Vertical, Horizontal and Residual Skills Mismatch in the Australian Graduate Labour Market

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Abstract

Studies of the Australian graduate labour market have found a substantial incidence of, and significant earnings effects from, vertical mismatch. This study extends the literature by examining horizontal mismatch, an important dimension of mismatch in its own right and which has been less studied. Over a quarter of Australian graduates are found to be mismatched although the incidence is reduced in the longer term. Graduates from fields of study which are more occupation-specific were found to be less likely to be mismatched. Earnings penalties were found for all forms of mismatched, and affected both general and specific fields of study.

Keywords: Labour market mismatch; Graduate earnings; Higher education policy

JEL Codes: J24, J31, J48

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Introduction

Higher education attainment rates have increased globally. Education statistics from the OECD (2014), for instance, indicate that university completions have increased by an average of 22 percent in OECD countries over the past 17 years, with strong university enrolment growth rates also being observed. In Australia, growth in higher education participation has been strong and steady, at approximately five percent per annum over the period 2005 to 2014 (Department of Education and Training 2016a). In particular, growth in commencing student enrolments has been strong since 2009, following the Bradley Review of higher education in 2008 and the move to a demand-driven university system in 2012, which essentially removed quotas on the amount of Commonwealth funded bachelor's degree places in universities (Department of Education and Training 2016b). Prior to 2012, funding for bachelor's degree places were 'capped', with quotas and the amount of funding differing by field of study, although it was not clear if these amounts were guided by analysis of the labour market outcomes of the graduates. Given the large amounts of investment into higher education by the state and the individuals, analyses of labour market outcomes of individuals who participated in higher education are important for the purposes of evaluating the return on investment.

There has also been increasing focus on the labour market outcomes, in particular, of whether the human capital endowments individuals receive through education and training are appropriate for the jobs they do. Individuals who have appropriate endowments of education and training for their jobs are termed 'matched'. In contrast, individuals who have educational levels in excess of job requirements are termed 'overeducated', 'underemployed', and 'overqualified', among other terms. In this paper, these are collectively referred to as 'vertical mismatched'. Nevertheless, as Sloane (2003) and Robst (2007) point out, it is possible for an individual to be mismatched in more than one form. That is, overeducation considers mismatch in terms of discrepancies between education levels and job requirements, while at the same time it is also possible for an individual to be mismatched on the basis of incompatible educational fields of study to the nature of his or her work. This has come to be known as 'horizontal mismatch'. A further form of mismatch is that of 'skills mismatch', one definition of which is being in a job that does not make use of the knowledge or skills possessed.

Thus far, a substantive literature has examined the phenomenon of vertical mismatch. Many studies find that labour market mismatch, whether in terms of over-education or over-skilling is associated with negative labour market outcomes in the form of lower wages, lower productivity, reduced job satisfaction and higher labour turnover. These negative effects are more marked when over-education and over-skilling occur together. This imposes costs on the employer, the individual worker and the state in so far as the last of these has subsidised educational provision. There may be over-crowding in some jobs which prevents certain individuals from obtaining jobs at a level appropriate to their level of qualifications and labour shortages in others, which force employers to upgrade some of their existing employees and/or drop their hiring standards. However, information on how or why certain individuals end up in jobs for which they are over-qualified or over-skilled is limited.

Information on mismatch can be obtained using three different methods; one is through job evaluation which provides information on the education and skills normally required in particular occupations, often referred to as the objective approach, though this information can become out of date in jobs subject to rapid change. The second is by asking individuals in surveys what education and skills were required to obtain and /or perform their current job, which is often referred to as the subjective method and is the approach adopted here. The third approach is the so-called empirical method, where mismatch is said to occur if the individual's level of education is above (or below) one standard deviation or more from the mean (or the mode) in a particular occupation. As this excludes minor deviations, this method is non-comparable with the other two.

Prior studies have shown that the effects of over-education, as measured by each of the three methods, on earnings and job satisfaction are similar despite the fact that each of them identifies non-identical groups of individuals as being over-educated. The subjective method is most commonly used as information is more readily available than for the objective method. While it has been suggested that certain individuals may exaggerate the level of education required for their job for reasons of prestige, there is no evidence that this is the case in practice and the former has the advantage that data are more readily available. It should be emphasised that our data relate to recent graduates rather than the total population of graduates making them more appropriate for examining how long it takes to be fully assimilated in employment. One Spanish study (Acosta -Ballesteros et al. 2017), for example, found that those initially mismatched were 40% more likely to be mismatched in later jobs.

There are a number of potential policy implications which could arise from studies looking at the causes and effects of mismatch. For example, if certain degree programmes produce better career openings and earnings possibilities, it is important to provide this information when students are selecting which courses to follow. If certain job finding methods are more successful than others again this should inform career guidance. McGowan and Andrews (2015) also suggest that differences in skill mismatch in general and across countries are related to differences in economic policies such as employment protection legislation, which may make it more difficult to get a first job, or housing policies which make it more difficult to move. Well-designed policies can make a contribution to increasing labour productivity in so far as they reduce skill mismatch.

This study uses Australian university graduate data to explore the incidence of being vertically, horizontally and skills mismatched, as well as the earnings impact of being mismatched in combinations of these forms. The remainder of this paper is organised as follows. A literature review of the mismatch literature is presented in section 2. Section 3 describes the data and methodology, and includes the way in which mismatches are defined in this study. Section 4 presents the results and discussion. Section 5 concludes.

Literature Review

A substantial literature on labour market mismatch has developed over the past decades. Seminal work in this area include the work of Freeman (1976), Hartog (2000) who succinctly summarises and compares measurement and methodological issues, and McGuinness's (2006) survey of the overeducation literature. More recently, a paper by Green and Henseke (2016) reviews the overeducation literature, as well as an examination of private and social benefits to higher education for 21 OECD countries[1]. In particular, Green and Henseke's (2016) study drew attention to the fact that overeducation has become a prevalent feature of the higher education labour market globally, and that research into labour market mismatch is crucial to policy making for both higher education and the workforce. Similarly, much research has been done in the Australian context, although these studies have mainly focussed on overeducation and overskilling. Studies of horizontal mismatch in the Australian labour market are rarer, presumably due to a lack of data to support such analyses. Nevertheless, a review of the vertical mismatch and overskilling literature is crucial, due to the relatedness between the various forms of mismatch. A review of the Australian literature is provided in Miller (2007). The remainder of this literature review looks at more recent Australian studies of labour market mismatch that have been published since Miller's (2007) review.

