Social Determinants and Regional Disparity of Unemployment Duration in Australia: A Multilevel Approach

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Abstract

The economic and social costs associated with unproductive time spent in labour market transitions between jobs and between unemployment and employment have been the subject of recent policy debate. There is now broad support for policies that provide both positive and negative incentives to those on unemployment benefits to influence relocation decisions to areas of better labour market opportunities. In this paper we examine the social determinants of time to exit from unemployment to employment and variation across functional economic regions, separately for men and women. Taking a life-course approach and using the first eight waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey we allow individuals to experience repeated episodes of unemployment over time by estimating a multilevel discrete-time event history model for the hazard of exit from unemployment. The model has a three-level hierarchical structure with episodes of unemployment nested within individuals, and individuals are themselves nested within regions. This enables an assessment of unobserved heterogeneity in unemployment duration among individuals and also among functional economic regions. The dataset is based on the HILDA employment calendar reporting schedule which collects information at three time points each month, matched to the dates of life transitions reported in the annual survey, and annual wave-based covariates. Applying a multilevel discrete-time piecewise constant hazard model across recurrent episodes of unemployment, we identify the social characteristics of individuals most at risk for periods of long-term unemployment. We focus on the differences between men and women and whether relocating to a new region may increase the probability of successful transition out of unemployment. While previous labour force experience in unemployment is associated with longer time to exit from unemployment for both men and women, we find that the social factors associated with the process of time in unemployment differ markedly for men and women. In particular, age and marital status are significant drivers for reducing men's time in unemployment, while the presence of children under the age of five years increases a woman's time in unemployment. We also find that duration in unemployment varies across functional economic regions for women even after accounting for social factors and previous labour force experience at the individual level.

Introduction

The trend in duration of unemployment is of national interest due to the economic and social costs associated with unproductive time spent in labour market transitions between jobs and between unemployment and employment. Perhaps more important are the financial and social costs borne by individuals, some of which are absorbed by welfare payments but many of which are faced by families and communities who may not have the capacity to absorb them without considerable dislocation. Unemployment not only means a loss of economic security but also feeds poverty and social dislocation as the ties of civil society are severed. In general, unemployment removes an important set of social relationships without which many people have little support or security in dealing with often profound economic hardship. The longer the duration in transition from unemployment to employment, the more these hardships are exacerbated.

A number of studies have shown that absences from employment are associated with the under use and underdevelopment of skills (Vickery, 1999), and the loss of human capital and limited occupational advancement (Burbidge, 2005). Such absences can also lead to the deterioration of labour market prospects, or scarring, in the form of relatively poor prospects of finding work (ABS, 2001; Saunders & Brown, 2004), loss of income whilst unemployed and lower wages on return to the workforce (Arulampalam, 2001; Green & Leeves, 2009; Stevens, 1997), vulnerability to repeated incidence of unemployment, and/or cycling between unemployment and low paid jobs (Gregg & Tominey, 2005; Stewart, 2007; Watson, 2008). Thus, the longer the period of time spent in unemployment, the lower an individual's likelihood of gaining employment. This is not only due to loss of skills, but also because employers may be reluctant to employ the long-term unemployed, in which case economic policies aimed at reducing unemployment may have limited success (ABS, 2001).

The characteristics of the geographical space in which people reside and work have implications for their ability to move between jobs, particularly for those living in regional and remote locations. Identifying the social and regional determinants of the risk of long-term unemployment can inform social policy to help minimise the duration and consequences of unemployment. The national labour market can be thought of as a spatial mosaic of overlapping local markets (Loveridge & Mok, 1979). In a spatial context, adjustments in the labour market occur both through labour migration involving a semi-permanent shift in workplace location and changes in commuting patterns (Gordon, 2001). The competitive equilibrium model of the labour market assumes that individuals will move

away from regions or localities with the least favourable employment opportunities. However, these assumptions concerning geographical mobility are challenged by structural factors that are associated with particular locations. These include: housing affordability and housing availability in the preferred locality (Dockery, 2000), the existence of income support in the existing locality, the existence of family and social networks in the existing locality and costs of travel to work in the new locality (Baum, Bill, & Mitchell, 2008a). In short, there may be a net loss in a mover's aggregate welfare after they relocate (see Bradbury and Chalmers (2003), Marshall et al (2003)). Changes and developments in transport and housing continually redefine the commuting propensities, the residential mobility opportunities and capacities of workers (Martin & Morrison, 2001).

The variability in labour market outcomes is to some degree a response to a 'spatial mismatch' between the available job opportunities and human capital, particularly skills, education, health and training. Spatial dynamics affected by new economic geography and changing connectivity via information and communication technologies have underpinned the characteristics of labour markets and patterns of work, particularly for areas which were based on historical patterns of industry and occupation (Boreham, Parker, Thompson, & Hall, 2008). Such a spatial mismatch between competitive areas, which are found to be globally connected and endowed with innovative technologies, investment and relevant skills and areas that are supported on local resources, has a strong bearing on the characteristics of employment transitions. In such situations, people living in relatively remote areas distant from and poorly connected to major centres of employment growth might face strong geographic barriers to finding a full-time job or keeping well-paid jobs (Inlanfeldt, 2005; Kain, 1968). The likelihood of an employment transition may become, in part, a function of the level of risk involved in changing place of work or increasing commuting time.

