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Transitioning Out of Unemployment: Analysis Using the ABS Longitudinal Labour Force Survey File*

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Abstract

What affects the probability that an individual who has just entered unemployment finds employment within a given timeframe? Does the probability of exiting unemployment depend on the length of the individual's unemployment spell?

This paper reflects on these questions and analyses the transitions from unemployment of those aged 20-65 years, over the 2008-2010 period. The analysis makes use of the ABS Longitudinal Labour Force Survey (LLFS) file – a dataset that includes households that were followed for eight consecutive months during the said period. This paper is the first longitudinal analysis conducted on the file.

Building on the job-search theoretical framework, the paper builds a model aimed at analysing the factors that influence transitions from unemployment. A range of methodological techniques are implemented, including the creation of time intervals and the subsequent discrete duration analysis; the adoption of the competing-risks framework, to account for the different forms of exits from unemployment; and the inclusion of random effects in the modelling of the observed as well as unobserved heterogeneity.

Keywords: Unemployment, Hazard Rate, Survival Analysis, Longitudinal Labour Force Survey

JEL Classification: J64, J60, C41, J24, J21

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1. Introduction

What affects the probability that an individual who has just become unemployed finds (full- or part-time) employment within a given timeframe? Does the probability of exiting unemployment depend on the length of the individual's unemployment spell?

This paper addresses these research questions and analyses the transitions from unemployment in Australia for those aged 20-65 years, over a three-year period, from the beginning of 2008 to the end of 2010. The study makes use of the recently constructed ABS Longitudinal Labour Force Survey (LLFS) file and is the first longitudinal analysis study conducted on the file.

Relevance

The research questions being addressed are of considerable relevance on a number of fronts. From an economic perspective, the questions are concerned with one of the major challenges faced by national economies; sustained unemployment imposing substantial economic, personal, and social costs (Feldstein, 1978). Its importance is widely highlighted in the literature with some studies considering it as 'the central dilemma for some of the most prosperous countries in Europe' (Sen, 1997) and 'one of the main challenges of the modern era in both the developed and developing countries' (Tansel and Tasci, 2010).

Following Hubbard *et al*., (2014), the costs of unemployment can be categorised as follows:

Costs to the individual

First, there is the loss of income to the unemployed. Although the affected individuals may be eligible for unemployment benefits and other forms of government assistance, they are still likely to experience serious hardships (e.g., in meeting their mortgage payments) and a substantial decline in their standards of living. In addition to the loss of current output, previous studies have shown that prolonged unemployment is associated with other pecuniary and non-pecuniary effects, such as the loss of self-esteem (Goldsmith *et al*., 1996); adverse effects on mental health (Jackson, 1984), well-being, and life satisfaction (Arulampalam, *et al*., 2001; Carroll, 2007); skills deterioration (Edin and Gustavsson, 2008); higher likelihood of experiencing unemployment incidents in the future (Arulampalam, *et al*., 2000); and lower wages when returning to work (Arulampalam, 2001).

Costs to the society

Besides imposing substantial costs on the individual, sustained unemployment also affects the individual's family, society, and the wider community. Amongst others, unemployment has been found to be linked to social deprivation and to be a factor in school dropouts, drug abuse and alcoholism, suicide, family break-ups, crime and racial inequality (Watts *et al*., 2000; Sen, 1997).

Costs to the economy

A rising unemployment increases the Government fiscal costs, due to higher welfare payments. These costs are in addition complemented by the potential losses of tax revenue and social security premiums that could have been collected had the unemployed individuals instead worked. Apart from these, there are other more indirect costs, such as the costs associated with retraining the individual, the deterioration of human capital, the decrease in spending on goods and services (as the unemployed are likely to experience a decline in spending power), and the subsequent loss of potential national output. (See, for example, Sen (1997) and Hubbard *et al*., (2014) for more details.)

From a policy perspective, the research questions have substantial implications for the design and targeting of labour market policies and programs. Understanding which (and the way in which) variables are associated with longer unemployment and which groups of individuals are more likely to experience long unemployment spells and/or are less likely to exit unemployment into employment can provide useful insights for designing efficient assistance programs.

From a theoretical perspective, the research questions are relevant in shedding some light on the recent debate over the concept of hysteresis of unemployment, advocated by Blanchard and Summers (1986). Contrary to conventional wisdom, the theory states that the natural rate of unemployment can be influenced by shifts in aggregate demand, via the hysteresis channels of actual unemployment. The theory, which has received little attention in the literature, has significant implications for macroeconomic and monetary policy. The paper will provide some valuable insights in this area by contributing to one important avenue of research suggested by Ball (2011) namely, on examining the dynamic behaviour of short-term unemployment.

The contributions of the paper

Due to the limited availability of longitudinal labour force data, a large proportion of studies that examined the labour market dynamics in Australia are descriptive in nature. Amongst the longitudinal analyses, these were mainly conducted on a restricted number of datasets and used retrospective duration data. Most notably, the datasets include:

- the ABS Survey of Employment and Unemployment Patterns (SEUP), which was conducted in the 1990s (see, for example, Chalmers and Guyonne, 2001; Carino-Abello, *et al*., 2000);
- the Longitudinal Survey of Australian Youth, which is restricted to young people (see, for example, Hardin and Kapuscinski, 1997; Chapman and Smith, 1992); and
- the Household Income and Labour Dynamics in Australia (HILDA) Survey, which began in 2001 (see, for example, Watson, 2008; Carroll, 2007 and Carroll, 2006).

This paper makes three contributions to the literature. First, it uses a new and an important longitudinal data source, namely, the LLFS file. By having more than 1.8 million records and around 150,000 households observed on a monthly basis, for a period of up to eight months, the dataset is well-suited for short-term dynamics of unemployment analyses. The sample also covers a period of considerable interest, the Global Financial Crisis (GFC).

The second is in its use of actual reported unemployment data (collected monthly) instead of retrospective data, which has been used by the other studies that analysed the duration of unemployment in Australia. As has been shown in the literature, retrospective data can suffer from recall bias.

The third contribution is in the approach taken in dealing with the new features of the dataset, which include the high frequency of the data, the limited number of waves, and the type of unemployment information (reported instead of retrospective). Most notably, the approach includes the use of the job search framework to build the model, the creation of time intervals and the subsequent discrete duration analysis, the adoption of the competing-risks framework to account for the different forms of exits from unemployment, as well as the inclusion of random effects in the modelling of the observed and unobserved heterogeneity.

Modelling approach

The paper adopts discrete duration models in a competing-risks framework. This approach is appealing in that it accounts for the discrete nature of the duration data – the data being collected on a monthly basis. Three types of exits from unemployment are considered. The first is when the unemployed individual gets employed on a full-time basis (denoted by 'FT'). The second is when the individual gets employed on a part-time basis (denoted by 'PT'). The third is when the individual leaves the labour force (denoted by 'OLF'). As indicated in Flinn and Heckman (1983) the alternatives could be behaviourally different market states and as such it is important to treat them separately.