[1] However, Australia was not among the countries studied by Green and Henseke (2016).

There have been a number of studies using the Household, Income and Labour Dynamics in Australia dataset. Thus, Mavromaras, McGuinness, O'Leary, Sloane and Wei (2013) show that that the relationship between mismatch and labour market outcomes is strongly influenced by unobserved heterogeneity and panel estimation reduces substantially the size of many relevant coefficients, raising questions about the results obtained from cross-section analyses. More particularly, over-education and over-skilling are found to be distinct phenomena with the most negative results occurring when they are found together. Mavromaras, Mahuteau, Sloane and Wei (2013) use a random effects dynamic probit model to estimate the effects of overskilling dynamics on wages, finding that over-skilling is highly persistent. Though persistence is lower for graduates, the effects of past overskilling on wages are greater for graduates than for any other education level. A study by Li and Miller (2015) of Australian university graduates from 1999 to 2009 also found evidence of non-linearity in the amount of earnings penalties, depending on the extent of overeducation.

Carroll and Tani (2013) use the 2010 wave of the Beyond Graduation Survey, used in this paper to analyse the effects of overeducation on employment and earnings. Carroll and Tani (2013) report an incidence of overeducation of between 24 and 27 percent at four months postgraduation for the 2007 cohort, although even higher incidences of overeducation in the Australian graduate labour market have been reported in Kler (2005) and Li and Miller (2015). The incidence of overeducation was also reported by Carroll and Tani (2013) to vary substantially over different fields of study. This is consistent with a separate Australian study of university graduates by Li and Miller (2013), who find that the field of study of university graduates is both an important predictor of overeducation as well as of earnings. In Carroll and Tani's (2013) study, the Heckman correction is used to control for selection bias since some graduates exit the labour force four years later. They also use a fixed effects model to control for unobservables and find that the earnings penalties for overeducated graduates become smaller and insignificant in line with the findings of Mavromaras, Mahuteau, Sloane and Wei (2013).

In a further paper, Carroll and Tani (2014) use the 2011 survey to examine the job search process. They find that jobs found through university careers offices are associated with a lower probability of overeducation relative to jobs found through advertisements and personal contacts, a result which is not influenced by gender or age. In contrast, direct employer contact is only beneficial to older males.

It should be noted, however that the present study extends the existing literature in a number of respects. First, Carroll and Tani (2013) use the job dictionary definition to identify mismatch by utilising educational requirements in occupations stipulated in the ANZSCO, rather than responses of graduates to questions on the importance of qualifications and field of study to their job. This means that they are unable to estimate the extent of horizontal mismatch in which we are particularly interested. As indicated at the beginning of the literature review, horizontal mismatch has not been well-studied in Australia. Nevertheless, findings from the international literature, such as those of Robst (2007) indicate that horizontal mismatch is an important facet of the US labour market. In Robst's (2007) paper, graduates who were horizontally mismatched earned substantially less than those who reported working in their field of study. Second, the present study examines a later time period (2012 -2014) compared to the 2010 cohort studied by Carroll and Tani (2013). As they state "it is important to note that the 2008 financial crisis and its knock on effects were still affecting graduate employment at the time of the 2010 survey wave". Third, Carroll and Tani (2013) do not consider the role of overskilling, which the present study will address. Furthermore, Robst's (2007) focussed only on horizontal mismatch, whereas the present study will look at vertical, horizontal and skill mismatches together.

Methodology and data description

Data description

The study utilises data from three waves of the Beyond Graduation Survey (BGS). The BGS is the longitudinal follow-up survey at three-years post-graduation which captures longer-term activities of the graduate respondents to the Graduation Destination Survey (GDS) which takes place four to six months after graduation.[2] The 2012-2014 waves of the BGS were utilised for this study.[3]

Most Australian universities have participated in the BGS, with 39, 36 and 40 universities (out of 43 universities in Australia) participating in the 2012, 2013 and 2014 waves, respectively. The response rates to the 2012-2014 BGS are in the high teens (Graduate Careers Australia 2015). Respondents to the BGS surveys responded via email, as they had provided a long-term

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[2] In the interests of brevity and conciseness, future reference to the time period of the GDS will be 'six months' or 'short term'.
[3] In other words, the respondents in the study sample were first surveyed in 2009-2011, and then followed up in 2012-2014.

email for follow-up in their response to GDS. The characteristics of the respondents to the BGS have been found to be generally representative to the broader graduate population in terms of sex, age and broad field of study (Graduate Careers Australia 2015).

In the present study, the sample is restricted to graduates who had completed a bachelor's degree pass or honours qualification, and who were employed at six months after graduation. There are 23,697 observations in the study sample. Selected descriptive characteristics of the study sample are presented in Appendix 1. In addition, Appendix 1 also presents descriptive statistics from the bachelor's degree graduate respondents to the 2008 to 2014 waves of the GDS for comparison. The GDS is an annual census conducted on all graduates who have completed a higher degree qualification from an Australian higher education institution. The survey is sent out to all graduates approximately four to six months after the completion of their qualification, and provides a snapshot of their activities after graduation, such as employment or further study. The GDS has been run since the 1970s by Graduate Careers Australia, and national response rates to the 2009 to 2011 waves of the GDS has been in the mid-sixties. Furthermore, a study on non-response to the GDS concluded that the Graduate Destination Survey is generally representative of the labour market outcomes of Australian university graduates (Guthrie and Johnson 1997). Hence, using the GDS sample as a benchmark for comparison with the study's BGS sample will provide useful pointers on the sample's representativeness.