In order to identify more vibrant, competitive and innovative areas and their relationship with transitions, an approach based on structural and functional characteristics can enable us to measure the level of economic exchange, dependency and spatial interaction between areas. In this paper we utilise the new functional economic regions (FERs) developed by Mitchell and Watts (2010) (see also Mitchell and Stimson (2010)). The FERs were developed using the Intramax hierarchical aggregation technique to group statistical local areas (SLAs) by commuting behaviour using the 2001 Journey-to-Work data collected from the Australian Bureau of Statistics 2001 Census of Population and Housing. According to Mitchell and Watts (2010) "The Intramax technique emphasises labour force flows and optimises SLA groupings based on higher than expected interactions between neighbouring

areas, and appears to provide a much closer approximation to a local labour market". That is, commuting to work behaviour is tightly self-contained within a FER and commutes across regional boundaries are minimised. It is well known that if spatial processes are in existence and are not accounted for in statistical analyses then estimates of effects of independent variables will be inaccurate and inference will be biased (Baller, Anselin, Messner, Deane, & Hawkins, 2001). Consequently, the development of these FERs is very important for the purpose of statistically analysing employment-related data because the spatial aggregation of data based on this new geography has been shown to overcome some of the problems associated with spatial autocorrelation (Mitchell & Stimson, 2010).

A range of labour market related and personal characteristics are known to be associated with the duration of unemployment spells. Time-varying demand side factors, (ie, how many jobs there are, the collapse or growth of particular industries) proxied for by the vacancy rate or rate of unemployment, appear to affect unemployment spell duration (Baum, Bill, & Mitchell, 2008b; Borland & Johnston, 2010). Several studies find that the duration of unemployment spells increases with age, and decreases with higher levels of education attainment (Hardin & Kapuscinski, 1997; Heath & Swann, 1999). Previous labour market experience tends to have a negative effect on the duration of unemployment spells (Borland & Johnston, 2010; Carroll, 2006). Persons who are married, and particularly those who have a spouse working, appear to have shorter unemployment spells (Stromback, Dockery, & Ying, 1998). The incidence of unemployment varies between demographic and skill groups in the labour force. Migrants generally have a longer duration of unemployment than Australian-born persons, and migrants from non-English speaking countries, particularly Asian countries, have a significantly higher duration of unemployment than those from English speaking countries (Junankar & Kapuscinski, 1991). Individuals whose last job was in a particular occupation, such as blue-collar type occupations, or particular industries, for example manufacturing, are more likely to experience a longer duration of unemployment (Borland & Kennedy, 1998; Junankar & Kapuscinski, 1991). If this is the case, then it is anticipated that regions with a higher presence of these types of industries or occupations will have poorer unemployment outcomes. As previously noted, lengthy or recurrent spells in unemployment can result in scarring/duration dependence. These issues are increasingly important in the context of significant economic, social and demographic change as more groups within the population such as mature age workers, women, the long-term unemployed, those with health problems, Indigenous people and school leavers face

exclusion from the labour market due to their personal attributes and skills, life course position and regional constraints (Ziguras, 2005).

In particular, we focus on the difference in employment trends for men and women. Women have often indicated a preference for part-time work as a way of attempting to combine child bearing and child rearing, home and non-child related caring responsibilities, for which women still bear the overwhelming responsibility (ABS, 2009; Hakim, 2000). Duration of unemployment for women is affected by their movement in and out of the labour force. Women may move in and out of part-time work more frequently, and also transition more frequently between full-time and part-time work. Many women with childrearing or home duties may move out of official unemployment altogether and for some, into the category of hidden or discouraged unemployed. These transitions lessen both the rate and average duration of unemployment.

In a recent study, Borland and Johnston (2010) analysed seven waves of HILDA survey data to examine the relation between an individual's job duration and prior labour market experience. They used a hazard model to examine a person's first spell following wave one for exit from employment and exit from unemployment and pool the data for men and women when modelling exit from unemployment. We extend this research by capturing repeated episodes of unemployment in our modelling approach, separately for both men and women, and by examining variation in the hazard of exiting unemployment among FERs. We use three-level multilevel discrete-time event history models to examine the social determinants of time in unemployment for recurrent episodes of unemployment and to capture unobserved heterogeneity among individuals and among FERs.

We address three key questions:

- Does the duration dependence for exit from unemployment to employment differ for men and women?
- What are the effects of social determinants and previous unemployment history on duration of unemployment, and do these differ for men and women?
- Does time in unemployment vary by Functional Economic Region?

Methodology

Data and variables

We use the first eight waves (2001-2008) of the Household Income and Labour Dynamics in Australia (HILDA) survey. HILDA is an annual household survey consisting of

7,682 households and 19,914 individuals in wave 1. If sample members move household, then all willing members of the new household who are over 15 years old become sample members and are also interviewed next wave. Our analyses are restricted to include respondents who have responded to all interviews and who were aged between 18 and 64 years old inclusive at the time of their first interview. With our methodological approach it is not necessary that survey participants respond to all waves of the data, however, due to the complexity of model estimation we have chosen to examine a balanced dataset for initial analyses. The balanced dataset containing all possible employment transitions includes data for 6,580 individuals. In order to more accurately assess the effect of economic region on individual outcomes, we have further restricted our datasets to exclude respondents from Functional Economic Regions which contain fewer than ten respondents. From the balanced dataset we analysed separately men and women who had had at least one spell of unemployment which was either ongoing or ended in employment. The final datasets contain 1381 individuals; 622 men (45%) and 759 women (55%).