The analysis is divided into two parts. The first is focused on non-parametric techniques, and includes raw hazard and survival functions. The second incorporates observed as well as unobserved heterogeneity in modelling the hazard function. This is done by using discrete duration models, where both the ordinary logit as well as the random effects logit models are examined.

The plan of the paper is as follows. Section 2 provides a conceptual background. Section 3 describes the data. The methodology used in the analysis is described in section 4. Section 5 presents the results. Section 6 concludes.

2. Conceptual background

This paper makes use of the job-search theoretical framework (see, Mortensen, 1970; Lippman and McCall, 1976a; and Lippman and McCall, 1976b) to analyse the factors that affect the duration of unemployment and the probability of exiting unemployment. To see how the model works, consider an individual who has just become unemployed. This could happen either because the individual has moved from employment to unemployment or because he has transitioned from being out of the labour force to an active state of searching for work. Assuming that the individual continues to search for work, the aim is to explain the factors that determine the expected duration of remaining in the current state of unemployment. This expected duration is assumed to be inversely proportional to the probability of moving from unemployment to employment, which in turn is assumed to depend on two essential aspects: (1) the probability of receiving a job offer, and (2) the probability of accepting the job offer conditional on having received the job.

The probability of receiving a job offer is determined, amongst other things, by the demand for the individual's labour in the current market (Holzer, 1986).

Amongst the things that employees look for are education, skills, previous occupation, and experience – factors that are aimed to make the individual more attractive to potential employers. Other factors that shift the demand include the local demand conditions, such as the business cycle and the phase of the local economy (e.g., the relative strength of the local economy and whether the economy is in recession) (Foley, 1997), as well as the search intensity of the individual (Holzer, 1986).

The probability of accepting the offer depends on the individual's reservation wage. This is the lowest wage at which the individual will accept a job offer. This wage depends on such factors as the expected wage in their particular occupation, marital status, family composition, other incomes in the household, unemployment benefits, as well as the probability of receiving future job offers and the expected work horizon (Long, 2009). Note that the reservation wage could also depend on some (or all) the determinants of the demand for the labour provided by the individual (Holzer, 1986).

From an econometrics perspective it is important to consider both aspects when analysing the determinants of unemployment duration. Failure to include one aspect might result in missing an essential component of the model which in turn could impact on the results. Note also that although the job-search model sets the theoretical framework for analysing the unemployment duration, empirical intervention is often needed to determine the effects (or the net effects) of the factors in the model.

As an example of the application of the model, consider the effects of the length of unemployment spell on the probability of exiting unemployment. On one hand, a longer unemployment spell could have negative consequences on the individual's prospects of finding work (Tansel and Tasci, 2010). One reason for this is the lack of investment in human capital due to the loss of valuable work experience during the unemployment spell. Another reason is the potential change in attitude, as the repeated failure to secure a job might discourage the individual from fully-exercising his skills in finding work (Foley, 1997). Finally, employers may be more reluctant to offer job offers to those with long unemployment spells. This is because they may perceive the long spell of unemployment as a signal of low productivity (Kroft *et al*., 2013). All these reasons are associated with a lower probability of receiving a job offer.

On the other hand, the individual might decrease his reservation wage as he gets closer to the end of his finite time horizon, so as to increase his prospects of securing a job (see, Lippman and McCall, 1976a; Lippman and McCall, 1976b). This in turn will increase the conditional probability of accepting an offer. As the two effects move in opposite directions, it is not clear from theory which of them dominates. Empirical application would be useful to settle this uncertainty.

3. Data and definitions

In this study, unemployment is defined as:

Persons aged 15 years and over who were not employed during the reference week, and

- had actively looked for full-time or part-time work at any time in the four weeks up to the end of the reference week and were available for work in the reference week; or
- were waiting to start a new job within four weeks from the end of the reference week and could have started in the reference week if the job had been available then. (Australian Bureau of Statistics, 2013)

The study uses data from the recently constructed ABS LLFS file that collects monthly information over a period of three years, from 2008 to 2010. The LLFS is compiled from 56 separate household surveys and records information about the labour market participation and employment transitions for all individuals in a household, over a period of up to eight consecutive months. Those in the scope of the survey are 15 years of age or older.

One main advantage of using the LLFS over other datasets is its wealth of information – the file includes more than 150,000 households and more than 1.8 million records. By recording monthly data for such a large number of households, over a period of up to eight consecutive months, the file is well-suited for in-depth analysis of short-term labour market dynamics.

For the purposes of this study, a number of restrictions were imposed. First, the sample was restricted to individuals who were between 20 to 65 years of age at the time of the first interview. This restriction avoids the inclusion of teenagers, whose labour market behaviour is likely to differ substantially from that of the other age groups, and the inclusion of those older than 65 years, who are more likely to retire. Second, only private dwellings were included. Both these restrictions were imposed due to the potential different labour market behaviour of the individuals in these groups. Third, due to the aim of the study of analysing the duration of unemployment, the sample was further restricted to those who experienced unemployment at least once during the interview period. Also note that similar to Foley (1997), for the persons who experienced more than one spell of unemployment, only the first spell of unemployment was considered. This approach avoids the serial correlation that could result otherwise. As an extension, one could use multiple spells in the analysis by treating them as separate records. One would then need to deal with the dependence across spells[1]. Note also that the analysis is restricted to the individuals who became unemployed during the interview period, i.e., restricted to the inflows in unemployment. This avoids the complexity of dealing with left truncation and potentially left-censoring[2].

Table 3.1 below shows the distribution of the different types of exits from unemployment. Around 47 per cent of the unemployed, in scope of this analysis, end in employment, of which around half end in full-time employment and half in part-time employment. Around 37 per cent of the unemployed exit by leaving the labour force, a proportion which is similar to what other studies have found (see, for example, Morison and Berezovsky, 2001). The balance of 16.5 per cent remains in unemployment.

Compared to females, a higher proportion of males end in employment and a substantially higher percentage end in full-time employment. Females, on the other hand, are more likely to exit the labour force. In terms of marital status, the results are not too different across the two groups.

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[1] The methods included in Rotaru (2013) could be implemented to deal with this type of dependence.
[2] Lancaster (1990) includes some techniques to deal with left-censoring and left-truncation. Apart from being considerably more complex, the methods rely on retrospective data (which might suffer from recall bias), in the case of left-truncation, and on additional assumptions, in the case of left-censoring.

Table 3.1 - Percentage distribution of the exit states from unemployment spells

Exiting unemployment via:	*All*	*Male*	*Female*	*Married*	*Not married*
Full- or part-time employment	46.9	51.3	42.7	43.3	41.9
Full-time employment	23.3	31.8	15.1	14.2	16.2
Part-time employment	23.6	19.5	27.6	29.1	25.8
Leaving the Labour Force (OLF)	36.6	31.2	41.8	43.4	39.9
Remaining in unemployment	16.5	17.5	15.5	13.3	18.2

4. Methodology

This paper models the transitions from the first unemployment spell of individuals observed during the eight consecutive-months period described in section 3. The aims are first, to model the probability of exiting unemployment and second, to account for the potential time dependence in the modelling.