As can be seen from Appendix 1, the demographic characteristics and field of study of the respondents in the GDS and BGS are generally consistent. The one exception is for age, where respondents to the BGS are slightly older with a mean age of 30.2 years, compared to 25.7 years for GDS respondents. Hence, it is reasonable to conclude in general that the BGS data is a good reflection of short and longer-term labour market conditions for Australian university graduates, although the slightly higher ages of BGS respondents need to be taken into account when considering the findings of the study.

Definition of mismatch

Measures of subjective self-assessment are used to define vertical mismatch, horizontal mismatch and skills mismatch in this study. For example, vertical mismatch is defined through the responses to a question in the surveys that asked "How important are the qualifications you have just completed to your main paid job?". The graduates were also asked "How important are the major fields of education you studied to your main paid job?" and "How important are other skills and knowledge you acquired during your course to your main paid job", which are used to define horizontal mismatch and residual skills mismatch, respectively. Respondents in the sample had the choice of the following responses to the three questions on mismatch: i) a formal requirement; ii) important; iii) somewhat important; and iv) not important. Graduates who answered 'not important' to the questions above are considered mismatched, in each of the respective mismatch dimensions. An important distinction to note about the definition of skills mismatches in the current study is that respondents were asked to self-report on the *other skills and knowledge* they acquired in their degree course, in addition to their formal qualification and specialisation field. This differs from much of the literature on skills mismatches, which tend to focus on skills-occupation mismatch of a general nature. Hence, from here on, this study uses the term residual skills mismatch to distinguish the nature of this form of mismatch from the traditional definition of skills mismatch in the literature.

Table 1: Incidence of Graduate Mismatch, Short- and Longer-Term Post-Graduation

Mismatch categories	Four Months (%)	Three Years (%)
Matched (not mismatched in any form)	72.1	79.8
Vertically mismatched	22.8	12.1
Horizontally mismatched	21.1	15.2
Residual skills Mismatch	14.1	10.7
Observations	23,697	21,555

The incidence of vertical, horizontal and residual skills mismatches for the graduate sample, in the short- and longer-term post-graduation, are presented in Table 1. The upper panel of Table 1 shows the proportion of graduates who are correctly matched and in each of the three mismatch categories, in the short and longer term. Note that the three mismatch categories are not mutually exclusive, that is, individuals who are vertically mismatched could also be horizontally or residual skills mismatched.

Looking at the incidences in Table 1, 23 percent of the graduates reported being vertically mismatched, 21 percent reported being mismatched in terms of their field and 14 percent reported being residual skills mismatched, in the short-term after graduation. In the longer term of three years post-graduation, the proportion in all three mismatch categories decreased. The largest decline in mismatch was in the vertical mismatch category, which almost halved, while the incidence of horizontal mismatch declined to almost 15 percent. The incidence of residual skills mismatch decreased marginally by three percentage points, to 11 percent of the graduate sample. Hence, there appears to be sizeable reductions in the incidences of vertical and horizontal mismatch as graduates transition into the labour market, but residual skills mismatch appear to be quite persistent.

Estimating equations

The determinants of mismatch statuses are examined through the use of a multivariate probit model. This is a more appropriate approach in estimating the incidence of graduate mismatches compared to univariate probit models, as the latter does not account for correlation across the outcomes of being vertically mismatched, horizontally mismatched and residual skills mismatched.

Hence, the multivariate probit model of graduate mismatches can be expressed as:

$$y_1^* = \beta_1 X + \varepsilon_1;\ y_1 = 1\ if\ y_1^* > 0, 0\ otherwise$$

$$y_2^* = \beta_2 X + \varepsilon_2;\ y_2 = 1\ if\ y_2^* > 0, 0\ otherwise \qquad (1)$$

$$y_3^* = \beta_3 X + \varepsilon_3;\ y_3 = 1\ if\ y_3^* > 0, 0\ otherwise$$

where y_1^*, y_2^* and y_3^* are the unobserved propensities to be vertically mismatched, horizontally mismatched or residual skills mismatched, respectively. y_1, y_2 and y_3 are dichotomous indicators of the observed labour mismatch statuses, set equal to 1 if the individual graduate was observed to be mismatched, 0 otherwise. X represents a vector of characteristics hypothesised to influence labour market mismatch including demographics, location, university study characteristics, employment characteristics, job search strategies and field of study. β_1, β_2 and β_3 are vectors of coefficients to be estimated on X for their respective labour market mismatch outcomes.

The distribution of the three graduate mismatch outcomes are assumed to be multivariate normal, such that $E[\varepsilon_1] = E[\varepsilon_2] = E[\varepsilon_3] = 0$, and $Var[\varepsilon_1] = Var[\varepsilon_2] = Var[\varepsilon_3] = 1$. As is standard in such models, the three stochastic elements of equation (1) are assumed to be jointly normally distributed with zero mean. They are allowed to be freely correlated, whilst maintaining the identifying assumption of unit variances. The advantages of this trivariate probit approach over individual univariate ones, are that if such correlations exist, the trivariate probit approach will not only consistently estimate these, but will also be a more efficient estimator of the structural parameters. Although computationally burdensome, such approaches are standard in many econometric packages nowadays. This can be expressed as:

$$Cov[\varepsilon_1, \varepsilon_2] = \rho_1$$

$$Cov[\varepsilon_1, \varepsilon_3] = \rho_2 \tag{2}$$

$$Cov[\varepsilon_2, \varepsilon_3] = \rho_3$$

The earnings effects of mismatch are analysed with Ordinary Least Squares regression, specified as a standard Mincerian earnings equation with controls for mismatch categories. This earnings model can be expressed as:

$$\ln(sal) = X\beta + M + \varepsilon \tag{3}$$

where *ln(sal)* denotes annual salary, expressed in natural logarithmic format. The vector *M* are dummy variables that represent the three forms of mismatch, namely, i) vertically mismatched; ii) horizontally mismatched, and; iii) residual skills mismatched. In order to address endogeneity of the mismatch variables in the earnings models, the two-stage residual inclusion approach of Terza et al. (2008) is adopted. Specifically, generalised residuals from the multivariate probit models of mismatch are calculated and then entered into the earnings model. These are the derivatives of the log-likelihood function with respect to the constant terms in the model (which were evaluated numerically).

