Labour mobility and hours worked mismatch in Australia

Lixin Cai[1], Kostas Mavromaras[1,3], Peter Sloane[1,2,3] and Zhang Wei[1,*]

[1] *National Institute of Labour Studies, Flinders University*

[2] *WELMERC, School of Business & Economics, Swansea University*
[3] *IZA, Bonn*

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Abstract

Using Australian data drawn from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, this paper examines a relatively under- researched type of labour market mismatch, namely that between actual and preferred working hours. It is found that labour mobility does not always lead to a reduction in the degree of mismatch, but this is partly a function of the level of education of the worker.

Keywords: labour mobility; hours worked mismatch; state dependence; dynamic estimation; job mismatch

JEL Classification: J21; J24; J62

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* Presenting Author: Kostas Mavromaras, National Institute of Labour Studies, Flinders University, GPO Box 2100, Adelaide, South Australia 5001. k.mavromaras@flinders.edu.au

1. Introduction

This paper aims to study the mismatch between actual and preferred working hours. We focus on both people who work more hours than they want and those who work fewer hours than they want. We investigate the prevalence and persistence of working hours mismatch and its relationship with both voluntary and involuntary labour mobility. The main question we address is the degree to which quits and layoffs lead to reduced hours mismatch as theory would predict (Altonji and Paxson 1988).

Mismatch in skills and qualifications have been shown to be prevalent in the labour markets of most OECD economies (Desjardins and Rubenson 2011, European Union 2012, Quintini 2011). Being mismatched has been shown to have serious economic repercussions (Bauer 2002, CEDEFOP 2010, Duncan and Hoffman 1981, Mavromaras et al. 2009, 2010 and 2013), and to also be persistent in its presence (Mavromaras and McGuinness 2012 and Mavromaras et al. 2013). Mismatch, in both skills and qualifications, has been shown to be strongly associated with the level of education of the workers, in that there are large differences in mismatch levels between higher education and vocational education graduates, which have been the subject of study in recent years (Black 2013, Mavromaras et al. 2012 and 2013).

However, the problem of mismatch in the labour market is much broader than just mismatch in skills or qualifications. Mismatch between actual hours worked by workers and their preferred working hours is an important type of mismatch that has received less attention in the literature. An early study by Moses (1962) draws attention to the distinction between income preferrers and leisure preferrers. Income preferrers will tend to demand overtime and if this is not available either quit or search for a second job. In contrast, leisure preferrers will seek to work fewer hours either through part-time employment or by being absent from work more often. Healy et al. (2012) have reported that about 50% of employers with skill shortages in the Business Longitudinal Database (Australian Bureau of Statistics, 2005-2007) respond by increasing the hours worked by their existing employees. Hours mismatch may arise from this response, especially in the case of salaried people who will not always be paid for the extra hours they work. In HILDA the hours question relates to a usual week and covers both paid and unpaid overtime.

Evidence from the HILDA survey shows an imbalance between hours actually worked and desired hours. In the years 2001 to 2013, 27 per cent of workers reported they would prefer to work fewer hours, 58 per cent worked close to their preferred hours, and 15 per cent would prefer to work more hours. Thus, twice as many would prefer to work fewer hours than would prefer to work longer hours. This paper investigates whether past mismatch and labour mobility influence present mismatch. The *a priori* expectation is that mobility should lead to improved hours outcomes (Altonji and Paxson 1998), but this cannot be an unqualified expectation. To begin with we provide a definition of mobility which distinguishes between changing employer, changing occupation or changing industry. There is much difference between these three types of mobility, in the way they can be expected to influence the type of work that may be offered to newcomers. We also make the important distinction between lay-offs and quits, as we would expect voluntary quits to result in improved hours outcomes more often than involuntary lay-offs. Finally, we distinguish between the mobility that follows working too many hours or too few hours.

In order for the paper to examine the degree to which mobility may lead to improved hours outcomes we employ a methodology which can account for several aspects of the data that could bias estimation. First and foremost we employ a panel estimation method. We use a random effects dynamic multinomial logit model to examine the persistence of working hours mismatch and control for unobserved individual heterogeneity. Second, we allow the dependent variable (in our case whether the worker is *under-employed* in that they would prefer to work more hours – an income preferrer – or whether they are *over-employed* in that they would prefer to work fewer hours – a leisure preferrer) to be persistent over time. We define persistence as the situation where past mismatch may in itself be influencing the likelihood of future mismatch, over and above all exogenous factors that may determine mismatch. This possibility is modelled by using a dynamic framework, which introduces the lagged dependent variable in the right hand side of the estimation, and which necessitates that we control for initial conditions. To this purpose we follow the method proposed by Wooldridge (2005). The paper also examines how the relationship between hours worked mismatch and mobility may vary by the level of the highest attained qualification of the worker, motivated by the empirical patterns observed, whereby over-employment (under-employment) increases (decreases) for higher (lower) qualified workers. We distinguish between workers without school completion, school graduates, vocational education graduates and university graduates.

The paper finds that mismatch in hours worked is highly prevalent with just under half the working population recording that their preferred and actual hours worked are not the same. We find that the incidence of mismatch differs by education level and that both types of mismatch (over-employed and under-employed) are highly persistent. The main finding of the paper regarding mobility is that for the overall sample quits do lead to improved hours outcomes for those who are seeking to work fewer hours (the over-employed) but that layoffs have no significant effect on hours mismatch. We find no evidence that occupational or industrial mobility influences mismatch and some evidence that mobility differs by education level.

The remaining paper is structured as follows. The next section discusses the economic background and the relevant literature. Section 3 presents the data and Section 4 the methodology. Section 5 presents and discusses the estimation results. Section 6 concludes. An Appendix contains descriptive statistics.