In order to meet these aims and to adequately deal with the particulars of the duration data – the data for each household in the survey being collected on a monthly basis, for a period of up to eight waves – a few challenges need to be addressed. The first challenge is dealing with left-censored/truncated duration data, as some individuals were already unemployed at the time of the first interview. As aforementioned, this was addressed by focusing on the individuals who entered unemployment during the interview period.

The second challenge is dealing with the spells of individuals who have not yet exited unemployment at the time of the last interview and with the discrete nature of the data, the data for each individual being collected on a monthly basis for a period of up to eight months. To address these aspects of the data, the paper constructs time intervals and implements discrete duration modelling techniques. As these techniques require a more thorough exposition, they are elaborated more fully below.

The third challenge is controlling for the effects of covariates that are not available in the dataset, such as motivation and ability. This is addressed by including random effects in the modelling.

The fourth challenge is accounting for the different ways of exiting unemployment. To address this, the paper adopts the competing-risks framework.

Finally, the fifth challenge is dealing with the longitudinal aspect of the constructed person-period dataset, in which each individual has multiple records, one for each period. For this challenge, it is important to note that by using the maximum likelihood estimation, the resulting likelihood function becomes a product of independent Bernoulli likelihood functions. This means that relatively simple techniques are needed to estimate the parameters and that the well-known inferential statistics can be applied in this case. (See, Singer and Willett, 2003; Singer and Willett, 1993; and Muthén and Masyn, 2005.)

Setting the Framework

In a general setting consider a random sample of N unemployed individuals that are observed over a period of time, which in the context of this study is up to eight months long. This period is allowed to vary across individuals and is recorded on a discrete scale. The aim is to track individuals from the time they entered into unemployment until they first exit that state (i.e., the focus is on single spells) and to analyse the characteristics that contribute to the differences in the duration experienced by the units in the sample.

The observed characteristics are captured in the vector $(X_1', X_2')'$, where in the context of the job-search model presented in Section 2, the first set of characteristics, assembled in vector X_1, determine the probability of being offered a job, whereas the second set, assembled in vector X_2, influence the probability of accepting the job offer. For example, X_1 could include previous occupation, education, English proficiency, and previous work experience, whereas, X_2 could include family composition, sex, and marital status. Note that the two sets need not be mutually exclusive. As emphasised in section 2, it is important to control for both sets of characteristics in the model. To further simplify the notation, all factors are collapsed into vector $X = (X_1', X_2')'$.

At the end of the spell, each unit i in the sample is assumed to end up in one of four states: exits unemployment and becomes employed full-time (z_i = 1); exits unemployment and becomes employed part-time (z_i = 2); remains unemployed (z_i = 3) – case when the observation is censored; or exits the labour force altogether (z_i = 4). Where here, as well as in the rest of the section, subscript i denotes the values for individual i. To simplify the exposition consider the case where there is only one exit state, i.e., only one destination, case when the values of z are collapsed into a binary variable y, where $y_i = 1$ if individual i exits unemployment, i.e., when $z_i \in \{1,2,4\}$, and $y_i = 0$ if the individual remains in the initial state of unemployment, i.e., when $z_i = 3$. Note that with more than one exit state one can use the competing-risks framework presented in Singer and Willett (2003) and Allison (2010).

Let T_i^* be a random variable capturing the duration of unemployment for individual i, i.e., the duration until $y_i = 1$, and let $(0,t_{n_i}] = (0,t_0] \cup (t_0,t_{n_i}]$ be the interval over which the individual is observed. As the analysis is restricted to the inflows into unemployment, $s_0 := (0,t_0]$ is the interval in which the individual becomes unemployed. Further, t_{n_i} captures the last time the individual's responses are recorded (for the censored cases) or the first time the individual is known to have exited unemployment. n_i is the number of waves until individual i exits unemployment or until censoring after becoming unemployed. It follows that for censored cases T_i^* is not observed and all that is known is that $T_i^* > t_{n_i}$. Further, with the current dataset, even when $y_i = 1$, one does not necessarily know the exact T_i^*, and rather only knows that $T_i^* \in (t_{n_i-1}, t_{n_i}]$. This is because the duration of unemployment is recorded on a monthly basis.

Although the approach taken by most empirical studies is to model the exact timing of event occurrence and treat duration as a continuous random variable, this paper takes a different path and instead models the probability that T^* falls into discrete time-intervals. To see how this works, consider again the interval $(0,t_{n_i}] = (0,t_0] \cup (t_0,t_{n_i}]$ over which individual i is observed. The main idea is to transform the continuous time horizon into a sequence of discrete intervals. Now, partition the interval where the individual is 'at risk' of leaving unemployment into n_i adjacent and mutually exclusive intervals, called periods, and which in the context of this study correspond to the time period between two consecutive waves of the survey, such that $(t_0,t_{n_i}] = (t_0,t_1] \cup (t_1,t_2] \cup ... \cup (t_{n_i-1}, t_{n_i}]$.

As a hypothetical example, consider an individual who is interviewed for all eight waves of the survey and whose responses are given in figure 4.1. In particular, at the time of the first interview he is employed full-time, in the second he is employed on a part-time basis, then he becomes unemployed and he remains so until before his sixth interview, at which time he indicates that he is employed part-time. During the time of the final two interviews he is out of the labour force.

Figure 4.2 shows how the intervals/periods were constructed. Note first that the analysis is focused on the period that starts with the entrance into unemployment (i.e., the period between 0 and t_0) and ends with the time at which the individual exits unemployment (i.e., the period between t_2 and t_3). Note also that as the information about his labour force status is collected at the time of the interview, it is unclear where exactly the transition between the different states of labour force occurred. As an example, consider the first interval s_0, where the individual enters unemployment. As it is only known that he was employed part-time at time 0 and that by the time of the next interview he has entered unemployment, it is unclear where exactly in the interval s_0 he entered unemployment. Rather than pinpointing to the exact time, the analysis instead focuses on intervals or periods. Using the same approach, the next two periods (s_1 and s_2) are constructed during which he is still unemployed. Finally, the final interval s_3 indicates the period when the individual exits unemployment into part-time employment.

By disaggregating the duration into discrete time periods, one can proceed with the analysis by considering the discrete random variable T_i taking values from $\{1,2,..., n_i\}$, values which correspond to the n_i intervals, such that $T_i = j(i)$ whenever $T_i^* \in (t_{j(i)-1}, t_{j(i)}] := s_{j(i)}$ for $j(i) = 1,2,..., n_i$. Note that hereafter, in order to simplify the notation, $j(i)$ will be replaced by j.

This strategy has therefore shifted the focus of analysis from the continuous random variable T^* to the discrete-random variable T. This is appealing in this study because (1) there are a limited number of observations for each individual and (2) the exact timing of events is unknown. Although the timing of the unemployment and the transition from this state might be captured by intervals, their exact timing is not covered in the data. By treating the time of duration using finite intervals, discrete survival models make adjustments for this limitation (Singer and Willett, 2003).