This earnings model is estimated separately for each of the two time periods in the panel dataset. However, it is noted that those employed in the longer term are a subset of the sample, as two percent of those employed in the short term were no longer working in the longer term. As such, an estimation of the earnings model could yield biased estimates of the earnings effects if the decision to exit the labour force in the longer term is non-random. To overcome this issue, equation (3) is estimated using a Heckman (1979) two-stage selection model. As the BGS data contained information on whether the graduates had children of minority age, this was entered into the Heckman selection model as an instrumental variable, in binary form. In addition, to take into account the unobserved time-invariant heterogeneity across the two time periods of the survey, equation (3) was also separately estimated with a fixed effects specification. One advantage of the fixed effects model is that the estimated coefficients from this model can be interpreted as mean differences in earnings growth rates, given the equivalence of fixed effects estimators to first difference estimators in panel data with two time periods. However, one well-known disadvantage of the fixed effects approach is its inability to identify the effects of any time-invariant variables. Moreover, any variables which only change when with individuals move jobs, would only be identified by this subset of individuals. However, neither of these adversely affects identification of our key variables in what follows.

Results

Determinants of Graduate Mismatch

The results from the multivariate probit model of graduate mismatch are presented in Table 2. For ease of interpretation, Table 2 presents the estimated average marginal effects from the estimated coefficients of the multivariate probit model. It is noted that the model included controls on demographic, university and employment characteristics, as well as job search strategies. The results from these additional controls are not discussed, although it is noted that the estimated effects are consistent with findings from the wider literature.[4]

Attention is first drawn to the estimated correlation coefficients, which are positive, statistically significant at the one percent level of significance, and of sizable magnitude with point estimates ranging from 0.772 to 0.912.[5] The large, positive correlations and statistical significance are observed for both time periods examined. At first glance, these correlation may appear potentially worryingly large, and correlations of close to unity would have adverse consequences on the modelling approach adopted here. However, we note that such "large" correlations are often found in relevant literature (Fleming and Kler 2008). Moreover, in no instances do 95% confidence intervals contain the value one; and it is not immediately clear what "large" actually means in such models where one is attempting to identify correlations across unobservables. Notwithstanding these observations, a factor analysis did suggest that

[4] There are nevertheless some results from the estimates of job search strategies that could be of interest. Job search strategies were more useful in the shorter term than the longer term, with very few estimates on job search strategies being statistically significant in the longer term. Search for employment through other university sources, approaching the employer directly and through networks were more effective, with modest reduced probabilities of being mismatched associated with these strategies. Searching for employment through the internet, through family and friends, and through recruitment agencies were associated with increased probabilities of being mismatched.

[5] It is not uncommon to find such high correlation coefficients reported in studies using the multivariate probit methodology. Fleming and Kler (2008), for instance, examined the relationship between overeducation (vertical mismatch) and several measures of workplace satisfaction. For instance, the bivariate probit model for overeducation and overall job satisfaction, overeducation and satisfaction with pay, and overeducation and satisfaction with working hours had ρ values of 0.71, 0.78 and 0.81, respectively.

the three indices could be collapsed into a single factor. Thus, as a robustness check, the model for the determinants of graduate mismatch was estimated on a single measure of mismatch.[6]

The graduates' field of study was found to be influential on the mismatch status. A number of general observations relating to the field of study and mismatch status can be made. First, the effects of field of study generally act in the same direction across the various mismatch statuses. That is, fields of study that are associated with increased likelihoods of a particular mismatch status would also have increased likelihoods of mismatch in the other forms, and vice versa. Second, the effect sizes of fields of study can be rather large, particularly for vertical and horizontal mismatch. For instance, in the short-term graduates in the fields of Society and Culture have an increased likelihood of being vertically mismatched by 11 percent, an increased likelihood of being horizontally mismatched by 13 percent and being residual skills mismatched by an increased six percent, relative to graduates from Management and Commerce. Third, these field of study effects on mismatch are generally persistent across time, although of reduced magnitude.[7] In some fields, the effect on mismatch status are observed to have halved over time, such as that observed for graduates in Human Studies. Fourth, a discernible pattern in the field of study effects is that fields which are of a general (specific) nature appear to be associated with increased (reduced) probabilities of mismatch. In particular, graduates from the general fields of Natural and Physical Sciences, Human Studies, Society and Culture, and the Creative Arts are observed to have increased propensities to be mismatched in all three forms, compared to the benchmark group. Conversely, graduates from the specific fields of Education, Allied Health and Nursing were observed to have reduced

[6] The dependent variable for this analysis took on the value of 1 if the graduate was mismatched in any one of the three forms, 0 otherwise. The findings that can be drawn from the results of this robustness check were very similar to those from the model of the determinants of graduate mismatches reported in Table 2. The signs of the estimated coefficients were identical across both approaches, and the size of the estimated coefficients were of comparable magnitude. For example, the estimated coefficients for field of study indicated that graduates from the fields of Society and Culture and Creative Arts were more likely to be mismatched in both the short and longer term, with an effect size of around ten percent. Graduates in Human Studies were 11 percent more likely to be mismatched in the shorter term and five percent more likely to be mismatched in the longer term. Graduates in Allied Health, Education, and Nursing were less likely to be mismatched, with effect sizes of around negative five percent for the former two fields and over ten percent less for the latter field.

[7] In an extension of the multivariate probit model of graduate mismatch, a multivariate probit model of the persistence of mismatch was constructed. This model analysed the determinants of binary indicators of persistence of the three forms of mismatch. For instance, the outcome variable for persistence of vertical mismatch takes on the value of 1 if the graduate was vertically mismatched in the short-term, and was also vertically mismatched in the longer-term, and likewise for horizontal and skills mismatch. The results from this model reinforced the findings of the main analysis, in that fields of study were important determinants of persistence of mismatch, and that graduates from general (specific) fields were more (less) likely to be persistently mismatched.

probabilities of being mismatched in the three forms. This is consistent with the findings of Robst (2007).