2. Background

The standard model of labour supply assumes that the preferred working hours of an individual employee will be determined by the optimal combination of income and leisure time, but this implies the individual is free to choose his or her desired combination of wages and hours. In practice, employers may limit this choice, because low hours increase adjustment costs and lower the return on human capital and overtime hours are expensive or unwarranted. Where there is collective bargaining, employers and unions may impose a standard work-week which, even if it optimises for the average employee, will not do so for all, given heterogeneous tastes among employees. However, collective bargaining has been declining in many countries and flexible working arrangements have become more common, increasing the possibilities for employees to optimise on their hours of work. Thus, in the Netherlands van Echtelt, Glebbeek and Lindenberg (2006) point out that (i) whilst the Working Hours Adjustment Act 2000 gives employees the right to increase or reduce their contractual hours unless this puts the interests of the employer at serious risk and (ii) while almost 80 percent of employers claim that reducing hours by 20 percent is not at all problematical, hours mismatch still occurs for a quarter of employees. In order to explain this paradox they conducted a survey of over 1000 employees in 30 Dutch organisations. They suggest that the need to complete tasks, regardless of the time it takes, means that not paying attention to time limits is taken by employers as a signal of the employees' commitment, causing employees to work longer hours than they would otherwise prefer.

In an early study referred to above Moses (1962) classified workers into two categories- namely income and leisure preferrers. In the former case the wage offer curve, showing the equilibrium combinations of wages and leisure for the employee, will intersect a vertical standard work week line; meaning that the worker can be made better off by the offer of overtime work at premium wage rates. If such an accommodation is not forthcoming the worker may resort to multiple job holding or demand higher wages. In contrast, the wage offer curve for a leisure preferrer will turn back before the standard workweek bites, indicating a preference for part-time work. If this is not available absence rates may rise among this group of workers. The literature which followed adopted a simpler classification by defining those who would prefer more hours than they are currently offered as under-employed and those who would prefer fewer hours than currently offered as over-employed. In each case employees will be off their labour supply curves. One implication of this, as pointed out by Altonji and Paxson (1998) is that constrained workers may be willing to sacrifice gains in wages for better hours when changing jobs. Conversely workers will only accept jobs with undesirable hours if there are large wage gains to be made. Their analysis of quits in the US Panel Study of Income Dynamics 1968-1991 broadly supports these propositions. Under-employed quitters have larger changes in hours than those quitters who were previously satisfied with their hours, who in turn have smaller hours changes than those who were initially over-employed. Mobility seems to lead to improved hours outcomes. However, it is not correct to interpret the difference between desired and actual hours as an accurate measure of the resulting loss in welfare as this will be a function of the size of the labour supply elasticity. Bender and Skatun (2009) use the US National Longitudinal Survey of Youth 1984 to estimate an unconstrained labour supply curve and the resulting deadweight loss for those who are hours mismatched. While reductions in the estimated surplus for being out of equilibrium are generally small, 10 percent of under-employed men and women experience losses of more than 34 and 50 percent of the surplus respectively.

How much preferred hours diverge from actual hours and the extent to which employees are able to adjust to this situation are the key questions. Some British studies have analysed the British Household Panel Study (BHPS) , which includes a direct question as below.

> ‘Thinking about the hours you work, and assuming you would be paid the same amount per hour, would you prefer to work fewer hours, work more hours, or the same number of hours than you do now?’

Using this question in the 1991 BHPS, Stewart and Swaffield (1997) show that over one third of male manual workers would prefer to work fewer hours at the prevailing wage and that desired hours per week are 4.3 less than actual. They hypothesise that job insecurity and scarcity of alternative job opportunities enable employers to set hours constraints which are in excess of employee preferences and that these will be an increasing function of the unemployment rate. When demand is high employees may be required to work overtime and when it is low short-time, but to test this requires longitudinal data. This is remedied by Boheim and Taylor (2003 and 2004), who analyse an unbalanced panel from the BHPS 1991-1999, which excludes workers in agriculture, the armed forces and those who hold two or more jobs. They find that employees who do not change either job or employer have a higher probability of remaining constrained in their labour supply. There is considerable hours constraint persistence. In particular, employer and job changes facilitate the downward adjustment of working hours among the over-employed. Contractual status, occupation, the prevailing level of wages and qualifications emerge as important determinants of over- and under-employment for both men and women, while family considerations are especially important for women. In fact there is evidence that women are becoming more constrained in the hours they are required to work. Upper boundaries in working hours, which are more relevant to men are more flexible than lower boundaries, which are more relevant to women. Altonji and Paxson (1992) analyse a sample of married women in the US PSID 1968-1983 and find that the effect of changes in the demographic structure of the family on wives' working hours is generally greater for those who change employers than those who do not. This is consistent with the idea that constraints on hours choices within individual firms limit the extent to which workers can change hours in line with changes in labour supply preferences. A natural extension is to consider the impact of hours mismatch on the welfare of partners. Using the German Socio-Economic Panel Wunder and Heineck (2013) find that a situation in which both partners in a marriage are under-employed is associated with a severe reduction in well-being equivalent to 40 % of the average welfare loss from disability. For males the loss from a double mismatch for each partner is fully equivalent to the utility loss from disability. Further, Wunder and Hieneck (2013) suggest that hours mismatch will have a deleterious effect on both job and life satisfaction and that it is necessary to consider men and women separately.

Our study is not the first to consider hours mismatch in Australia. The question in the HILDA survey is slightly different from that in the BHPS. Namely,

> 'If you could choose the number of hours you work each week, *and taking into account how that would affect your income,* would you prefer to work…fewer hours than you do now, about the same number of hours as you do now, or more hours than you do now?'

This seems less restrictive than the BHPS question. A further question in HILDA asks those who are mismatched

> ’in total how many hours a week on average, would you choose to work? Again, taking into account how that would affect your income?’