Figure 4.1 - Example of a response

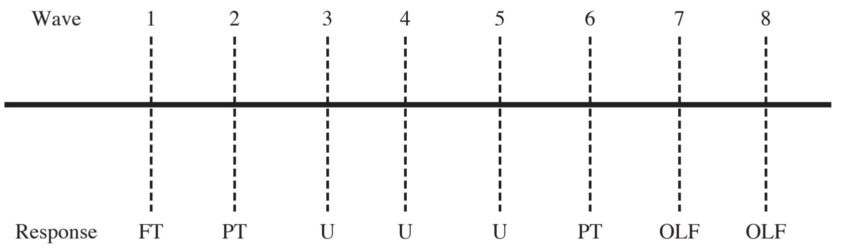
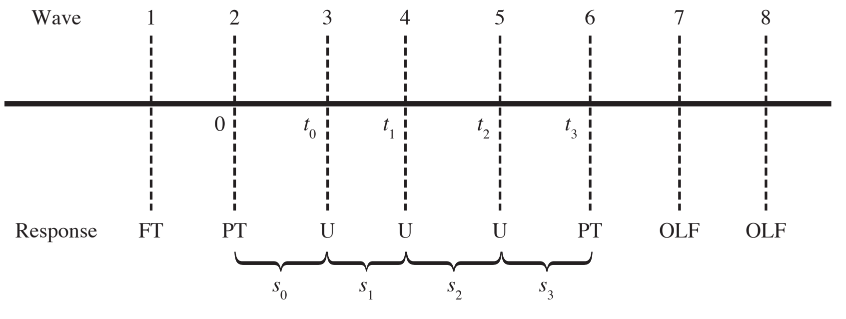


Figure 4.2 - Example of a response – constructing the intervals



Modelling

The research question then analyses the duration T, given the observed characteristics X, the unobserved characteristics W, and the dependence over time, after controlling for the effect of censoring.

Since T is by assumption intrinsically conditional (as it is assumed that individuals experiencing the target event have not experienced it before), interest lies in deriving its conditional probability function. The hazard function, which is well-suited and is central at analysing duration data, can be used for this scope.

In a discrete-time context, the hazard h_{ij}, is defined as the conditional probability that individual i exits the state of unemployment in period j, which corresponds to interval $(t_{j-1}, t_j]$, given that the event has not occurred prior to period j. Mathematically this is given by

$$h_{ij} := h_{ij}(x_{ij}, w_{ij}) := P(T_i = j \mid T_i \geq j, X_{ij} = x_{ij}, W_{ij} = w_{ij}) \qquad (4.1)$$

where X_{ij} and W_{ij} are the vector of observed and respectively unobserved covariates for individual i and where x_{ij} and w_{ij} denote some particular values of X_{ij} and W_{ij}, respectively. Note that the hazard given in (4.1) is very flexible in that it includes covariates that are allowed to vary over time, as indicated by the subscript j.

An important attractive feature of the hazard described in (4.1) is that since T_i is discrete, the hazard is simply a propensity and thus, one can use discrete choice models to model the duration of unemployment. In particular the common logit (used in this paper), the probit, and the complementary log-log models can be used. Specifically, the conditional probability of exit can be modelled as

$$P(T_i = j \mid T_i \geq j, X_{ij} = x_{ij}, \phi_i) = F(\gamma_m + x_{ij}'\beta + \phi_i) \tag{4.2}$$

where γ_m is a polynomial that needs to be specified by the researcher and which captures the duration dependence across the periods in the dataset, $F(.)$ is the *cdf*, and ϕ_i is a random component with known distribution which controls for the effects of the unobserved covariates. For example, if the logistic distribution is imposed, after some simple mathematics, (4.1) and (4.2) lead to the conditional log-odds:

$$\log[h_{ij} / 1 - h_{ij}] = \gamma_m + x_i'\beta + \phi_i \ . \tag{4.3}$$

Given the discrete-time framework and the limited period of analysis, this paper assumes that $\gamma_m = \alpha_1 D_1 + ... + \alpha_m D_m$, which is a complete general specification for time. Here $\alpha = (\alpha_1, ..., \alpha_m)'$ is a vector of coefficients to be estimated, D_i are period indicators (duration dummies) with a value of 1 for period i and 0 otherwise ($i = 1,..., m$), and m is the number of risk periods in the dataset. Note also that by dropping ϕ_i from equation (4.3) one gets back to the standard logit model applied to discrete-duration data.

5. Model application

One of the main aims of this analysis is to investigate the factors that affect the probability of exiting unemployment. As there are different exit states, the analysis uses the competing-risks framework to examine the duration of unemployment. Under this framework, one important assumption is that after conditioning on the regressors included in the model, the occurrence of each of the three events is non-informative for all the other states. This assumption allows for relatively simple parallel analyses where the analysis for each exit state is conducted on the same person-period dataset and where adjustments are only made to the censoring variable – i.e., treating the competing events as censored.

This section has three parts. The first identifies the explanatory variables used in modelling the unemployment duration. The second presents the non-parametric results. Included are raw hazard rates for the whole sample as well as for some key covariates and a life table. The third part focuses on the modelling results of the discrete hazard function presented in section 4. This part includes both the ordinary logit as well as the random effects logit models.

Explanatory variables

In choosing the explanatory variables to be included in the models, the paper considered the information available in the dataset, the relevant literature, and the job-search theoretical framework. Attention has been paid to include both, variables that are expected to affect the probability of receiving a job offer as well as variables that are likely to influence the reservation wage.

The following personal characteristics were included: age, gender, marital status, family composition, educational attainment, previous occupation, whether the individual has previous work experience, English-speaking ability, and period since arrival in Australia.

From this list, educational attainment, previous occupation, English-speaking ability, period since arrival in Australia, and previous work experience are expected to influence the probability of receiving a job offer. These variables tend to be widely used in the literature as proxies for skill or human capital and are therefore likely to affect the attractiveness for the individual's supply of labour (Borland, 2000). Two other variables, namely, marital status and family composition are expected to influence the reservation wage (see Long, 2009; Carroll, 2006).

In addition to these, the paper also includes the geographical location of the individual (state and section of state) and a variable indicating the quarter when the individual first became unemployed. This latter variable is expected to capture some of the economic cycles and is particularly relevant since the dataset includes the GFC. The variables are expected to play important roles in affecting both the probability of receiving a job offer as well as the conditional probability of accepting it (see, Borland, 2000; Productivity Commission, 2014; Long, 2009).

Non-parametric results

Before proceeding with the regression analysis, this section begins with some simple nonparametric plots – raw hazard and survival function plots – and a life table. The results are presented in table 5.1, figure 5.1, and figure 5.2.

The results in table 5.1 indicate that the proportion of individuals moving out of unemployment decreases the longer they are unemployed. In particular, the largest proportion of exits occurs during the first period after they have become unemployed (around 60 per cent) and decreases thereafter for each of the consecutive periods.

Figures 5.2 and 5.3 provide two graphical displays of this phenomenon. Figure 5.2, which displays the raw hazard rate function, shows that if the heterogeneity across individuals is ignored, the risk of leaving unemployment peaks during the first time interval and decreases thereafter, pretty sharply at first but quite smoothly after that. Figure 5.3, which shows the survival function, describes the same phenomenon – the survival function declining most sharply during the first time interval and decreasing at a decreasing rate thereafter. The results are similar to those found by Foley (1997) and Tansel and Tasci (2010).