Employment status spells

Within each personal interview is a detailed calendar where respondents report their labour force state for every third of a month for up to eighteen months preceding the interview (unless otherwise stated, 'time period' refers to units of a third of a month throughout this manuscript). We aggregate labour force states into three categories: employed, unemployed, and not in the labour force. Respondents reporting that they have had one or more jobs during this reasonably short time period are classified as employed, irrespective of hours worked and inclusive of periods of paid leave. With the exception of the wave one interview, discrimination between full-time and part-time jobs is not included in the calendar. Respondents reporting that they do not have a job and are looking for work are classified as unemployed and respondents reporting that they do not have a job and are not looking for work are classified as 'not in the labour force'. Calendars for consecutive years have up to six months of responses that overlap. In cases where there is discrepancy between responses in this overlap, we use the response from the earlier wave to reduce the effect of recall bias, as that response is recorded most closely in time to the reporting period (Borland & Johnston, 2010). Missing values for employment status are carried forward from the previous labour force state, up to a maximum of one year. Respondents with longer spells of missing data were excluded from the analysis.

For each employment status (employed/unemployed/not in the labour force) at each time point, we calculate duration in each employment status as well as the number of spells in each employment status that the respondent has experienced during the time surveyed. For spells which begin prior to the respondents' first interview, the length of time in that labour force state is included in the spell length of the initial labour force state. Calendar data reported at wave 1 is not included in our dataset, as the start date of the employment status spell is only recorded for the spell in progress at the time of the first interview. Respondents are classified as transitioning into another employment status if they change employment state in the following month-third. Therefore, transitions are recorded as transitions out of a particular labour force state, and are recorded against the final time period a person spends in that spell. As the substantive interest of this study is the time spent in unemployment, spells are conceptualised as spells of a continuous labour force status, not necessarily continuous periods spent in the same job or activity. Following Aassve et al (2006) a person who holds a series of short-term jobs across a one year period and does not report in any intervening month-third that they are unemployed or not in the labour force, is considered to be continuously employed for that year, irrespective of the fact that they are employed in a series of different jobs. This is one of the first analyses of HILDA calendar-based labour force data that includes multiple episodes of unemployment and durations per individual.

Respondents recorded up to a maximum of four different employment status spells per year, averaged over the number of years in which they were included in the sample. The advantage of using the HILDA employment calendar to examine multiple durations per respondent, is that such rapid cycling though employment statuses can be captured in our models. This fine level of granularity will be overlooked in studies which use the annual periodicity of the HILDA interviews rather than the month-third data captured in the calendar.

Dependent variable

The dependent variable in our analyses is the transition from unemployment to employment; that is, whether the unemployed respondent becomes employed in a particular time period or continues in their spell of unemployment. Unemployment transition is a binary variable, where a transition to employment is coded as 1, and continuation of the unemployment spell is coded as 0.

Covariates

Unemployment duration in each time period is treated as a piecewise categorical variable, where time from the beginning of the unemployment spell is calculated as one of the

following: less than or equal to three months; three to six months; six to twelve months; twelve to eighteen months; eighteen months to two years; over two years.

We summarise labour-market history for each respondent by the proportion of time spent in unemployment prior to starting the HILDA survey and after leaving full-time education. We included covariates on age at entry to the survey in order to capture cohort effects, gender, Indigenous Australian or Torres Strait islander descent, highest education level attained, the section of state in which respondent resides, whether respondent has a long term health condition that limits the type or amount of work they may perform, and level of English (whether respondent speaks English poorly or not at all and speaks another language at home).

Additional major life events may be reported as a number of months and/or years prior to an interview or as yes/no responses to whether an event happened in the last 3 months, 4-6, 7-9 or 10-12 months. We therefore approximate the dates of these life events to the month-third level. Derived variables from such dates include marital status, whether the respondent has children under five years old and whether respondent has moved residential location. Marital status is defined as whether the respondent reports that they are married, cohabiting, or not partnered in each time period. The variable indicating whether the respondent has children under five years old combines both resident and non-resident children, since for births which occurred prior to wave one it is not possible to determine who the child lived with. The date of residential relocation is combined with the respondent's geographic location to produce a derived variable which indicates if and when they have relocated to a different functional economic region since the period of unemployment began (see below).

Regions

We include spatial information on respondents by linking Statistical Local Areas (SLAs) in the HILDA dataset to FERs, developed by the Centre of Full Employment and Equity at the University of Newcastle (Mitchell & Watts, 2010)[1]. This is particularly useful for minimising spatial autocorrelation encountered when using regions defined for political or administrative reasons (for example Local Government Areas) to summarise economic or labour-force measures. We group respondents according to FER to determine whether time in unemployment varies significantly across FERs of different labour force characteristics.

[1] Permission was given from FaHCSIA to link the HILDA In-Confidence Survey data to a non-standard geography in order to conduct this analysis.