The acquisition of an honours degree is observed to reduce the propensity to be mismatched in any form, with moderate effects sizes around five percent in the shorter term, reducing to around three percent in the longer-term. It is unclear if these observations can be attributed to the increased human capital these graduates possess from a lengthier period of education compared to bachelor degree graduates, or the likely superior academic performance these graduates might have, which are could be a prerequisite to enrolment in honours degrees in some fields and/or institutions.[8]

The type of contract of employment appears to be an important determinant of graduate mismatch. An interesting pattern emerges in this regard. Graduates who are employed on temporary or casual contracts are more likely to be mismatched in comparison to graduates on permanent contracts. In contrast, graduates who are on fixed-term contracts are less likely to be mismatched, regardless of the contract length. These effects are persistent into the longer term, albeit of reduced magnitude. One possible explanation for this is that job security in the form of permanent or on-going employment is being traded off against employment mismatch and its adverse consequences.

[8] In Australian institutions, honours degrees can be either straight honours courses where there is no option, or an optional degree where additional study of usually a year is required to complete with honours. Unfortunately, this is not captured in the dataset and hence no further analyses can be done to explore this.

Table 2 Average Marginal Effects from the Multivariate Probit Models of Graduate Mismatch, Short and Longer-term

Variable	Vertical Mismatch		Horizontal Mismatch		Skills Mismatch	
	Short-Term	Longer-Term	Short-Term	Longer-Term	Short-Term	Longer-Term
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.012**	-0.005	-0.001	-0.002	-0.011**	-0.011**
	(-2.24)	(-0.96)	(-0.15)	(-0.31)	(-2.31)	(-2.47)
Age (at sample mean)	-0.003***	-0.004	-0.004***	-0.003***	-0.002***	-0.001***
	(-5.57)	(-0.91)	(-8.49)	(-5.96)	(-5.19)	(-3.67)
Honours degree	-0.061***	-0.034***	-0.046***	-0.036***	-0.053***	-0.024***
	(-6.29)	(-3.76)	(-4.96)	(-3.70)	(-6.44)	(-2.86)
Studied part-time	0.050***	0.046***	0.015**	0.032***	0.020***	0.028***
	(7.15)	(7.74)	(2.18)	(4.81)	(3.33)	(4.88)
Field of Study (omitted: Management and Commerce)						
Natural and physical sciences	0.075***	0.030***	0.078***	0.041***	0.048***	0.013
	(7.37)	(3.23)	(7.89)	(3.89)	(5.74)	(1.44)
Information technology	0.030**	0.006	0.028**	0.004	0.021*	0.008
	(2.28)	(0.49)	(2.09)	(0.31)	(1.79)	(0.74)
Engineering	-0.034***	-0.026**	-0.017	-0.003	-0.014	-0.006
	(-2.78)	(-2.49)	(-1.43)	(-0.29)	(-1.37)	(-0.64)
Architecture	-0.051***	-0.019	-0.003	0.019	0.004	-0.006
	(-2.72)	(-1.25)	(-0.19)	(1.14)	(0.30)	(-0.44)
Education	-0.051***	-0.048***	-0.037***	-0.036***	-0.028***	-0.031***
	(-5.17)	(-5.73)	(-3.79)	(-3.90)	(-3.29)	(-3.86)
Agriculture	0.034*	-0.017	0.042**	0.018	0.017	0.020
	(1.85)	(-1.02)	(2.31)	(1.02)	(1.08)	(1.33)
Human studies	0.102***	0.039***	0.116***	0.069***	0.060***	0.011
	(10.35)	(4.51)	(11.97)	(7.12)	(7.16)	(1.33)
Psychology	0.089***	0.000	0.076***	0.002	0.059***	-0.018*
	(7.47)	(0.01)	(6.46)	(0.15)	(5.92)	(-1.66)
Law	0.011	-0.006	-0.006	-0.008	0.006	-0.005
	(0.77)	(-0.48)	(-0.46)	(-0.60)	(0.47)	(-0.46)

Variable	Vertical Mismatch		Horizontal Mismatch		Skills Mismatch	
	Short-Term	Longer-Term	Short-Term	Longer-Term	Short-Term	Longer-Term
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Economics	-0.007	0.020	0.018	0.013	-0.010	0.032*
	(-0.30)	(1.00)	(0.78)	(0.57)	(-0.49)	(1.77)
Society and culture	0.107***	0.060***	0.132***	0.092***	0.058***	0.036***
	(9.66)	(6.46)	(12.26)	(8.68)	(6.20)	(3.86)
Allied health	-0.033***	-0.049***	-0.030***	-0.045***	-0.030***	-0.041***
	(-3.14)	(-5.37)	(-2.89)	(-4.43)	(-3.29)	(-4.62)
Medicine	0.017	-0.052***	0.033*	-0.059***	0.025	-0.031*
	(0.83)	(-2.80)	(1.70)	(-2.93)	(1.48)	(-1.84)
Nursing	-0.128***	-0.149***	-0.091***	-0.129***	-0.054***	-0.111***
	(-8.51)	(-10.70)	(-6.39)	(-9.21)	(-4.29)	(-8.63)
Creative Arts	0.098***	0.072***	0.088***	0.079***	0.063***	0.037***
	(9.19)	(8.03)	(8.44)	(7.78)	(7.22)	(4.24)
Contract Length						
Long-term contract (> 1 year)	-0.063***	-0.025***	-0.042***	-0.012	-0.010	-0.017**
	(-6.05)	(-2.96)	(-4.21)	(-1.34)	(-1.17)	(-2.11)
Short-term contract (< 1 year)	-0.076***	-0.024***	-0.047***	-0.013	-0.041***	-0.001
	(-9.03)	(-3.01)	(-5.92)	(-1.51)	(-5.53)	(-0.16)
Casual work	0.187***	0.074***	0.148***	0.083***	0.131***	0.078***
	(19.88)	(8.98)	(16.36)	(8.72)	(15.99)	(9.76)
University Group						
Group of Eight	0.018***	0.000	0.009	-0.003	0.013**	-0.005
	(2.72)	(0.08)	(1.37)	(-0.47)	(2.39)	(-0.86)
Australian Technology Network	-0.011	-0.004	-0.013	-0.006	-0.011	-0.007
	(-1.27)	(-0.54)	(-1.49)	(-0.75)	(-1.43)	(-0.96)
Innovative Research University	0.009	0.004	0.014	0.007	0.009	0.001
	(1.00)	(0.53)	(1.54)	(0.87)	(1.11)	(0.17)
Rural University Network	0.004	-0.013	0.021**	-0.007	0.006	-0.004
	(0.39)	(-1.46)	(2.05)	(-0.75)	(0.69)	(-0.53)
Other demographic variables	Yes	Yes	Yes	Yes	Yes	Yes
Other university variables	Yes	Yes	Yes	Yes	Yes	Yes
Other employment variables	Yes	Yes	Yes	Yes	Yes	Yes
Geographical variables	Yes	Yes	Yes	Yes	Yes	Yes