To complement these results, appendix A includes other exploratory results in the form of a life table for the different types of exits and hazard functions for sex and marital status. The results indicate that after ignoring the heterogeneity across individuals, the hazard rates tend to be decreasing with time for all exit types and that there seem to be differences in the hazard functions across both sex and marital status.

Table 5.1- Life table describing the number of periods spent in unemployment

		Number of those			*Proportion of those*	
Period	*Time Interval*	*Unemployed at the beginning of the period (Risk set)*	*Who left unemployment*	*Censored at the end of the period*	*Unemployed at the beginning of the period who left at the end of the period (Hazard function)*	*Still unemployed at the end of the period (Survival function)*
0	[0,1)	11,073	-	-	-	1.000
1	[1,2)	11,073	6,719	854	0.607	0.393
2	[2,3)	3,500	1,553	401	0.444	0.219
3	[3,4)	1,546	588	216	0.380	0.136
4	[4,5)	742	246	150	0.332	0.091
5	[5,6)	346	99	85	0.286	0.065
6	[6,8)	162	40	122	0.247	0.049

Figure 5.1- Hazard function for the duration of unemployment

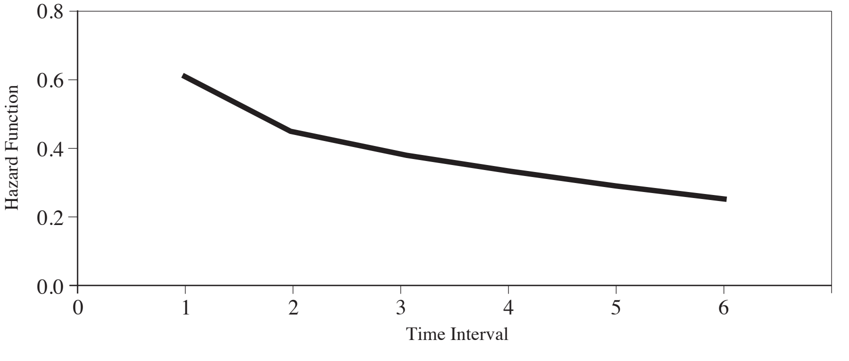
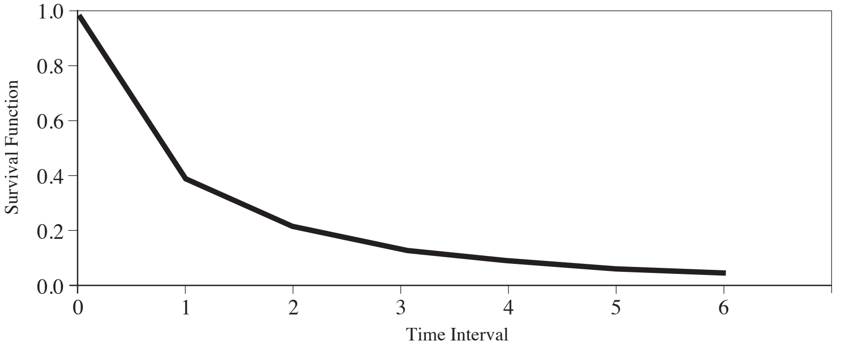


Figure 5.2 - Survival function for the duration of unemployment



Modelling results

Table 5.2 reports the results of the Ordinary Logit model, whereas table 5.3 those of the RE Logit model. In both cases the coefficients of the models are reported as hazard ratios. As the results of the two models are similar, unless otherwise indicated, the discussion below is based on the Ordinary Logit model results.

Personal characteristics

The results differ by age groups with the odds of exiting into full-time employment, after controlling for the effect of the other covariates, generally decreasing with age. The odds of exiting into part-time employment or exiting the labour force, on the other hand, are generally increasing with age, although the increase is small across the second, third, and fourth age groups. These results are consistent with the findings of Borland (2000).

One exception to these patterns is the youngest group (aged 20-24), which has significantly lower odds of exiting into full-time employment than those aged 25-34 and one of the highest odds of exiting into part-time employment. There is however, no significant difference between their odds of exiting the labour force and those of the other age groups – between the ages of 25 and 54.

For the older workers (aged 55-65), the results suggest that once unemployed they are considerably less likely to exit into full-time employment and much more likely to exit out of the labour force than all the other age groups. To put it in perspective, when compared to the odds of the youngest group, the oldest group have around 52 per cent lower odds of exiting into full-time employment and 73 per cent higher odds of exiting the labour force. In the context of recent debates on youth unemployment and mature age workers remaining in the labour force longer, these results are particularly relevant.

In terms of gender and marital status, being male increases the odds of exiting into full-time employment by 27 per cent, whereas being female increases the odds of exiting into part-time employment by 40 per cent. For males, being married increases the odds of exiting into full-time employment, but decreases the odds of leaving the labour force and exiting into part-time employment. The results indicate that being male and married almost doubles the odds of exiting into full-time employment.

Compared to those with only secondary school completed, having higher education (Bachelor or TAFE) increases the odds of exiting into full-time employment (by at least 23 per cent) and decreases the odds of exiting the labour force (by at least 28 per cent). These results support the findings of Borland (2000).

Overall, the individuals with a higher- or middle-skilled last occupation are more likely to exit into full-time employment and are less-likely to exit into part-time employment than those with a lower-skilled last occupation – these results being in line with the findings of Productivity Commission (2014)[3]. There are two exceptions to this. The first relates to the results of those who last worked as machine operators

[3] The paper uses the categories defined in the Productivity Commission (2014) report, where occupations are classified as higher-skilled occupations – managers and professionals; middle-skilled occupations – technicians and trade workers; community and personal services workers; and clerical and administrative workers; and lower-skilled occupations – sales workers; machinery operators and drivers; and labourers.

or drivers and which are not significantly different from those who last worked in a higher-skilled occupation. A reason for this might be due to the employment growth in mining operations that occurred during the period covered by the file and which is likely to have impacted on the demand for labour from this occupation. The second is with regards to those who last worked as community or professional service workers and who are associated with a much lower propensity of exiting into full-time employment and a much higher propensity of exiting into part-time employment. These findings reflect the particular nature of work in this occupation, with workers being more likely to work part-time and with women and older workers constituting a major part of the workforce ABS (2011).

One particular result that stands out is the considerably lower odds of exiting into employment and the considerably higher odds of exiting the labour force for those who have last worked more than two years ago or who are looking for work for the first time.

Overall, when compared to couples with no children and no other dependents, couples with dependents (children or other dependents) have lower odds of exiting unemployment via full-time work and higher odds of exiting unemployment via part-time work or into the OLF status. Based on the magnitude of the estimated coefficients, one-parent families with children are associated with the lowest odds of exiting unemployment via full-time employment, followed by couples with children. One-parent families with children have also the second highest odds of exiting the labour force, surpassed only by one-parent families with no children under 15 years, but with other dependents.

Those from a non-English speaking background are associated with lower odds of exiting unemployment via full-time employment and the odds are lower if the individual arrived recently (i.e., after 2001). These results support those found in Carroll (2006) and Borland (2000). Non-English speakers who arrived after 2001 are associated with higher odds of exiting unemployment via part-time employment or into the OLF status.