To avoid issues of very small sample sizes within FERs, all respondents living in FERs which contained fewer than ten male or fewer than ten female survey respondents were removed from the analysis. Of the 115 FERs occupied by the respondents in the balanced dataset, fifty FERs contained fewer than ten female respondents, and forty-nine FERs contained fewer than ten male respondents. Our models for women are based on respondents grouped into sixty-five FERs and our models for men are based on respondents grouped into sixty-six FERs. As this reduces the size of our sample, in future analyses we will investigate combining FERs containing low numbers of individuals with neighbouring FERs. We include the unemployment rate in each of the analysed FERs as a contextual FER level covariate to help explain the variation between regions. Unemployment rate in each FER is calculated by CoFFEE from the 2006 Census of Population and Housing.

Modelling Approach

The likelihood of a person transitioning out of unemployment and into employment was modelled using a three-level multilevel discrete-time event history model with a piecewise-constant hazard. An individual can experience repeated episodes of unemployment and exit to employment across the course of the survey and this is captured in the model by specifying the individual as a level with a random intercept. The episodes of unemployment are considered as level one observations clustered within an individual which becomes the level two unit. The third level in the model is the FER in which the individual resides during the time of unemployment. Because our time periods are quite small, we use a logit link function to estimate the time to exit from unemployment and the associations with social covariates, and specify random intercepts for individuals and FERs to examine unobserved heterogeneity. The `xtmelogit` function in Stata software (version 11) was used to estimate the models. The models for women and men were estimated separately to accommodate the gendered social processes that influence episodes and time in unemployment. Similar models for recurrent employment transitions using data from the British Household Panel Survey have recently been considered by Steele (2011) and Aassve et al (2006).

Six models were built up in a stepwise manner, where blocks of explanatory variables corresponding to different social processes were added sequentially, creating a series of increasingly complex models. The models are defined as follows:

Model 1: contains only the piecewise duration of unemployment as an independent variable, creating the baseline hazard model for transitioning to employment.

Model 2: builds on the hazard model with the addition of covariates for personal characteristics including age at entry to the HILDA survey, ATSI status, country of birth, whether the respondent self reports poor English fluency, and whether the respondent has a health condition which limits their ability to work.

Model 3: includes the additional educational and labour market variables, such as the highest educational qualification obtained, and the proportion of time between leaving school and entering the HILDA survey where the respondent was unemployed or not in the labour force.

Model 4: introduces the respondent's relationship ties, that is, their marital status and whether or not they have children under five years old.

Model 5: contributes variables which indicate both the broad geography in which the respondent lives (locality size) as well as whether the respondent has moved to a different FER since their spell of unemployment began.

Model 6: includes a measure of the 2006 unemployment rate for the FER as a contextual variable associated with a region that may influence an individual's unemployment duration.

Descriptive Analysis

Incidence of Unemployment Episodes

The HILDA survey calendar data for employment does not contain the full history of employment spells for an individual prior to wave one. Therefore, it is not possible to determine how many episodes of employment an individual has experienced since leaving school. To describe trends in employment transitions over the life-course we first considered the number of people who have experienced an employment transition sometime during the eight waves of HILDA categorised by age cohort. Table 1 shows that over all age cohorts approximately 50% of individuals underwent an employment transition during some period between 2001 and 2008. However, this pattern changes markedly with age cohort and differs for men and women. For the entire sample, the proportion of individuals who experienced a transition was greatest for those in the 18-24 age category at wave 1 at 0.74. This proportion was reduced to 0.57 for the 25-34 age cohort and reduced further to 0.46 for the 35-44 age cohort. This proportion did not change for the older age cohorts. For women in the 18-24 age

cohort, the proportion who experienced an employment transition was 0.81 compared to 0.66 for men of the same cohort. Women experience employment transitions more often than men up until the 55-64 age cohort. This trend reflects women's more frequent movement in and out of part-time and full-time work as they balance work and family commitments.

INSERT TABLE 1 HERE

For the 3,273 respondents who did not report a transition in labour-force status, Table 2 summarises the distribution of men and women in the sample by employment status. All individuals that did not experience an employment transition were employed either full-time or part-time (0.88 for men and 0.70 for women) or not in the labour force. No person was unemployed and looking for work for the whole period of the survey. The majority of men from in the three youngest age cohorts (18-44) were employed, however, the older cohorts of men were more likely to be in the NILF category (0.11 for age cohort 45-64 and 0.56 for age cohort 55-64) as they moved into the retirement period. Women, on the other hand, were more likely than men to be in the NILF status (0.15 from age cohorts 25-44, 0.23 from age cohort 45-54 and 0.76 from the oldest cohort at wave 1, 55-64).

INSERT TABLE 2 HERE

INSERT TABLE 3 HERE

The average and median number of any labour force episode experienced by an individual who has undergone a transition, and also the number of unemployment spells, are shown by sex and age category at wave 1 in Table 3. For the cohorts who were under 55 in wave 1, women tend to experience more labour force episodes than men with the highest number occurring for age cohort 18-24 (4.97 for women and 4.34 for men). However, more unemployment episodes are experienced by men for all age cohorts except the oldest, 55-64. On average, women of the youngest cohort, 18-24 years, experienced 2.11 unemployment episodes compared to men who experienced 2.24 episodes of unemployment. However, women in the oldest cohort, 55-64 years, experienced 2.40 episodes of unemployment on average while men in the same age cohort experienced only 1.50 episodes.

