166	0.013	0.113
Agriculture, environment and related studies	0.028	0.164	0.016	0.124
Medicine	0.018	0.131	0.022	0.145
Nursing	0.020	0.141	0.140	0.347
Other health-related	0.031	0.172	0.085	0.279
Education	0.140	0.347	0.274	0.446
Law	0.035	0.184	0.032	0.176
Society and culture	0.116	0.320	0.153	0.360
Creative arts	0.019	0.137	0.034	0.181
Food, hospitality and personal services	0.006	0.079	0.004	0.066

Note: Mean (standard deviation). The sample consists of all working age graduate employees from HILDA 2001-2012, and includes 7412 person-wave males and 9220 person-wave females.

Table A2: Mismatch transitions

	Status at t				
Status at t-1	Well matched	Horizontal mismatch only	Vertical mismatch only	Both horizontal and vertical mismatch	Total
			Definition 1		
Well matched	7,264	522	205	137	8,128
Horizontal mismatch only	485	3,242	88	221	4,036
Vertical mismatch only	237	104	788	131	1,260
Both horizontal and vertical mismatch	168	275	133	763	1,339
Total	8,154	4,143	1,214	1,252	14,763
			Definition 2		
Well matched	9,813	393	425	84	10,715
Horizontal mismatch only	376	931	71	71	1,449
Vertical mismatch only	496	84	1,384	91	2,055
Both horizontal and vertical mismatch	110	94	92	248	544
Total	10,795	1,502	1,972	494	14,763