Geographical location

The results differ by geographical location, with NT, ACT, WA, and Qld (in that order) being associated with the highest odds of exiting unemployment via full-time employment. SA and Tasmania, on the other hand, have the lowest odds. These findings mirror the differences in unemployment rates across states reported in Borland (2000). They are also consistent with the findings of Productivity Commission (2014) – the mining states having the highest employment growth rates over the last decade. An interesting finding is that for the other exit types the differences in the odds across states are very small. This is informative in that although other previous studies, summarised by Borland (2000), report similar differences in employment across states, they do not distinguish between full-time and part-time employment. This paper provides evidence that these differences are mainly driven by full-time employment.

In addition, the results indicate that, compared to the balance of the state/territory, the capital cities are associated with significantly higher odds of exiting into full-time employment, significantly lower odds of exiting into part-time employment, and similar odds of exiting the labour force.

Initial unemployment quarter

The results for the initial unemployment quarter variable suggest a potential GFC effect. This is indicated by the big change in the magnitude of the odds around the first quarter of 2009. In particular, the individuals who have entered unemployment during this quarter have much lower odds of exiting unemployment via full-time or part-time employment. Those individuals who have entered unemployment during the first two quarters of 2009 are also associated with the largest odds of exiting into the OLF status. This is an interesting result that warrants further investigation.

Baseline hazard function

For the time interval, the results provide evidence that the probability of exiting unemployment into employment depends on the duration of the spell, which is consistent with the findings of other studies, such as Caroll (2006), Borland and Johnston (2011), and Trivedi and Hui (1987). The results were maintained after controlling for unobserved heterogeneity. In addition, the baseline logit hazard function confirms the previous results, as it is generally decreasing over time for all exit types. This is interesting result as it indicates that, on one hand, contrary to the discouraged job seeker effect, the conditional probabilities of exiting into employment as well as that of exiting into the OLF status are lower with a longer unemployment spell. On the other hand, the discouraged job seeker effect cannot be ruled out, as the decline in the hazard rates, of exiting unemployment into employment, could also be explained by a decline in search intensity (the repeated failure to secure a job discouraging the unemployed individuals from fully-exercising their skills when searching for work). Besides, the employer's perception might also be a factor, the employers being reluctant to offer jobs to those with long unemployment spells.

Ordinary vs RE model

Table 5.3 shows the estimation results of the random effects (RE) logit model. The RE logit model was applied to account for unobserved covariates, like motivation, ability, or the intensity of job search.

Overall, the RE logit model results are similar to those of the ordinary probit model, with the likelihood ratio test rejecting the null hypothesis in favour of the random effects model only in the case of the exits into full-time employment. However, even in this case, the rejection is only marginal at the 5 per cent significance level. When complementing these results with the reported AIC and BIC, there does not seem to be sufficient evidence to support selecting one model from among the two (i.e., ordinary and random effects models). Other studies have found similar results, see, for example, Borland and Johnston (2011) and Tansel and Tasci (2010).

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Table 5.2 - Effect of covariates on exit rates – Ordinary logit model – hazard ratios

Variables	*FT*	*PT*	*OLF*
Age Group *(20-24 years)*			
25 - 34 years	1.252 ***	0.736 ***	0.960
35 - 44 years	1.043	0.769 ***	0.997
45 - 54 years	0.925	0.807 ***	1.043
55 - 65 years	0.482 ***	1.038	1.730 ***
Sex *(Female)*			
Male	1.273 ***	0.712 ***	0.856 **
Marital Status *(Not married)*			
Married	0.812 **	1.250 **	1.168 *
Male*married	2.309 ***	0.668 ***	0.703 ***
Education *(Secondary completed)*			
Bachelor	1.242 **	1.080	0.718 ***
TAFE	1.229 ***	1.024	0.708 ***
Secondary not completed	1.147	0.781 ***	0.858 **
Missing	1.322 ***	0.671 ***	0.776 ***
Family Composition *(Couple, no children, no dependents)*			
Couple, no children, other dependents	0.691 ***	1.265 **	1.242 **
Couple, children, other dependents	0.640 ***	1.276 ***	1.449 ***
One parent, children, other dependents	0.486 ***	1.024	1.498 ***
One parent, no children, other dependents	0.753	1.061	1.621 ***
One parent, no children, no other dependents	0.828	0.855	1.177
Lone person	0.814 *	0.971	1.023
Others	0.968	1.358 ***	1.005
Last Occupation *(Professional)*			
Manager	0.934	0.589 ***	1.155
Technician	1.184 *	0.676 ***	1.207 *
Community	0.531 ***	1.274 ***	1.259 **
Clerical	1.017	0.736 ***	1.105
Sales	0.728 ***	0.874	1.140
Operator	0.955	0.621 ***	1.069
Labourer	0.590 ***	1.004	1.289 ***
Last worked more than 2 years ago	0.046 ***	0.154 ***	3.165 ***
First time looking for work	0.098 ***	0.164 ***	2.751 ***
Missing	0.142 ***	0.127 ***	18.897 ***
State *(NSW)*			
Vic	0.897	1.138 **	0.989
Qld	1.206 ***	1.015	0.850 **
SA	0.799 **	1.076	0.957
WA	1.344 ***	1.082	1.096
Tas	0.765 **	1.169	1.018
ACT	1.455 ***	1.039	1.020
NT	2.036 ***	0.946	1.043
Language Spoken *(English)*			
Non-English	0.770 ***	0.907	1.062
Year of Arrival in Australia *(Before 2001)*			
After 2001	0.801 **	1.223 **	1.204 **
Initial Unemployment Quarter *(Quarter 1, 2008)*			
Quarter 2 ,2008	0.854	0.885	1.147
Quarter 3, 2008	0.853	0.923	0.968
Quarter 4, 2008	0.837 **	0.874	0.932
Quarter 1, 2009	0.613 ***	0.656 ***	1.189 *
Quarter 2, 2009	0.763 **	0.820 *	1.218 *
Quarter 3, 2009	0.813 *	0.829	1.065

Table 5.2 - Effect of covariates on exit rates – Ordinary logit model – hazard ratios (continued)

Variables	*FT*	*PT*	*OLF*
Quarter 4, 2009	0.745 ***	0.934	0.999
Quarter 1, 2010	0.651 ***	0.838 *	0.945
Quarter 2, 2010	0.964	0.771 **	1.057
Quarter 3, 2010	0.720 **	0.961	0.970
Quarter 4, 2010	0.892	1.047	0.881
Time Interval			
1	0.333 ***	0.409 ***	0.145 ***
2	0.212 ***	0.268 ***	0.128 ***
3	0.179 ***	0.214 ***	0.125 ***
4	0.147 ***	0.173 ***	0.115 ***
5	0.149 ***	0.136 ***	0.094 ***
6	0.020 ***	0.274 ***	0.082 ***
Area of Usual Residence *(Balance of state/territory)*			
Capital City	1.203 ***	0.810 ***	0.994
Log likelihood	-6307.3	-6676.4	-7895.2
AIC	12724.6	13462.7	15900.4
BIC	13151.5	13889.7	16327.4
Observations (n)	17369	17369	17369

Note: *** p< 0.01; ** p< 0.05; * p<0.10. Reference category is in brackets. Robust standard errors were computed.