Duration in Unemployment

For those who experienced a transition in employment status, the duration of the episode was computed for all episodes that ended with an exit transition (episodes that are right-censored at wave 8 are excluded from this analysis). Table 4 shows the average duration in months that an individual was in an episode, by employment status and age category. As most people strive to remain employed, it is not surprising that the average time in employment increases with age. The average time in employment is 2.5 years for the 18-24 age cohort and this increases to just over 11 years for the 55-64 age cohort. The variation in the duration of unemployment across age cohorts is much smaller, ranging from 5 months for the 18-24 age cohort to 10.5 months for the 55-64 age cohort. Table 5 shows the distribution by age category at wave 1 separately for men and women. For women, the average duration in unemployment is more stable across the age cohorts increasing to 7 months for the 45-54 age cohort and then 8 months for the oldest cohort. On the other hand, men's time in unemployment almost doubles from 6.5 months in the 35-44 age cohort, to 12.5 months for the oldest cohort.

INSERT TABLE 4 HERE

INSERT TABLE 5 HERE

Relocation between functional economic regions (FERs)

Tables 6 and 7 show the proportion of respondents who had a household move event and the average number of move episodes during the period of the HILDA survey, respectively. Both tables show similar trends for men and women with almost 50% of individuals moving households at least once. It is clear that household moves (3.34 times) occurred more frequently for people in the youngest age cohort (88%) and least frequently (1.44 times) for the oldest age cohort (29%).

To determine whether duration in unemployment was lower for people who relocated between FERs, we identified individuals who relocated during the period of the HILDA survey while unemployed. Of the 1436 respondents in the analysis who reported being unemployed at least once, only 88 reported having relocated between FERs. A binary variable was created to indicate whether a move had occurred while unemployed and this was included in Models 5 and 6.

Results from Multilevel Models

The results from the estimation of the multilevel discrete-time event history models with repeated episodes of unemployment are shown separately for women and men in Tables 8 and 9, respectively. To capture the correct structure of the data, the models are specified so that repeated episodes of unemployment are nested within individuals who are further nested within FERs. We discuss the results for each of our research questions in turn.

INSERT TABLE 8

INSERT TABLE 9

Does the duration dependence for exit from unemployment to employment differ for men and women?

- Some evidence that increased duration of unemployment for women decreases likelihood of getting a job particularly for long-term unemployment greater than 2 years - but much weaker effect than for men.
- Increased duration of unemployment significantly decreases men's chances of getting a job.

What are the effects of social determinants and previous unemployment history on duration of unemployment, and do these differ for men and women?

For women:

- No effect of age on likelihood of employment
- Some evidence that ATSI women are less likely to find work (this did not apply for men)
- Women born in non-English speaking countries less likely to exit unemployment to work than women born in Australia, even controlling for English fluency
- Limiting health conditions reduce likelihood of gaining employment
- No impact of education on likelihood of finding work (this may certainly impact on likelihood of finding satisfactory work or number of hours, but as we're treating all work the same, this would have to be explored in future research).
- Marital status does not influence women's likelihood of finding work, but having children under 5 significantly reduces a woman's likelihood of exiting unemployment.

- The higher the proportion of work history spent in either unemployment or outside the labour force, the less likely women are to find work, but the effect is much stronger for unemployment than for NILF.
- Women living in smaller urban locations (pop between 1000 & 100000) are less likely to find work than women living in major urban locations (no effect of locality for men)

For men:

- Unlike for women who have no effect for age cohort, men have a negative effect of age cohort on likelihood of gaining work
    - No difference between 18-24 and 25-35
    - Some evidence that men who were 35-44 years old on entry to the HILDA survey are less likely to transition out of unemployment than men where were 25-34.
    - Significantly less likelihood of transitioning for men 45-54 & 55-64 cf 25-34
- No effect for ATSI (cf negative effect for women)
- Men who were born outside Australia less likely to transition into employment, even controlling for English fluency
- Some evidence that a limiting health condition negatively impacts on employment chances for men
- Time spent in unemployment or NILF between school and wave 1 significantly reduces chances of transitioning to work.
    - Effect is greater for unemployment
- Unlike for women, who have no effect of marital status, both married and cohabiting men are more likely to find work than single men (breadwinner pressure?)
- Some evidence that unlike for women (for whom children under 5 decrease likelihood of employment), for men, young children increase chances of transitioning to work
- Unlike for women, where there is some effect for locality, there is no effect for men

Does time in unemployment vary by functional economic region?

For women:

- No evidence that relocating to a different FER during a spell of unemployment increases the likelihood of finding employment

- The higher the unemployment rate in the Functional Economic Region in which a woman lives, the lower her likelihood of exiting unemployment to employment
- For Model 1 which represents the baseline hazard model for exit from unemployment the between-FER variance is significant and Figure 1 shows that 8 FERs have above average unemployment duration and 2 FERs have below average unemployment duration for women.
- Figure 2 shows that this unobserved heterogeneity is reduced when individual level characteristics and the unemployment rate in the FER are included in the model suggesting that there are important social clustering or contextual effects acting on unemployment duration at the level of the FER. This needs to be explored further.

INSERT FIGURE 1

INSERT FIGURE 2

For men:

- No evidence that moving FER increases chances of finding work
- The higher the unemployment rate in a FER, the less the likelihood of men finding work
- For men, Table 9 shows that the best fitting model is Model 3 with a BIC of 6708. For men, unobserved heterogeneity is greatest at the individual level, rather than the regional level, and for Model 4 with the inclusion of marital status, variation among individuals or FERs is no longer significant (see Figures 3 and 4).
- For Model 1 which represents the baseline hazard model for exit from unemployment the between-FER variance is not significant. Figure 3 shows that there is no significant variation in outcome due to FER in the baseline hazard model, and Figure 4 shows that with the addition of individual level variables and unemployment rate there is still no unexplained variability due to FER.