Variable	Vertical Mismatch		Horizontal Mismatch		Skills Mismatch	
	Short-Term	Longer-Term	Short-Term	Longer-Term	Short-Term	Longer-Term
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Job search variables	Yes	Yes	Yes	Yes	Yes	Yes
N	23,697	21,555	23,697	21,555	23,697	21,555
Correlation Coefficients	Short-term	Longer-term				
Vertical-Horizontal	0.912***	0.884***				
	(239.62)	(167.16)				
Vertical-Skills	0.798***	0.732***				
	(108.24)	(88.30)				
Horizontal-Skills	0.816***	0.839***				
	(116.99)	(124.69)				

Note: Marginal effects are average marginal effects. Short- and long-term refers to the 6-month and 3-year period, respectively. ***, ** and * denote the statistical significance at one, five and ten percent levels, respectively. ‘t’-values are in parentheses. Longer-term sample consists of people who had some form of employment during both the short- and longer-term. Age was entered as a linear and quadratic term, and a composite effect of those terms at the sample mean is reported in the table. Other demographics variables are English speaking background, Australian residency status and disability status. Other university variables are engagement in further study, part-time study and off-campus study. Other employment variables are self-employment status, sector of employment and part-time work. Geographical variables are variables for each Australian state, and a regional or remote location indicator. Job search strategies are university careers office, careers fair, other university sources, print media, internet sources, online resumes, family and friends, approaching employers directly, recruitment agencies and work networks.

Earnings effects of graduate mismatch

The results from the earnings effects of mismatch are presented in Table 3. The first column in Table 3 presents the results from the OLS model of earnings in the short term post-graduation. The second column presents the estimates from the model of earnings in the longer term, and where estimates have been corrected via a Heckman selection model.[9] The third column presents estimates of earnings effects from a fixed effects linear model.

Attention is first drawn to the results for the earnings effects of graduate mismatch. Unsurprisingly, the majority of estimated coefficients for the mismatch variables are negative. A notable exception is the estimated earnings effect for those who were residual skills mismatched in the short term, who are observed to earn five percent more than correctly matched graduates in the short term. However, the estimated earnings effect for this group is negative in the longer term and in the fixed effects specification, with an effect size of around three percent. The graduates who were vertically mismatched experienced a three percent earnings penalty in the shorter term, a five percent earnings penalty in the longer term and a five percent earnings penalty in the fixed effects model. Being horizontally mismatched appeared to have a negligible earnings impact in the short term, and a modest three percent penalty in the longer term.[10]

Contract type was associated with strong earnings effects. Graduates on temporary and casual contracts, as expected, fared the worst, and earned up to 33 percent less than those on permanent contracts. Those on fixed term contracts fared better than those on temporary or casual contracts, but still had earnings lower than those on permanent contracts. Estimates from the fixed effects model show that those on fixed term contracts of more than 12 months and less than 12 months earned four and nine percent less than those on permanent contracts, respectively. The finding that those on permanent contracts earned the most adds weight to the

[9] A Hausman test was conducted in order to see if the use of a Heckman selection model is more appropriate compared to an OLS model. The Hausman test returned a value of 1049.34, and is significant at the one percent level. Hence, the Heckman selection model is more appropriate than OLS in examining the long-term earnings of university graduates.

[10] A binary probit model for being mismatched in all three forms was also estimated, to confirm whether the field of study patterns established in the multivariate probit model of graduate mismatch hold. In general, the same conclusions can be drawn. Graduates in general fields are prone to being mismatched in all forms, while graduates in specific fields are less susceptible to this form of mismatch. Specifically, graduates from Natural and Physical Science, Human Studies, Society and Culture, and Creative Arts have increased probabilities of being mismatched in all three forms, significant at the one percent level. Conversely, graduates from the Education and Nursing fields are less likely to be mismatched in all three forms, significant at the one percent level. These results hold from the short to longer term.

earlier argument that these graduates might be trading off other employment positives against the detrimental effects of being mismatched.

The graduates' fields of study were also found to be strong predictors of graduate earnings. In the short term, fields such as Natural and Physical Science, Medicine and Creative Arts were associated with earnings penalties up to 18 percent. In the longer term, however, outcomes differed amongst the various fields. In fields such as Natural and Physical Sciences and Health, graduate earnings were found to converge with those from the field of Management and Commerce in the longer term. For Medicine graduates, their adverse position of lower earnings in the short term were reversed, and Medicine graduates earned 14 percent more than Management and Commerce graduates in the longer term. For other fields, such as Human Studies and Society, Other Society and Culture, and Creative Arts and Others, the earnings disadvantages were persistent and they earned substantially less in the short and longer terms. These fields of study earnings effects were also observed in the fixed effects model.[11]

While the results reported above demonstrate clear earnings penalties with regards to graduate mismatch as well as large earnings differences between fields of study, it is not clear whether the earnings effects of mismatch differ by the type of field of study. In particular, do graduates from fields of study that are general in nature experience differences in earnings penalties due to being mismatched, from graduates who are mismatched and who are in specific fields of study? To address this question, the fixed effects model of graduate earnings was estimated separately for general and specific fields of study.[12,13] The earnings disadvantages of being mismatched were all large and statistically significant at the one percent level for both general and specific fields of study. Graduates from general fields of study were found to have earnings penalties from being mismatched negative five, negative four and negative three percent for vertical, horizontal and residual skills mismatch, respectively. Graduates from specific fields of study had earnings penalties from mismatch, in the same order, at negative four, negative four and negative three percent. Hence, while the earnings penalties from mismatch for graduates from general fields of study were higher, it was only marginally so.