This enables one to analyse how the degree of mismatch affects welfare. In the first Australian study of this phenomenon Wilkins (2007) uses HILDA 2001 to examine the effects of under-employment on outcomes such as income, welfare dependence and subjective well-being. Negative effects are found for both part-time and full-time under-employed workers, but the effects are greater for the former, and particularly for those who would like to work full-time. Interestingly, by 2004 the proportion under-employed, which had been on a rising trend since 1978, exceeded the proportion unemployed. Wooden, Warren and Drago (2009) use an unbalanced panel from the first five waves of HILDA to analyse the impact of hours mismatch on subjective well-being. They use a one period lag to control for state dependence in their fixed effects OLS model, but do not allow for the initial conditions problem. Their three main findings are that it is not the number of hours that matters for subjective well-being, but rather working time mismatch; over-employment is a more serious matter than under-employment; and that relative to other variables, such as disability, the effect of over-employment is quite large. The only significant gender differences relate to part-time work. In a further study limited to two waves of HILDA, Drago, Wooden and Black (2009) consider the issue of long working hours, which though not strictly relevant to the work here does point to the fact that for some(volunteers) long hours are a matter of choice, while for others (conscripts) it is a matter of necessity.

In this study we use dynamic panel estimation methods over a much longer time period (thirteen waves) to consider the trend in the relationship between past working time mismatch and resulting mismatch after different types of mobility. Using thirteen waves of data allows us to refine our analysis in several useful directions by splitting mismatch into over- and under-employment, mobility into quits, layoffs, occupation and industry change, and by educational level in five different categories ranging from those who have not completed school to university graduates.

3. The Data

The paper uses the data from the first thirteen waves of the HILDA survey. Modelled on household panel surveys undertaken in other countries, the HILDA survey began in 2001 (wave 1) with a large national sample of Australian households and their members.[1] The sample used in this paper is an unbalanced panel which includes all working-age employees (16-64 for males and 16-59 for females) who provide complete information on the variables of interest. Self-employed and full-time students are excluded. The sample retained by the paper for the econometric analysis that follows is approximately 5,000 observations per wave.

In the HILDA survey, as mentioned earlier, employees were asked: whether they would prefer to work *"fewer"* hours, *"about the same"* number of hours, or *"more"* hours. We define a person to be *over-employed* if he or she answers "*fewer*" and *under-employed* if the answer is "*more*". The rest of the sample, who answer "*about the same*", are categorised as *well-matched*. Under this definition, 58.1 percent of the workforce are satisfied with their current working hours, as shown in Table 1. Over-employment is substantially more prevalent than under-employment (27.1 percent versus 14.7 percent). This implies that skills shortage can be a more severe issue than skills under-utilisation in Australia. Table 1 does not show any discernible gender difference.

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

Table 1: Work hours mismatch status by gender

	Males		**Females**		**Total**	
	Persons	%	Persons	%	Persons	%
Over-employed	12,028	27.6	11,090	26.7	23,118	27.1
Well-matched	25,657	58.8	23,905	57.5	49,562	58.1
Under-employed	5,951	13.6	6,613	15.9	12,564	14.7
Total	43,636	100	41,608	100	85,244	100

Notes: HILDA waves 2001-2013. Unit of observation is person-years. Percentages are of the total in each column.

As also noted above, employees who answered “more” or “fewer” to the previous hours mismatch question were further asked how many hours they would choose to work. Table 2 compares the average actual and preferred work hours of Australian employees, showing that on average male employees have both more actual and more preferred hours than females. Moreover, both men and women in general prefer fewer hours than they actually do. This finding is consistent with what was observed in Table 1, indicating that skills shortage dominates underemployment in the Australian labour market.

Table 2: Average of actual and preferred hours by gender

	Actual hours	Preferred hours	Difference	Person-years
Males	43.0	41.1	-1.88	43,616
Females	33.3	31.8	-1.49	41,591
Total	38.2	36.5	-1.69	85,207

Note: Negative difference implies that workers would like to work less.

Table 3 below describes the overall transitions between the three hours matching possibilities in the data. We find that the majority of workers report that their current hours worked are very similar to their preferred hours worked. Just under half of all workers report that they would like to work more or fewer hours. The status that is most prevalent (59.3 percent of the total) and also changes least over time (72.6 percent remain well matched) is the well matched, with those who would want to work more (the under-employed) being the least prevalent (12.7 percent of the total) and the least likely to continue being mismatched (44.2 percent).

Table 3: Transitions by mismatch status

	Current work hours mismatch status at t							
	Over-employed		Well-matched		Under-employed		Total	
	Obs.	*%*	*Obs.*	*%*	*Obs.*	*%*	*Obs.*	*%*
Past work hours mismatch status (at t-1)								
Over-employed	10,979	59.3	6,772	36.6	749	4.0	18,500	100
Well-matched	7,182	18.2	28,671	72.6	3,618	9.2	39,471	100
Under-employed	893	9.3	4,467	46.5	4,242	44.2	9,602	100
Total	19,054	28.2	39,910	59.1	8,609	12.7	67,573	100

Note: *Obs.*is person-years. Percentages are of the total in each row.

We use information about employment between two consecutive waves to define labour mobility. We distinguish between the following three different categories: 1) employer change, where an individual’s employer has changed since the last interview; 2) change in occupation, where occupational class is defined using 1-digit codes from ANZSCO 2006; 3) change in industry, where industrial class is defined using 1-digit codes from ANZSIC 2006.

Table 4 presents the mismatch status by different forms of mobility since the last interview. It shows that the proportion being well-matched is similar between movers and stayers. However, the proportion being under-employed (over-employed) is higher (lower) among movers than stayers. In addition, involuntary movers (layoffs) contain a lower proportion of well-matched workers and a higher proportion of workers who would prefer to work more hours (under-employed) than the voluntary movers (quits).

Table 4: Work hours mismatch by labour mobility

	Work hours mismatch status at t							
	Over-employed		**Well-matched**		**Under-employed**		**Total**	
	Persons	*%*	*Persons*	*%*	*Persons*	*%*	*Persons*	*%*
Labour mobility status (t-1,t)								
Layoffs	461	21.9	1,145	54.3	502	23.8	2,108	100
Quits	1,790	22.9	4,619	59.2	1,393	17.9	7,802	100
No job change	16,636	29.2	33,708	59.2	6,563	11.5	56,907	100
Change in occupation	4,618	27.6	9,793	58.4	2,350	14.0	16,761	100
No change in occupation	14,430	28.4	30,102	59.3	6,267	12.3	50,799	100
Change in industry	3,920	24.9	9,302	59.1	2,507	15.9	15,729	100
No change in industry	14,914	29.1	30,202	59.0	6,062	11.8	51,178	100

Note: Percentages are of the total in each row.