INSERT FIGURE 3

INSERT FIGURE 4

- Tables 10 and 11 show the rank ordering of FERs by random intercept associated with the likelihood of exiting unemployment to employment after controlling for individual level characteristics and unemployment rate of the FER. These orderings are different for men and women, underscoring the finding that social and spatial processes

influencing exit from unemployment to employment are different for men and women. Further investigation is required to assess the social and contextual variables at the FER level.

INSERT TABLE 10

INSERT TABLE 11

Discussion

- On the whole, the detected associations between the social determinants, previous labour force experience and hazard of exiting unemployment agree with previous studies including Borland & Johnston (2010) and Carroll (2006) among others.
- We extend on previous research by identifying differences in process of exiting unemployment between men and women, and by modelling repeated episodes of unemployment.
- We use multilevel models with individuals nested in FERs as developed by Mitchell et al (2010), demonstrating that duration of unemployment varies by FER to some extent for women.
- FERs are a good measure of region because they capture commuting behaviour to work to a large extent and reduce spatial autocorrelation when analysing data across FERs.
- The use of FER as a level in our models captures unobserved regional heterogeneity that would not otherwise be included and explained in the model.
- We identify the FERs in which transitions out of unemployment are more likely to occur, particularly for women, but further research is required to investigate the structural characteristics of these regions.
- We hypothesise that contextual effects associates with living and working in a FER will influence time spent in unemployment. There is some evidence that inclusion of individual level characteristics reduces the between-FER variability, perhaps indicating that there are regional contextual effects of social clustering on the hazard of exit from unemployment to employment. Further research should use census data to compute measures of social characteristics aggregated to the level of the FER. These could include industry mix or educational attributes for example.

- There is no evidence that moving between FERs during a period of unemployment significantly impacts on the likelihood of exiting unemployment to employment. This could be due to the small number of unemployed individuals who moved FERs in the sample, which may reflect the lack of mobility available to unemployed persons during a time of financial and social stress.
- The results raise questions about what attributes of the FERs are associated with positive and negative effect on duration of unemployment.

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Table 1: Proportion (and count) of respondents by labour force transition during the 8 waves of HILDA, categorised by gender and age at wave 1.

	Women			Men			Overall		
	Transition		Sample	Transition		Sample	Transition		Sample
Age Cat.	Yes	No		Yes	No		Yes	No	
18-24	0.81	0.19	321	0.66	0.34	282	0.74	0.26	603
25-34	0.70	0.30	801	0.42	0.58	674	0.57	0.43	1475
35-44	0.53	0.47	1019	0.38	0.62	853	0.46	0.54	1872
45-54	0.47	0.53	819	0.38	0.62	709	0.43	0.57	1528
55-64	0.39	0.61	583	0.52	0.48	519	0.45	0.55	1102
Total									
Prop.	**0.56**	**0.44**		**0.44**	**0.56**		**0.503**	**0.497**	
Count	**1974**	**1569**	**3543**	**1333**	**1704**	**3037**	**3307**	**3273**	**6580**

Table 2: Proportion (and count) of respondents in each labour force state for respondents who did not transition during the 8 waves of HILDA, categorised by gender and age at wave 1.

	Women			Men			Overall		
	State		Sample	State		Sample	State		Sample
Age Cat.	Emp.	NILF		Emp.	NILF		Emp.	NILF	
18-24	0.95	0.05	62	1.00	0.00	95	0.98	0.02	157
25-34	0.85	0.15	241	0.99	0.01	389	0.94	0.06	630
35-44	0.86	0.14	478	0.98	0.02	529	0.93	0.07	1007
45-54	0.77	0.23	431	0.89	0.11	443	0.83	0.17	874
55-64	0.24	0.76	357	0.44	0.56	248	0.32	0.68	605
Total									
Prop.	**0.70**	**0.30**		**0.88**	**0.12**		**0.79**	**0.21**	
Count	**1094**	**475**	**1569**	**1506**	**198**	**1704**	**2600**	**673**	**3273**

Nb. No respondents reported being unemployed for the complete survey.

Table 3: Average number (and s.e.) of labour-force spells per respondent during the 8 waves of HILDA, categorised by gender and age at wave 1.

Age Cat.	Women Spell type		Men Spell type		Overall Spell type	
	Any	Unemp	Any	Unemp	Any	Unemp
18-24	4.97 (0.2)	2.11 (0.11)	4.34 (0.25)	2.24 (0.16)	4.67 (0.16)	2.17 (0.1)
25-34	3.84 (0.11)	1.69 (0.07)	3.00 (0.13)	2.23 (0.13)	3.46 (0.09)	1.93 (0.07)
35-44	2.97 (0.08)	1.85 (0.08)	2.53 (0.1)	1.97 (0.1)	2.77 (0.06)	1.90 (0.06)
45-54	2.75 (0.1)	1.69 (0.11)	2.27 (0.1)	1.96 (0.15)	2.53 (0.07)	1.82 (0.09)
55-64	2.36 (0.13)	2.40 (0.49)	2.57 (0.12)	1.50 (0.12)	2.46 (0.09)	1.83 (0.2)
Total						
Mean	**3.19 (0.05)**	**1.85 (0.05)**	**2.75 (0.06)**	**2.06 (0.06)**	**2.99 (0.04)**	**1.94 (0.04)**

Table 4: Average duration (and s.e.) in months of completed labour-force spells per transitioning respondent during the 8 waves of HILDA, categorised by age at wave 1.