Table 5.3 - Effect of covariates on exit rates – Random effects logit model – hazard ratios

Variables	*FT*	*PT*	*OLF*
Age Group *(20-24 years)*			
25 - 34 years	1.297 ***	0.705 ***	0.958
35 - 44 years	1.053	0.744 ***	0.997
45 - 54 years	0.918	0.784 **	1.045
55 - 65 years	0.432 ***	1.044	1.775 ***
Sex *(Female)*			
Male	1.326 ***	0.680 ***	0.849 **
Marital Status *(Not married)*			
Married	0.796 *	1.279 **	1.172 *
Male*married	2.622 ***	0.639 ***	0.696 ***
Education *(Secondary completed)*			
Bachelor	1.260 **	1.095	0.708 ***
TAFE	1.252 **	1.036	0.697 ***
Secondary not completed	1.163	0.758 ***	0.855 **
Missing	1.383 ***	0.645 ***	0.769 ***
Family Composition *(Couple, no children, no dependents)*			
Couple, no children, other dependents	0.644 ***	1.307 **	1.252 **
Couple, children ,other dependents	0.589 ***	1.313 ***	1.473 ***
One parent, children, other dependents	0.440 ***	1.015	1.525 ***
One parent, no children, other dependents	0.726	1.071	1.650 ***
One parent, no children, no other dependents	0.794 *	0.834	1.184
Lone person	0.801 *	0.963	1.022
Others	0.962	1.412 ***	1.003

Table 5.3 - Effect of covariates on exit rates – Random effects logit model – hazard ratios (continued)

Variables	*FT*	*PT*	*OLF*
Last Occupation *(Professional)*			
Manager	0.910	0.544 ***	1.158
Technician	1.220 *	0.640 ***	1.217 *
Community	0.480 ***	1.357 **	1.270 **
Clerical	1.004	0.702 ***	1.112
Sales	0.686 ***	0.858	1.141
Operator	0.959	0.576 ***	1.071
Labourer	0.536 ***	1.012	1.300 ***
Last worked more than 2 years ago	0.035 ***	0.125 ***	3.370 ***
First time looking for work	0.077 ***	0.134 ***	2.881 ***
Missing	0.116 ***	0.107 ***	21.200 ***
State *(NSW)*			
Vic	0.884	1.163 *	0.988
Qld	1.255 ***	1.025	0.841 **
SA	0.771 **	1.080	0.953
WA	1.413 ***	1.096	1.096
Tas	0.742 **	1.197	1.017
ACT	1.550 ***	1.052	1.022
NT	2.277 ***	0.936	1.039
Language Spoken *(English)*			
Non-English	0.739 ***	0.890	1.065
Year of Arrival in Australia *(Before 2001)*			
After 2001	0.782 *	1.279 *	1.213 **
Initial Unemployment Quarter *(Quarter 1, 2008)*			
Quarter 2 ,2008	0.824	0.862	1.155
Quarter 3, 2008	0.817	0.908	0.966
Quarter 4, 2008	0.808 **	0.862	0.931
Quarter 1, 2009	0.567 ***	0.616 ***	1.200 *
Quarter 2, 2009	0.730 **	0.790 *	1.234 *
Quarter 3, 2009	0.781 *	0.791 *	1.071
Quarter 4, 2009	0.704 ***	0.919	0.999
Quarter 1, 2010	0.600 ***	0.814 *	0.944
Quarter 2, 2010	0.931	0.740 **	1.060
Quarter 3, 2010	0.680 **	0.944	0.970
Quarter 4, 2010	0.870	1.049	0.875
Time Interval			
1	0.284 ***	0.362 ***	0.135 ***
2	0.207 ***	0.267 ***	0.125 ***
3	0.196 ***	0.232 ***	0.125 ***
4	0.173 ***	0.201 ***	0.119 ***
5	0.187 ***	0.166 ***	0.100 ***
6	0.026 ***	0.350 **	0.090 ***
Area of Usual Residence *(Balance of state/territory)*			
Capital City	1.237 ***	0.783 ***	0.993
Log likelihood	-6305.7	-6675.7	-7894.8
Sigma	0.887	0.851	0.413
Rho+	0.193 **	0.180	0.049
AIC	12723.4	13463.5	15901.6
BIC	13158.1	13898.2	16336.3
Observations (n)	17369	17369	17369

Note: *** p< 0.01; ** p< 0.05; * p<0.10; + = likelihood ratio test for rho = 0. Reference category is in brackets. Robust standard errors were computed.

6. Concluding remarks

Building on the job-search theoretical framework, this paper examines the transitions from unemployment using the ABS Longitudinal Labour Force Survey file. The file covers a three-year period, from the beginning of 2008 to the end of 2010, and includes more than 1.8 million records from around 150,000 households observed over a period of up to eight consecutive months.

From a methodological perspective, the paper implements the following techniques to deal with the specific features of the data and of the analysis. First, the analysis is restricted to those who become unemployed during the eight-month interview period. This approach avoids the reliance on retrospective information and the model complexities involved with dealing with left censoring/truncation. Second, to capture the discrete nature of the duration data and to deal with left censoring, discrete duration models are implemented. This strategy shifts the focus of the analysis from modelling a continuous random duration variable to that of an analysis conducted on time intervals. Third, to separately consider the different unemployment exits, the analysis adopts the competing-risks framework and separately examines the transition into three different exit states: full-time employment, part-time employment, and out of the labour force. Finally, to account for unobserved heterogeneity, random effect models are considered.

From an empirical perspective – and also in response to the two questions posed in the introduction – the following can be noted. First, the results differ by age groups with older workers (aged 55-65) having significantly lower odds of exiting unemployment into full-time employment and with much higher odds of exiting the labour force. In the context of debates on youth unemployment and mature age workers remaining in the labour force longer, the markedly higher exit rates to employment for the youngest group (aged 20-24) compared, in particular, to the oldest group are particularly relevant.

Second, the hazard rates are significantly affected by the potential determinants of the probability of receiving a job offer, such as education, English language proficiency, work experience, and last occupation. These characteristics, as Borland (2000) indicates, are often used as proxies for skill or human capital. In particular, the results indicate that higher education, English language proficiency, work experience, and a higher-skilled last occupation are all associated with higher odds of exiting into full-time employment. One interesting finding is that those who last worked two years ago or longer, or are first time looking for work, have substantially lower hazard rates of exiting into employment and substantially higher rates of exiting the labour force.

Third, the variables which are likely to affect the reservation wage, in particular marital status and family composition, are equally important in explaining the heterogeneity across individuals. For males, being married increases the odds of exiting into full-time employment, but decreases the odds of exiting into part-time employment and leaving the labour force. For females, the opposite results are observed. Note also the markedly different results for one-parent families. In particular, when compared to the other types of families, lone parents with children have the lowest odds of exiting into full-time employment. These results point towards the importance of considering both types of variables when analysing the duration of unemployment, those affecting the demand of an individual's labour as well as those affecting the reservation wage.