Table 5 below compares the mismatch status among employees with different education levels. It shows that the proportion of the well-matched category does not vary substantially across education levels. In contrast, the proportion of being over-employed increases in education level and the proportion of being under-employed decreases in education level. Overall, employees with a university degree are 16.3 (36.7-20.4) percentage points more likely to be over-employed and 11.4 (19.7-8.3) percentage points less likely to be under-employed than those with no post school qualification, which implies that skill shortages may be more prevalent for the workers with a higher level of qualification.

Table 5: Work hours mismatch status by level of education

	Over-employed		**Well-matched**		**Under-employed**		**Total**	
	Persons	*%*	*Persons*	*%*	*Persons*	*%*	*Persons*	*%*
Did not complete school	3,808	20.4	11,222	60.0	3,676	19.7	18,706	100
Only completed school	2,959	21.0	8,385	59.4	2,773	19.6	14,117	100
Certificates III/IV	4,776	24.4	11,646	59.5	3,139	16.0	19,561	100
Diplomas	2,499	30.8	4,713	58.1	899	11.1	8,111	100
University graduates	9,062	36.7	13,568	55.0	2,053	8.3	24,683	100
Total	23,104	27.1	49,534	58.2	12,540	14.7	85,178	100

Note: Percentages are of the total in each row.

4. Methodology

The statistical model

While employment with matched-hours is preferred to any form of mismatch, there is not a clear order of preference between under-employment and over-employment. As such, ordered logit or probit models do not fit the outcome variables here. Instead, we estimate a random effects dynamic multinomial logit model to examine the persistence of working hours mismatch and control for unobserved heterogeneity. Under this modelling framework, at a point of time t, an individual *i* is in one of the three mutually exclusive working hours match/mismatch sates: under-employment, well-matched employment, and over-employment (denoted by $k = 1, 2,$ and 3). The probability of individual *i* in state *k* at time *t* (i.e., $P_{i,k,t}$) is assumed to be determined by the individual's previous working hours match/mismatch status and a vector of other observed and unobserved individual characteristics, including variables on work mobility,

$$(1) \qquad P_{i,k,t}\left(\mu_{i,j}, j = 1,2,3\right) = \frac{\exp\left(L_{i,t-1}\alpha_k + x_{i,t}\beta_k + \mu_{i,k}\right)}{\sum_{j=1}^{4}\exp\left(L_{i,t-1}\alpha_j + x_{i,t}\beta_j + \mu_{i,j}\right)}; k = 1,2,3;\; t = 1,\ldots,T,$$

where $L_{i,t}$ is a (row) vector of dummy variables indicating working hours match/mismatch status of individual *i* at time *t*; $x_{i,t}$ is a (row) vector of observed characteristics of the individual at time *t*, such as education level and age; $\mu_{i,k}$ summarizes unobserved individual factors that could affect working hours match/mismatch and that do not change over time; and $(\alpha_j, \beta_j; j = 1,2,3)$ are the coefficient parameters to be estimated.

In the model we allow $\mu_{i,j}$ and $\mu_{i,k\neq j}$ to be freely correlated with each other. This relaxes the Independence of Irrelevant Alternatives (IIA) assumption which can be a problem encountered in the conventional multinomial logit model (Greene 2002).[2]

The inclusion of unobserved individual heterogeneity in the model, and the fact that in the data we do not observe individuals from the beginning of their working life, implies that the initial working hour match/mismatch status observed in the data (i.e., $L_{i,0}$) is unlikely to be random or exogenous. This is known as the *initial conditions* problem. It has been examined by Heckman (1981), who proposed separately specifying a reduced form model for the initial hours mismatch status and jointly estimate the initial condition model with the dynamic model. Simpler to compute estimators have been proposed by Orme (1997), Arulampalam and Stewart (2009), and Wooldridge (2005).[3] We follow Wooldridge (2005) that proposes modelling the distribution of unobserved individual heterogeneity ($\mu_{i,j}$) conditional on the initial value of the dependent variable ($L_{i,0}$) and other exogenous explanatory variables.

[2] This IIA assumption states that the odds of any two alternatives do not depend on the inclusion or exclusion of other alternatives. This is often not true and it is also an assumption that does not need to be made in the estimation methodology we follow in this paper.
[3] Arulampalam and Stewart (2009) put Heckman's and the other estimators cited above to a comparative test. They emphasise the benefits of allowing for correlated random effects obtained from using the Mundlak correction and point out that all estimators provide similar results, except when the number of periods is very small. Given that our panel is sufficiently long at more than 10 waves, we employ the Wooldridge (2005) method for the purpose of this research, primarily for its considerable computational simplicity.

In addition, to relax the assumption in a typical random effects model that the observed explanatory variables and unobserved individual heterogeneity are independent, we take the Mundlak (1978) approach to specify [4]

$$(2) \qquad \mu_{i,j} = L_{i,0}\lambda_j + \bar{z}_i\theta_j + \nu_{i,j}, \ \ j=1,2,3,$$

where $\bar{z}_i$ is a vector containing the means (over time) of the exogenous variables ($z_{i,t}$). $z_{i,t}$ is typically a subset of the time varying variables in $x_{i,t}$. $\nu_{i,1}, \nu_{i,2}$, and $\nu_{i,3}$ represent the random effects independent of any observed explanatory variables. They are assumed to follow a multivariate normal distribution with mean zero and a covariance matrix Σ_ν. The parameters in Σ_ν are estimated along with the coefficient parameters in the model.

When we substitute equation (2) into (1), the probability of individual *i* in state *k* at time *t*, conditional on observed individual characteristics and unobserved random effects ($\nu_{i,j}; j = 1,2,3$), becomes,

$$(1') \qquad P_{i,k,t}\left(\nu_{i,j}, j = 1,2,3\right) = \frac{\exp\left(L_{i,t-1}\alpha_k + x_{i,t}\beta_k + L_{i,0}\lambda_k + \bar{z}_i\theta_k + \nu_{i,k}\right)}{\sum_{j=1}^{4}\exp\left(L_{i,t-1}\alpha_j + x_{i,t}\beta_j + L_{i,0}\lambda_j + \bar{z}_i\theta_j + \nu_{i,j}\right)},$$

where $k = 1,2,3;\ t = 1, \dots, T$.