Age Cat.	Labour force state		
	Employed	Unemployed	NILF
18-24	31.17 (1.56)	5.13 (0.49)	10.41 (1.13)
25-34	44.53 (1.67)	4.49 (0.37)	28.01 (2.28)
35-44	59.79 (2.57)	5.93 (0.71)	54.32 (4.28)
45-54	93.47 (4.3)	7.68 (0.87)	51.16 (5.61)
55-64	136.58 (7.25)	10.52 (2.01)	60.65 (6.46)
Total			
Mean	70.78 (1.76)	6.03 (0.33)	41.24 (1.91)

Nb. Respondents who do not transition are and spells that do not end with a transition into another labour-force state excluded from the average.

Table 5: Average duration (and s.e.) in months of completed labour-force spells per transitioning respondent during the 8 waves of HILDA, categorised by gender and age at wave 1.

Age Cat.	Women Labour force state			Men Labour force state		
	Employed	Unemployed	NILF	Employed	Unemployed	NILF
18-24	30.6 (2.02)	5.01 (0.69)	13.06 (1.75)	31.99 (2.48)	5.28 (0.68)	6.23 (0.75)
25-34	41.95 (1.94)	4.82 (0.55)	36.38 (3.07)	48.95 (3.06)	4.01 (0.46)	6.71 (0.94)
35-44	54.11 (3.01)	5.31 (0.38)	69.61 (5.76)	68.18 (4.53)	6.74 (1.57)	20.6 (4.32)
45-54	82.26 (5.08)	6.97 (0.86)	58.23 (7.43)	109.37 (7.39)	8.71 (1.73)	38.56 (8.19)
55-64	107.6 (8.6)	7.9 (3.15)	68.49 (10.36)	161.06 (10.99)	12.32 (2.61)	53.59 (7.97)
Total						
Mean	**59.8 (1.88)**	**5.57 (0.32)**	**49.93 (2.58)**	**85.97 (3.25)**	**6.64 (0.63)**	**24.98 (2.51)**

Nb. Respondents who do not transition are and spells that do not end with a transition into another labour-force state excluded from the average.

Table 6: Proportion of respondents who had a household move event during the HILDA survey, categorised by gender and age at wave 1.

	Women			Men			Overall		
	Move		Sample	Move		Sample	Move		Sample
Age Cat.	Yes	No		Yes	No		Yes	No	
18-24	0.89	0.11	321	0.86	0.14	282	0.88	0.12	603
25-34	0.66	0.34	801	0.7	0.3	674	0.67	0.33	1475
35-44	0.43	0.57	1019	0.45	0.55	853	0.44	0.56	1872
45-54	0.34	0.66	819	0.37	0.63	709	0.36	0.64	1528
55-64	0.29	0.71	583	0.28	0.72	519	0.29	0.71	1102
Total									
Prop.	**0.48**	**0.52**		**0.5**	**0.5**		**0.49**	**0.51**	
Count	**1974**	**1569**	**3543**	**1333**	**1704**	**3037**	**3307**	**3273**	**6580**

Table 7: Average number of move spells, per respondent, over the 8 waves of HILDA (one spell corresponds to no move through the survey).

	Women		Men		Overall	
Age Cat.	No. spells	Sample	No. spells	Sample	No. spells	Sample
18-24	3.43 (0.09)	321	3.34 (0.09)	282	3.39 (0.06)	603
25-34	2.35 (0.05)	801	2.45 (0.05)	674	2.39 (0.04)	1475
35-44	1.75 (0.03)	1019	1.80 (0.04)	853	1.77 (0.03)	1872
45-54	1.57 (0.03)	819	1.59 (0.04)	709	1.58 (0.02)	1528
55-64	1.44 (0.03)	583	1.44 (0.04)	519	1.44 (0.03)	1102
Total						
Mean	**1.94 (0.02)**		**1.98 (0.02)**		**1.96 (0.02)**	
Count		**3543**		**3037**		**6580**

Table 8: Multilevel random effects model for duration of unemployment for unemployed women