[11] Note, however, that it is unclear whether graduates from certain fields of study had different propensities to exit the labour market in the longer term. Hence, a probit model was estimated for the period three years postgraduation to uncover which graduates were likely to exit the labour force then. Graduates from many fields had slightly increased propensity to exit the labour force then. However, Natural and Physical Science graduates had the largest estimated effect in this regard, and were eight percent more likely to leave the labour force.

[12] The specific fields of study were Engineering, Architecture, Education, Law, Medicine, Nursing and Health. All other fields were classified as general fields of study.

[13] Results for the full model are available on request.

There is one other finding of note from the earnings models of graduate mismatch. This relates to the large earnings advantage associated with graduation from a Group of Eight university.[14] Specifically, graduation from a Group of Eight university was associated with a nine percent earnings premium in the short and longer terms, compared to graduation from an Unaligned university. For graduates from the Australian Technological Network, no institutional earnings effect in the short term was observed, but a moderate premium of around four percent was estimated in the longer term and three percent in the fixed effects model. Other remaining estimates on graduation from a university from the Innovative Research University and Regional University Network groups are statistically insignificant. These institutional earnings effects are larger than those from past studies. For instance, Li and Miller (2013) reported a modest earnings premia of 1.9 percent and 3.5 percent for Group of Eight and Australian Technological Network universities, respectively, while Koshy, Seymour and Dockery (2016) found evidence of an earnings premia only for female graduates.[15]

Table 3: Results from the Earnings Models of Graduate Mismatch

Variables	Short term OLS	Longer-term Heckman	Fixed Effects
Mismatch Status (omitted: Correctly Matched)			
Generalised residual - Vertical mismatch	-0.032***	-0.052***	-0.048***
	(-4.83)	(-6.39)	(-8.47)
Generalised residual - Horizontal mismatch	0.009***	-0.030***	-0.038***
	(-4.80)	(-3.88)	(-6.81)
Generalised residual - Skills mismatch	0.054***	-0.025***	-0.034***
	(-3.58)	(-2.99)	(-5.50)
Hours worked	-0.051***	0.017***	0.019***
	(39.31)	(27.70)	(42.90)
Female (omitted: Male)	0.114***	-0.101***	-0.098***
	(-7.68)	(-7.97)	(-11.83)
Age (evaluated at sample mean)	-0.019***	0.009***	0.015***
	(20.64)	(8.33)	(21.18)
Field of Study (omitted: Management and Commerce)			
Natural and Physical Sciences	0.004***	0.010	-0.134***
	(-7.44)	(0.40)	(-7.92)
Information Technology	0.131	-0.049	-0.037*
	(-0.96)	(-1.51)	(-1.79)

[14] Universities from the Group of Eight are the most research-intensive, sandstone universities in Australia, and are consistently ranked as the top Australian universities in global rankings. For brevity, university groupings are not discussed in depth in this paper, however, a discussion of the Australian university sector and university groupings can be found in Koshy, Seymour and Dockery (2016).

[15] To compare the university group estimates in this study with results from other studies in the literature, some sensitivity analyses were performed. This included estimating the earnings models with the mismatch variables removed, and estimating the full earnings model on male and female samples, separately. The institutional premia reported in Table 3 remained robust to these alternate specifications, with the Group of Eight earnings premia estimated at around nine percent (statistically significant at the one percent level), and the Australian Technological Network premia estimated at around three percent (statistically significant at the one percent level).

Engineering	0.049*	0.057**	0.056***
	(1.77)	(2.13)	(3.21)
Architecture	-0.112***	-0.147***	-0.142***
	(-3.21)	(-3.65)	(-5.40)
Education	-0.147***	-0.140***	-0.140***
	(-7.33)	(-6.64)	(-10.06)
Agriculture and Environment	-0.025***	-0.088**	-0.144***
	(-4.41)	(-2.05)	(-5.11)
Human Society and Studies	0.040***	-0.147***	-0.153***
	(-5.93)	(-6.05)	(-9.59)
Psychology	-0.114**	-0.027	-0.072***
	(-2.08)	(-0.90)	(-3.61)
Law	-0.140	0.024	-0.007
	(-0.93)	(0.76)	(-0.36)
Economics	-0.156	-0.050	-0.043
	(-0.89)	(-0.91)	(-1.21)
Other Society and Culture	-0.113***	-0.140***	-0.172***
	(-6.54)	(-5.01)	(-9.37)
Health	-0.041***	0.022	-0.021
	(-3.02)	(0.96)	(-1.42)
Medicine	-0.024***	0.137***	-0.021
	(-5.64)	(3.40)	(-0.81)
Nursing	-0.046***	-0.034	-0.055***
	(-4.68)	(-1.26)	(-3.13)
Creative Arts and Others	-0.143***	-0.165***	-0.180***
	(-7.56)	(-6.25)	(-10.29)
<u>Contract Length (omitted: Permanent Contracts)</u>			
Fixed-term contract > 1 year	-0.190	-0.052***	-0.042***
	(-0.52)	(-2.85)	(-3.03)
Fixed-term contract < 1 year	-0.114***	-0.064***	-0.094***
	(-5.47)	(-3.66)	(-8.65)
Temporary or Casual	-0.162***	-0.329***	-0.370***
	(-17.77)	(-15.68)	(-25.73)
<u>University Group (omitted: Unaligned Universities)</u>			
Group of Eight	-0.012***	0.090***	0.089***
	(6.94)	(5.92)	(8.97)
Australian Technological Network	0.011	0.044**	0.029**
	(0.25)	(2.18)	(2.19)
Innovative Research University	0.050	-0.025	0.002
	(0.87)	(-1.27)	(0.13)
Regional Universities Network	-0.055	-0.034	-0.014
	(-0.35)	(-1.50)	(-0.94)
Constant	-0.078***	10.316***	9.377***
	(128.17)	(42.60)	(179.21)
Other demographic variables	Yes	Yes	Yes
Other university variables	Yes	Yes	Yes
Other employment variables	Yes	Yes	Yes
Job search strategies	Yes	Yes	Yes
Observations	23,697	21,555	21,555
Adjusted R^2	0.449		0.359

Lambda	-0.740*** (0.01)	

Notes: Robust 't'-statistics are presented in parentheses. ***, ** and * denote statistical significance at the one, five and ten percent, respectively. Age was entered as a linear and quadratic term, and a composite effect of those terms at the sample mean is reported in the table. Other demographics variables are English speaking background, Australian residency status and disability status. Other study variables are Honours degree qualification, engagement in further study, part-time study, off-campus study and year of graduation. Other employment variables are self-employment status, sector of employment and part-time work status.