For model identification purposes, one set of the coefficient parameters and one random effect associated with a particular employment state have to be normalised to zero. We normalise to zero the set of the parameters and the random effect associated with well-matched employment. In the text of the paper, we report the marginal effect estimates rather than the coefficient estimates. We note that it does not matter which set of parameters and random effects are normalised to zero when calculating the marginal effects.

[4] In the multinomial logit model framework it is infeasible to estimate a fixed effects model. On the other hand, the assumption that unobserved heterogeneity is independent of all observed variables in a random effects model is often too strong. The model specified in this study, often referred to as correlated random effects models, can be seen as a compromise between fixed effects models (which is technically infeasible in our case) and random effects models (with unrealistic assumptions).

Estimation strategy

The probability of observing individual *i* to be in a sequence of hours match/mismatch states over the time period from *t=1* to *T*, conditional on observed individual characteristics and unobserved random effects, is the product of the probability of being in the observed hours match/mismatch status each year, as given in equation (1'), and can be written as[5]

$$(3) \qquad \mathrm{P_i}\left(\nu_{i,j}, j = 2,3\right) = \prod_{t=1}^{T} \prod_{k=1}^{3} [\mathrm{P}_{i,k,t}\left(\nu_{i,j}, j = 2,3\right)]^{D_{i,k,t}} ,$$

where $D_{i,k,t} = 1$ if individual *i* is observed to be in state *k* at time *t*; $D_{i,k,t} = 0$ if observed state for individual *i* is not *k* at time *t*.

The likelihood function of individual *i* without conditioning on unobserved heterogeneity can be written as

$$(4) \qquad L_i = \int P_i\left(\nu_{2,}\nu_3\right) dG(\nu_{2,}\nu_3),$$

where $G(\nu_{2,}\nu_3)$ is the joint distribution function of the random effects ν_2, and ν_3 . The two-dimensional integral is evaluated using simulation methods, with $G(\nu_{2,}\nu_3)$ assumed to be normal with a mean of zero and a covariance matrix Σ_ν[6]

$$(5) \qquad \widetilde{L_\imath} = \frac{1}{R} \sum_{r=1}^{R} P_i(\nu_2^r, \nu_3^r),$$

where R is the number of random draws from the distribution of $G(\nu_{2,}\nu_3)$; ν_2^r, and ν_3^r are the r^{th} random draws from their joint distribution. We use Halton sequence to generate 50 random draws to simulate the likelihood function.[7] It has been shown that Halton sequence draws perform better than simple random draws in terms of approximating the objective

[5] Note that $\nu_{.,1}$ is normalised to 0.
[6] The two-dimensional integral can also be evaluated using the Gaussian-Hermite quadrature method (Butler and Moffitt 1982). But the simulation method we use in this paper is easier to implement and Stewart (2006) shows that the two methods produce very similar results in dynamic Probit models.
[7] Halton sequences are not truly random, but are more evenly spaced points across the spectrum than true random points. However, in empirical work, Halton sequences are preferred to random numbers because of their better performance (Train 2003).

function (Train 2003). The log-likelihood function of a sample with N individuals is the sum of the log of equation (5) over the sample,

(6) $\quad LL = \frac{1}{N}\sum_{i=1}^{N} \log(\widetilde{L_i})$.

The parameters are then estimated by maximising equation (6) with respect to the parameters.[8]

Simulated mean marginal effects (SMME)

Due to the highly nonlinear nature of the multinomial model, it is difficult to interpret the coefficient estimates. The sign of the coefficient on a variable shows the direction of the variable's impact on the probability of being in an hours match/mismatch state relative to the base state (i.e. well-matched employment). However, the non-linear nature of the model means that the coefficient does not tell how the probability of being in one state changes when the variable in question changes. In addition, the inclusion of unobserved individual heterogeneity makes the computation of marginal effects more complicated.

To assess the effects of the explanatory variables on the probability of being in a particular hours match/mismatch state, we calculate a simulated marginal effect – this is the average marginal effect from repeated draws from the distribution of the unobserved individual heterogeneity. To be consistent with the model estimation, these draws are the same as those used in the model estimation. We calculate the simulated marginal effects for each individual in the sample and we report the mean (over the sample) of the simulated marginal effects in the tables in this section. For completeness, the coefficient estimates are reported in the appendix.

[8] The authors estimated the model using a GAUSS program they wrote, which can be obtained on request.

The simulated mean marginal effects are calculated (SMME) as follows

(8) $$SMME_{x_k} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{1}{R}\sum_{r=1}^{R} ME_{x_k}(\nu_2^r, \nu_3^r)\right],$$

where (ν_2^r, ν_3^r) is the r^{th} draw of unobserved individual heterogeneity; R is the number of draws of (ν_2^r, ν_3^r); $ME_{x_k}(\nu_2^r, \nu_3^r)$ is the marginal effect of variable x_k with a random draw (ν_2^r, ν_3^r); and N is the number of observations.

The standard errors of the SMME estimates are also simulated. We calculate the standard errors by taking 500 draws of the parameters from their estimated joint distribution, calculating the SMME for each draw, and then obtaining their standard errors.

The model contains the following control variables: age, age square, sex, four education qualification dummies, disability status, marital status, with children below 5 years old and between 5 and 14 years old, urban residence, two migrant status dummies (one for English speaking and one non-English speaking country of origin), indigenous status, hours worked per week, tenure with employer, tenure in occupation, four firm size dummies proportion of time spent in unemployment in the last year, union membership, and wave dummies.