Fourth, the results differ significantly across regions with the ACT and the mining states of WA, NT, and Qld being associated with the highest odds of exiting unemployment into employment. Interestingly, a recent Productivity Commission report on geographical labour mobility found that exactly the same states and territories are associated with the lowest unemployment rates and the strongest employment growth, Productivity Commission (2014). These and the previous results can be useful, for example, in targeting the groups with low probability of leaving unemployment for employment or those with high probability of exiting the labour force.

Fifth, the hazard rate seems to be affected by economic cycles. Most notably, the results point towards potential GFC effects. These effects are depicted by the sudden drop in the odds of exiting into any type of employment during the last quarter of 2008 and by the sudden peak of exiting the labour force during the last quarter of 2008 and the first quarter of 2009.

Sixth, the results indicate that the probability of exiting unemployment depends on the length of unemployment spell with the baseline hazard function decreasing over time for all exit types. The results persist even after controlling for unobserved heterogeneity. In the light of the hysteresis of unemployment theory, these results provide some evidence for path dependence of unemployment.

The shape of the baseline hazard functions suggests, on one hand, that contrary to the discouraged job seeker effect, the probabilities of exiting into employment as well as the probability of exiting into the OLF status are lower with a longer unemployment spell. On the other hand, the discouraged job seeker effect cannot be ruled out, as the decline in the hazard rates, of exiting unemployment into employment, could also be attributed to a decline in search intensity. Besides, the employer's perception might also be a factor. This is an interesting result that is worthy of further investigation.

Finally, the results indicate that the groups in most need of assistance (specifically, for securing full-time employment) include those who last worked two years ago or longer, those who are first time looking for work, single parent families with children, and the individuals aged 55-65 years. These are interesting results that deserve further examinations. It should also be noted that as the time period covered by this study is relatively short and as it includes the GFC, a further extension would be to examine these results over a longer and a different time period.

Appendices

A1. Analysis results

Table A.1 - Hazard and survival functions for exiting unemployment

Hazard Functions				
Time Period	*Any Exit*	*FT*	*PT*	*OLF*
0	-	-	-	-
1	0.607	0.171	0.173	0.263
2	0.444	0.123	0.125	0.196
3	0.380	0.107	0.102	0.171
4	0.332	0.084	0.082	0.166
5	0.286	0.081	0.064	0.142
6	0.247	0.012	0.105	0.130
Survival Functions				
Time Period	*Any Exit*	*FT*	*PT*	*OLF*
0	1.000	1.000	1.000	1.000
1	0.393	0.829	0.827	0.737
2	0.219	0.727	0.723	0.593
3	0.136	0.650	0.649	0.491
4	0.091	0.595	0.596	0.410
5	0.065	0.547	0.558	0.352
6	0.049	0.540	0.500	0.306

Figure A1.1 - Hazard function for the duration of unemployment by sex

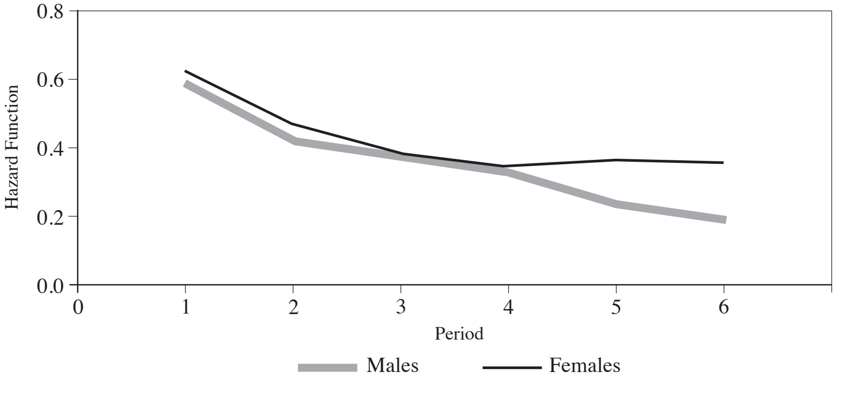
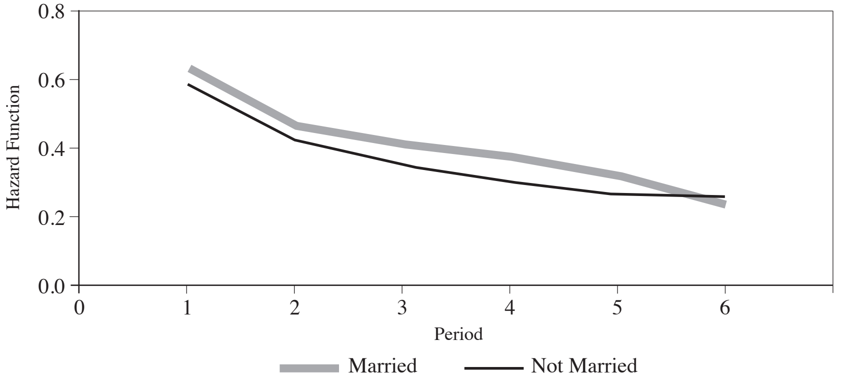


Figure A1.2 - Hazard function for the duration of unemployment by marital status



A2. List of variables

This section includes the list of variables used in the models.

State
NSW
Vic
Qld
SA
WA
Tas
NT
ACT

Sex
Male
Female

Age Group
20-24
25-34
35-44
45-54
55-65

Marital Status
Married
Not married

Occupation
Managers and administrators
Professionals
Technicians and trade workers
Community and professional service workers
Clerical and administrative workers
Sales workers
Machinery operators and drivers
Labourers
Last worked more than 2 years ago
First time looking for work
Missing

A2. List of variables (continued)

Education
Degree – Bachelor or Postgraduate degree
TAFE – Diploma or Certificate
Secondary school completed
Secondary school not completed

Language Spoken
English
Non-English

Year of arrival in Australia (non-English speakers)
Before 2001
After 2001

Initial Unemployment Quarter
Quarter 1, 2008
Quarter 2, 2008
Quarter 3, 2008
Quarter 4, 2008
Quarter 1, 2009
Quarter 2, 2009
Quarter 3, 2009
Quarter 4, 2009
Quarter 1, 2010
Quarter 2, 2010
Quarter 3, 2010
Quarter 4, 2010

Family Composition
Note:
First digit: family
Second digit: number of parents (1 – single and 2 – couple)
Third digit: whether the family has children under 15
Fourth digit: whether the family has other dependents

0000 – Lone person
1100 – One parent family with no children and no other dependents
1101 – One parent family with no children under 15 and other dependents
1111 – One parent family with children under 15 and other dependents
1200 – Couple family with no children and no other dependents
1201 – Couple family with no children under 15 and other dependents
1211 – Couple family with children under 15 and other dependents
9999 – Others

Time Interval
Note: this splits the period of 8 waves into intervals
1
2
3
4
5
6 (i.e., the last two periods were combined because of the small sample sizes)

Area of Usual Residence
Capital city
Balance of state/territory

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