Models of alternate labour market measures

In addition to the analyses performed above, other labour market outcomes are briefly considered in this section. The motivation for consideration of alternate labour market measures stems from the findings of the preceding models, which indicate that aside from fields of study effects, contract length and type appear to be an important determinant of mismatch and earnings. Specifically, graduates who are in permanent jobs appear to be rewarded with higher earnings, but are more susceptible to mismatch. Hence, a probit model was estimated, with the dependent variable *temporary job* taking on the value of one where the graduate was in short-term contracts (less than a year) or casual employment. This model was estimated for the short and longer-term separately. As expected, mismatched graduates were generally more likely to be in temporary jobs. In particular, graduates mismatched in all three forms were ten percent more likely to be in a temporary job in the short term, although this effect is partially reversed in the longer term, where graduates mismatched in all forms were four percent less likely to be in a temporary job.

Sizeable probabilities of being in a temporary job were observed for the various fields of study. These effects were generally persistent across time, with no change in the sign of the estimated effects and little change in the magnitudes. Relative to the benchmark group of Management and Commerce graduates, Natural and Physical Science graduates were about 16 percent more likely to be in a temporary job, with large estimates also observed for Education (approximately 22 percent) and Other Society and Culture (12 percent) graduates. For specific fields of study, estimated effects were smaller, with Nursing graduates 14 percent more likely to be in a temporary job in the short term, and of a negligible magnitude close to zero in the longer term. Engineering graduates were four percent less likely to be in a temporary job in the short term, compared to Management and Commerce graduates.

The second ancillary outcome considered is the propensity to be in part-time work. Again, probit models were estimated for the short and longer term, with the dependent variable *part-time work* taking on the value of 1 if the graduate is working part-time. Graduates from four mismatch categories were observed to have substantially increased probabilities of being in part-time work. These were graduates in the mismatch categories of vertical mismatch only, vertical and horizontal mismatches, vertical and residual skills mismatches, and all mismatches. In particular, the largest effects were observed for graduates mismatched in all forms, with an increased probability of being in part-time work by 21 percent in the short term, and graduates who were vertically and horizontally mismatched, with an increased probability of 13 percent. These estimates were all statistically significant at the one percent level. These effects persisted into the longer term, but with reduced magnitudes of approximately half of those estimated for the short-term. The field of study estimates for these models once again demonstrates a divergence in outcomes by discipline. Engineering, Law and Medicine graduates had substantial reduced likelihoods of being in part-time work, at up to six percent lesser for Law graduates. However, Nursing graduates were 14 percent more likely to work part-time in the short term and 19 percent more likely to work part-time in the longer term. The propensity to work part-time, therefore, does not have to a clear general-specific discipline divide, unlike those considered for other labour market outcomes above.

Conclusion

In analysing mismatch, it is important to consider vertical, horizontal (field of study) and residual skills mismatch elements. This study has added to the literature by providing a comprehensive analysis of the determinants and consequences of vertical, horizontal and residual skills mismatches. The various forms of mismatch have been found to be highly correlated, and where graduates were found to be mismatched, they tend to be mismatched in more than one form. Further, the results of the analysis of earnings indicate that penalties are associated with all forms of mismatch. While the incidences of mismatch decrease over time, horizontal and residual skills mismatches appear to be relatively persistent.

It was found that graduates of fields of study which are general in nature have increased likelihoods of mismatch compared to those which are specific in nature, and for these mismatches to persist in the longer run. The earnings disadvantages associated with mismatch however do not appear to be limited to either general or specific fields of study, and are of similar magnitude.

Furthermore, in addition to being mismatched, graduates in general fields were more likely to be in fixed term or casual contracts, or to be in part-time work. From the policy perspective, it is important not only that graduates find employment, but that these employment are ones in which they are appropriately matched. The findings from this study indicate the presence of a wide disparity in labour market outcomes across fields of study. This highlights the need for policy to facilitate the matching between university degree fields and jobs in areas of relative labour market demand. Careers guidance has a potentially important role to play.

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Appendix

Appendix 1: Selected Descriptive Statistics for the Graduate Population, Comparison of the GDS and BGS

	GDS		BGS	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Demographics				
Female	0.618	0.486	0.638	0.481
Age	25.681	7.075	30.119	10.204
Non-English Speaking Background	0.172	0.377	0.148	0.355
Not of Australian Residency Status	0.070	0.256	0.063	0.242
Has Disability	0.023	0.151	0.023	0.151
Primary Field of Study				
Natural and Physical Science	0.070	0.256	0.077	0.266
Information Technology	0.033	0.177	0.035	0.184
Engineering	0.060	0.238	0.057	0.232
Architecture	0.027	0.163	0.021	0.142
Agriculture and Environment	0.015	0.121	0.125	0.331
Education	0.095	0.293	0.019	0.136
Management and Commerce	0.240	0.427	0.076	0.265
Human Studies	0.062	0.241	0.046	0.210
Psychology	0.035	0.185	0.037	0.188
Law	0.027	0.162	0.010	0.101
Economics	0.011	0.105	0.052	0.222
Other Society and Culture	0.046	0.209	0.093	0.291
Allied Health	0.095	0.293	0.023	0.151
Medicine	0.017	0.127	0.062	0.242
Nursing	0.089	0.284	0.060	0.237
Creative Arts and Other fields	0.078	0.269	0.077	0.266
Observations	193,271		23,697	