5. Estimation results and discussion

Table 6 presents the SMME estimates from the whole sample, and the results suggest that both under- and over-employment are persistent after observed and unobserved individual heterogeneity has been controlled for. Other thing equal, those who were under-employed (over-employed) one year earlier have an eight (eleven) percentage points higher probability of being under-employed (over-employed) in the present year compared with those whose working hours were well-matched in the previous year. The initial condition variables are also highly significant in both estimations. The estimates on the initial condition variables suggest that the persistence of hours mismatch could last for more than one year.

For the job mobility variables, only the variable on quits is found to be significant in affecting over-employment and matched-employment. The estimates show that quits increase the probability of matched-employment by about 2 percentage points, and this is largely through reducing over-employment. Our results suggest that people who report that they work too much quit their jobs and find another job where they need to work less.

Table 6: The effects of labour mobility on work hours mismatch (overall sample)

	Under-employment at t		Matched employment at t		Over-employment at t	
	SMME	S.E.	SMME	S.E.	SMME	S.E.
Under-employment at t-1	0.0755**	0.0381	-0.0522*	0.027	-0.0234	0.0282
Over-employment at t-1	-0.0064	0.0209	-0.1053***	0.028	0.1118***	0.0333
Initial under-employment	0.0838**	0.0422	-0.0643**	0.0311	-0.0195	0.0302
Initial over-employment	-0.0117	0.0288	-0.1416***	0.0387	0.1533***	0.0463
Quits	0.0066	0.0088	0.0213**	0.0104	-0.0279**	0.0119
Layoffs	0.0169	0.0132	-0.0057	0.0117	-0.0112	0.0119
Change in occupation	-0.0056	0.0053	-0.0013	0.0051	0.0069	0.0049
Change in industry	0.0051	0.0044	-0.0042	0.0042	-0.0008	0.0038
No. of observations			61,849			
Log-likelihood			-41044.82			

Note: Significance is denoted by *** p<0.01, ** p<0.05, * p<0.10.

Mismatch by education qualifications

This sub-section presents the same set of estimations as in Table 6 above, but using samples that have been split by five education qualification categories, beginning with university graduates and finishing with the lowest qualification of not having completed school education.

Table 7 suggests that the persistence of under-employment is slightly lower while the persistence of over-employment is slightly higher among university graduates than that for the whole sample. The estimates also suggest that among university graduates, those who are working more than they want address their problem through quitting. However, those who are laid off find that they have to work even more hours when they get re-employed. Changes in occupation or industry are also found to increase over-employment, largely at the expense of matched-employment. This seems to be at odds with at least some of the previous literature, but is consistent with the proposition of it being easier to find a new job where there is excess demand for labour and pressure to increase the number of hours worked.

Table 7: The effects of labour mobility on work hours mismatch (University graduates)

	Under-employment at t		Matched employment at t		Over-employment at t	
	SMME	S.E.	SMME	S.E.	SMME	S.E.
Under-employment at t-1	0.0600**	0.0258	-0.0554***	0.0102	-0.0046	0.0242
Over-employment at t-1	-0.005	0.0174	-0.1183***	0.0148	0.1233***	0.022
Initial under-employment	0.0495**	0.0248	-0.0249***	0.0087	-0.0246	0.0237
Initial over-employment	-0.017	0.0279	-0.1427***	0.0187	0.1596***	0.0325
Quits	-0.0016	0.0059	0.0433***	0.0082	-0.0416***	0.0088
Layoffs	0.0015	0.0086	-0.0510***	0.0102	0.0495***	0.0118
Change in occupation	-0.0056	0.0064	-0.0087	0.0053	0.0143**	0.007
Change in industry	-0.0002	0.0038	-0.0092**	0.0046	0.0093**	0.0043
No. of observations			18,735			
Log-likelihood			-11787.64			

Note: Significance is denoted by *** p<0.01, ** p<0.05, * p<0.10.

The estimates for those who are Diploma graduates in Table 8 suggest that quits increase the probability of under-employment at the expense of matched-employment, while layoffs reduce over-employment and increase matched-employment. Change in industry is also found to reduce over-employment and increase matched-employment. Mobility affects this group differently than it does graduates, perhaps reflecting the narrower range of jobs open to this group due to the more specific training imparted through vocational qualifications.

Table 8: The effects of labour mobility on work hours mismatch (Diplomas and Advance Diplomas)

	Under-employment at t		Matched employment at t		Over-employment at t	
	SMME	S.E.	SMME	S.E.	SMME	S.E.
Under-employment at t-1	0.0996***	0.0327	-0.0537***	0.0181	-0.0459	0.0289
Over-employment at t-1	-0.0057	0.0153	-0.1091***	0.0129	0.1148***	0.0181
Initial under-employment	0.0681***	0.0262	-0.0290**	0.0145	-0.0391	0.0238
Initial over-employment	0.0025	0.0133	-0.1555***	0.0169	0.1530***	0.02
Quits	0.0248*	0.0127	-0.0301**	0.0137	0.0054	0.0123
Layoffs	-0.0034	0.0147	0.0411***	0.0153	-0.0377***	0.0121
Change in occupation	-0.0031	0.0057	-0.0038	0.0069	0.0069	0.006
Change in industry	0.0048	0.0077	0.0179***	0.0062	-0.0226***	0.0079
No. of observations			6,164			
Log-likelihood			-3985.52			

Note: Significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

The estimates for those with Certificate III/IV in Table 9 indicate that both quits and layoffs tend to reduce over-employment and increase matched-employment. Unlike in the above cases changes in occupation or industry do not seem to address hours mismatch for this group of workers.

Table 9: The effects of labour mobility on work hours mismatch (Certificates III/IV)

	Under-employment at t		Matched employment at t		Over-employment at t	
	SMME	S.E.	SMME	S.E.	SMME	S.E.
Under-employment at t-1	0.0805***	0.0302	-0.0589***	0.0195	-0.0216	0.0244
Over-employment at t-1	-0.0046	0.0181	-0.1103***	0.0183	0.1149***	0.0247
Initial under-employment	0.1085***	0.0384	-0.0898***	0.0262	-0.0187	0.0298
Initial over-employment	-0.0129	0.0251	-0.1447***	0.0249	0.1576***	0.0344
Quits	-0.001	0.0071	0.0225***	0.0083	-0.0216***	0.0072
Layoffs	0.0061	0.01	0.0220**	0.0102	-0.0281***	0.01
Change in occupation	-0.0049	0.0056	0.0014	0.0057	0.0035	0.0049
Change in industry	0.0013	0.0059	0.0025	0.0056	-0.0038	0.0046
No. of observations			14,634			
Log-likelihood			-10053.26			

Note: Significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table 10 presents the estimates for those who only completed secondary schooling. The results here suggest that workers who completed school education but did not go ahead with any post-school qualifications and who report that they work too many hours can address their mismatch through quitting, which is similar to what we found for university graduates.

Table 10: The effects of labour mobility on work hours mismatch (Only completed school)

	Under-employment at t		Matched employment at t		Over-employment at t	
	SMME	S.E.	SMME	S.E.	SMME	S.E.
Under-employment at t-1	0.0855***	0.0278	-0.0699***	0.0186	-0.0156	0.0218
Over-employment at t-1	-0.0111	0.0193	-0.0984***	0.0192	0.1096***	0.026
Initial under-employment	0.0849***	0.028	-0.0770***	0.0197	-0.0079	0.0216
Initial over-employment	-0.0079	0.0243	-0.1446***	0.0268	0.1525***	0.0339
Quits	0.0017	0.009	0.0272***	0.0087	-0.0289***	0.009
Layoffs	0.0381**	0.0173	-0.0165	0.0142	-0.0216	0.0162
Change in occupation	-0.0069	0.0091	-0.0167**	0.0079	0.0236**	0.0094
Change in industry	0.0035	0.0069	0.0103	0.0063	-0.0138**	0.007
No. of observations			9,443			
Log-likelihood			-6397.84			

Note: Significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

For this group of workers, Table 10 shows that layoffs are found to increase under-employment. Changes in occupation increase over-employment, largely at the expense of matched-employment, while changing industry is found to reduce over-employment.

Finally, Table 11 shows that the least well qualified of all workers who would like to be working fewer hours, do manage to reduce their mismatch through quitting, but they are likely to end up in under-employment rather than in matched employment. In contrast, those who would like to work more hours may reduce their mismatch through any type of mobility except for changing occupation. Table 11 suggests that mobility rarely improves the lot of the least well qualified employees, and that when it happens, they can expect to become worse off through almost all different types of mobility.

Table 11: The effects of labour mobility on work hours mismatch (Did not complete school)

	Under-employment at t		Matched employment at t		Over-employment at t	
	SMME	S.E.	SMME	S.E.	SMME	S.E.
Under-employment at t-1	0.0764***	0.0234	-0.0520***	0.0159	-0.0243	0.0192
Over-employment at t-1	0.0028	0.0119	-0.0843***	0.0174	0.0815***	0.0195
Initial under-employment	0.1103***	0.0301	-0.0880***	0.02	-0.0223	0.0232
Initial over-employment	-0.0151	0.0222	-0.1212***	0.0288	0.1362***	0.0351
Quits	0.0252*	0.0133	0.0074	0.0132	-0.0326**	0.015
Layoffs	0.0364***	0.0136	-0.0252*	0.0144	-0.0112	0.0143
Change in occupation	-0.0087	0.0054	0.0157**	0.0078	-0.007	0.0059
Change in industry	0.0122***	0.0047	-0.0227***	0.007	0.0105	0.0064
No. of observations			12,873			
Log-likelihood			-8560.50			

Note: Significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

The estimates by different levels of education attainment suggest a different pattern for under- and for over-employment. The persistence of under-employment is weaker among university graduates than those with a lower education qualification, while the persistence of over-employment is stronger among university graduates than the others.

6. Conclusion

The paper has examined the relationship between labour mobility and hours worked mismatch using an appropriate econometric methodology which allows us to control for state dependence in mismatch using a dynamic multinomial logit model and for unobserved heterogeneity using the Mundlak (1978) approach. Results support our choice of methodology. We have presented two sets of estimations, the first using the whole sample and the second splitting the sample by highest attained education qualification.

We find that mismatch is highly persistent in all estimations without exception. This implies that people who find themselves working either too many or too few hours find it difficult to escape their mismatch. This result is in accordance with our broader understanding of mismatch as a negative labour market outcome which tends to be self-perpetuating, thus acting as a trap for those who are subjected to it. It is worth noting that self-persistence remains present after we have controlled successfully for unobserved time-invariant individual heterogeneity. We also find that the main type of mobility that seems to be making any difference regarding hours mismatch are quits of people who work more hours than they would like: these workers quit and get a job where they can work fewer hours. This is the only instance where we find a strong result showing that mobility leads to improved outcomes.

Splitting the sample by education qualifications we find that for those university graduates who report that they work too many hours, becoming laid off makes things worse, as they end up having to work even more hours in their next job. Clearly, a lay off does not improve the labour market choices of graduates. However, quitting from an hours-mismatched job is shown to improved matters for university graduates. For diploma graduates quits increase under-employment at the expense of matched employment, while layoffs tend to reduce over-employment. Changes in industry tend to reduce over-employment and increase matched employment. This is very different from the case of university graduates. For certificates both quits and lay-offs reduce over-employment, but changes of occupation and industry are not helpful in this regard. Those who completed school can reduce over-employment by quitting, but layoffs do not help. A change of industry helps, but a change of occupation makes matters worse. In the case of those who did not complete school quits reduce over-employment, but increase under-employment. Neither layoffs nor changes of industry and occupation help. Therefore, there is a distinctive but complicated pattern among mismatched leavers with different levels of education in the sense that quits and layoffs have different effects across each one of the educational groups we examined.

We started this paper by noting that there is a strand of research on the relationship between mismatch in general and hours mismatch in particular and different types of labour mobility and another strand of research on the relationship between mismatch in general and educational level. Our research examined in detail the empirical relationship between hours mismatch and different types of mobility. By splitting our mismatch and mobility estimations by education qualifications we combined these two strands, directly linking education levels with mismatch-caused labour mobility. Our findings suggest that the main instance where mobility appears to be working to the benefit of employees is that of the highest qualified employees (university graduates) who are working more hours than they wish and who appear to be quitting and finding a new job where they work for the hours they wish to, whilst their mismatch does not appear to be associated with their layoff probability. In contrast, we find that for the lowest qualified employees (not completed secondary education) mismatch is not impacting on quits, but is associated with an above average layoff probability.

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APPENDIX

Table A1: Descriptive statistics

	Mean	Standard deviation
Female	0.488	0.500
Age	38.123	11.857
Age square/100	15.940	9.229
Only completed school	0.166	0.372
Certificates III/IV	0.230	0.421
Diplomas	0.095	0.294
University graduates	0.290	0.454
Disability	0.153	0.360
Married	0.675	0.468
Urban	0.881	0.323
Migrants (English speaking country)	0.092	0.289
Migrants (non-English speaking country)	0.104	0.305
Aboriginal or Torres Strait Islander (ATSI)	0.020	0.139
Hours worked per week	38.193	13.277
Tenure in the current occupation	8.519	9.214
Tenure with the current employer	6.220	7.452
Firm has less than 5 employees	0.086	0.280
Firm has 5 to 9 employees	0.122	0.327
Firm has 10 to 19 employees	0.140	0.347
Firm has 20 to 49 employees	0.182	0.385
Children aged under 5	0.127	0.333
Children aged [5, 14]	0.248	0.432
Per cent time spent unemployed in last financial year	2.576	11.647
Union member	0.284	0.451

Note: Pooled data from HILDA 2001-2013. Number of observations is 85,373.

Table A2: Full estimation results

	Under-employment at t		Over-employment at t	
	Coef.	*S.E.*	*Coef.*	*S.E.*
Under-employment at t-1	-0.989***	0.041	-1.107***	0.064
Over-employment at t-1	-0.012	0.063	0.806***	0.067
Initial under-employment	-1.109***	0.059	-1.187***	0.079
Initial over-employment	0.045	0.067	1.136***	0.079
Quits	-0.086	0.066	-0.314***	0.079
Layoffs	-0.262**	0.106	-0.339***	0.13
Change in occupation	0.090*	0.053	0.141**	0.061
Change in industry	-0.085	0.055	-0.087	0.065
Female	0.600***	0.056	1.282***	0.07
Age	-0.016	0.014	0.042**	0.017
Age square/100	0.043**	0.018	-0.003	0.022
Only completed school	0.232***	0.067	0.493***	0.088
Certificates III/IV	-0.004	0.062	0.128	0.08
Diplomas	0.446***	0.093	0.881***	0.116
University graduates	0.770***	0.070	1.360***	0.087
Disability	-0.013	0.068	0.178**	0.079
Married	0.187***	0.070	0.454***	0.085
Urban	-0.003	0.148	0.086	0.175
Migrants (English speaking country)	0.113	0.089	0.130	0.110
Migrants (non-English speaking country)	-0.699***	0.076	-0.866***	0.094
Aboriginal or Torres Strait Islander (ATSI)	-0.316**	0.150	-0.457**	0.216
Hours worked per week	0.142***	0.003	0.260***	0.003
Tenure in the current occupation	0.002	0.004	0.008*	0.005
Tenure with the current employer	0.007	0.007	0.016**	0.007
Firm has less than 5 employees	-0.309***	0.093	-0.268**	0.114
Firm has 5 to 9 employees	-0.136*	0.078	-0.105	0.094
Firm has 10 to 19 employees	-0.229***	0.075	-0.164*	0.089
Firm has 20 to 49 employees	-0.102	0.066	-0.044	0.077
Children aged [5, 14]	0.215***	0.071	0.206**	0.081
Children aged under 5	0.358***	0.071	0.524***	0.083
Per cent time spent unemployed in last financial year	-0.007**	0.003	-0.006	0.005
Union member	-0.052	0.065	-0.064	0.076
m(quits)	-0.299**	0.148	-0.166	0.186
m(layoffs)	-0.358	0.244	-0.422	0.319
m(change in occupation)	0.083	0.104	0.136	0.13
m(change in industry)	0.114	0.107	-0.064	0.13
m(disability)	-0.223**	0.107	-0.193	0.134
m(married)	0.308***	0.093	0.234**	0.115
m(urban)	0.076	0.165	0.191	0.2
m(hours worked per week)	-0.057***	0.003	-0.100***	0.004
m(tenure in the current occupation)	0.001	0.006	-0.003	0.007
m(tenure with the current employer)	0.027***	0.008	0.014	0.01
m(firm has less than 5 employees)	0.098	0.138	-0.22	0.181

m(firm has 5 to 9 employees)	-0.047	0.127	-0.204	0.158
m(firm has 10 to 19 employees)	0.173	0.122	-0.023	0.151
m(firm has 20 to 49 employees)	-0.063	0.109	-0.168	0.133
m(children aged [5, 14])	-0.133	0.101	-0.087	0.12
m(children aged under 5)	-0.284**	0.128	-0.253	0.158
m(per cent time spent unemployed in last financial year)	-0.016**	0.007	-0.025**	0.01
m(union member)	-0.281***	0.093	-0.455***	0.112
Year 2003	0.152*	0.088	0.192*	0.102
Year 2004	0.123	0.089	0.234**	0.105
Year 2005	0.252***	0.090	0.334***	0.105
Year 2006	0.314***	0.089	0.353***	0.105
Year 2007	0.401***	0.090	0.408***	0.106
Year 2008	0.363***	0.088	0.292***	0.104
Year 2009	0.301***	0.089	0.228**	0.106
Year 2010	0.215**	0.088	0.126	0.103
Year 2011	0.162*	0.089	0.020	0.106
Year 2012	0.199**	0.085	0.018	0.101
Year 2013	0.246***	0.086	-0.018	0.102
Constant	-1.189***	0.285	-8.268***	0.368

Note: m(.) denotes the Mundlak correction terms; *** p<0.01, ** p<0.05, * p<0.1.