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Log odds of transitioning from unemployment to employment					
Unemployment duration						
3 months or less (ref)	-	-	-	-	-	-
3 – 6 months	- 0.19*	- 0.17#	- 0.11	- 0.11	- 0.08	- 0.08
6 – 12 months	- 0.41**	- 0.37*	- 0.29*	- 0.27*	- 0.23#	- -0.23#
12 – 18 months	- 0.39*	- 0.32#	- 0.20	- 0.19	- 0.12	- 0.11
18 – 24 months	- 0.71*	- 0.69*	- 0.57#	- 0.56#	- 0.46	- 0.45
Over 24 months	- 1.36***	- 0.99***	- 0.81**	- 0.81**	- 0.62*	- 0.61*
Age at wave 1						
18 - 24		0.01	0.12	0.05	0.06	0.08
25 – 34 (ref)		-	-	-	-	-
35 - 44		- 0.11	- 0.03	- 0.10	- 0.09	- 0.09
45 – 54		- 0.07	- 0.08	- 0.15	- 0.17	- 0.18
55 - 64		- 0.05	- 0.06	- 0.14	- 0.16	- 0.14
ATSI (1=yes)		- 0.51*	- 0.38#	- 0.41#	- 0.39#	- 0.41#
Country of Birth						
Australia (ref)		-	-	-	-	-
Major English speaking		- 0.04	- 0.06	- 0.06	- 0.08	- 0.11
Other		- 0.37**	- 0.43***	- 0.43**	- 0.46***	- 0.45***
Non-fluent English (1=yes)		- 0.35	0.18	- 0.17	- 0.19	- 0.03
Limiting illness (1=yes)		- 0.38***	- 0.33**	- 0.35**	- 0.37**	- 0.37**
Education						
Year 12 (ref)			-	-	-	-
University			0.15	0.15	0.15	0.16
Diploma			- 0.05	- 0.04	- 0.07	- 0.05
Certificate			- 0.19	- 0.21#	- 0.21#	- 0.18
Under year 12			- 0.21#	- 0.21#	- 0.21#	- 0.18
Proportion post-school unemployed			- 0.93**	- 1.0***	- 0.93**	- 0.99**
Proportion post-school NILF			- 0.54***	- 0.59***	- 0.60***	- 0.60***
Marital status						
Not partnered (ref)				-	-	-
Married				- 0.04	- 0.06	- 0.07
Cohabiting				0.15	0.14	0.12
Children under 5 (1=yes)				- 0.22*	- 0.23*	- 0.23*
Section of State						
Major urban (ref)					-	-
Other urban					- 0.29**	- 0.22#
Bounded locality					- 0.08	- 0.03
Rural balance					- 0.09	- 0.07
Moved FER since unemployment (1=yes)					- 0.30	- 0.32
FER unemployment rate						- 8.81**
Constant	- 2.34***	- 2.18***	- 1.95***	- 1.84***	- 1.72***	- 1.27***

Number of observations	15103	13653	13607	13607	13607	13607
Number of individuals	759	701	695	695	695	695
Number of FERs	65	65	65	65	65	65
Between-FER variance	.0935**	.0963**	.0821*	.0793*	.0575#	.0329
Standard error	(.0339)	(.0369)	(.0352)	(.0347)	(.0331)	(.0287)
Between-person variance	.0657	.0657	.0542	.0572	.0872	.0904
Standard error	(.0595)	(.0579)	(.0531)	(.0522)	(.0582)	(.0592)
LR test vs Logistic regression	31.38***	26.02***	19.42***	19.09***	13.31*	8.06*
AIC statistic	7924	7182	7110	7109	7109	7104
BIC statistic	7985	7310	7283	7305	7335	7338

#p<0.10, *p<.05, **p<.01, ***p<.001

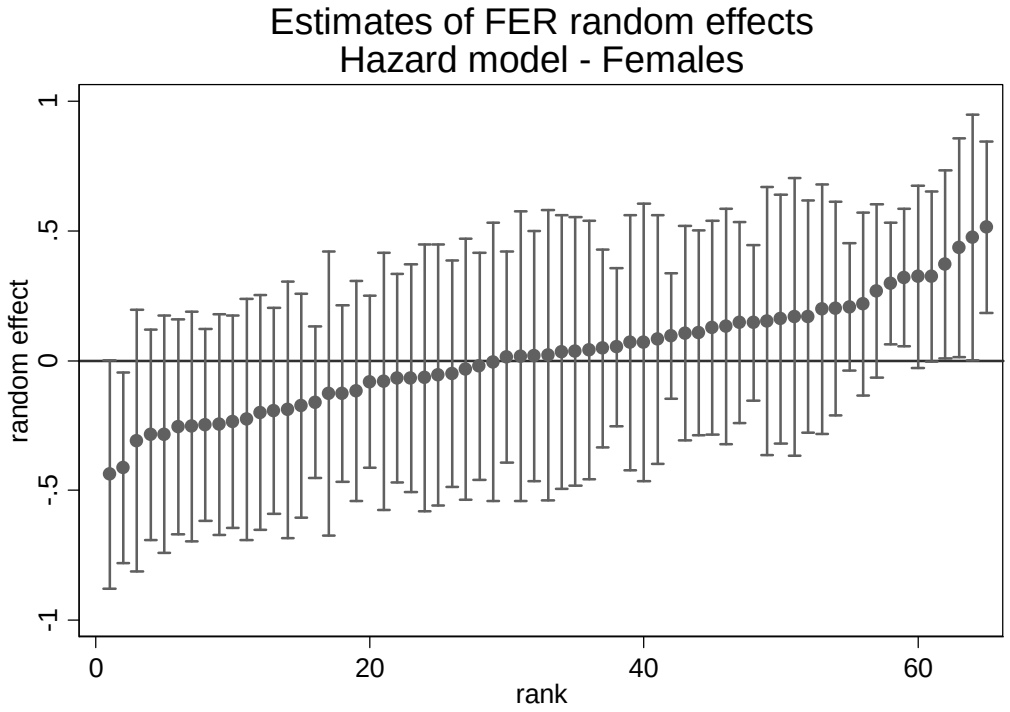

Figure 1: Estimates of Random intercepts for FER from Model 1, Women only

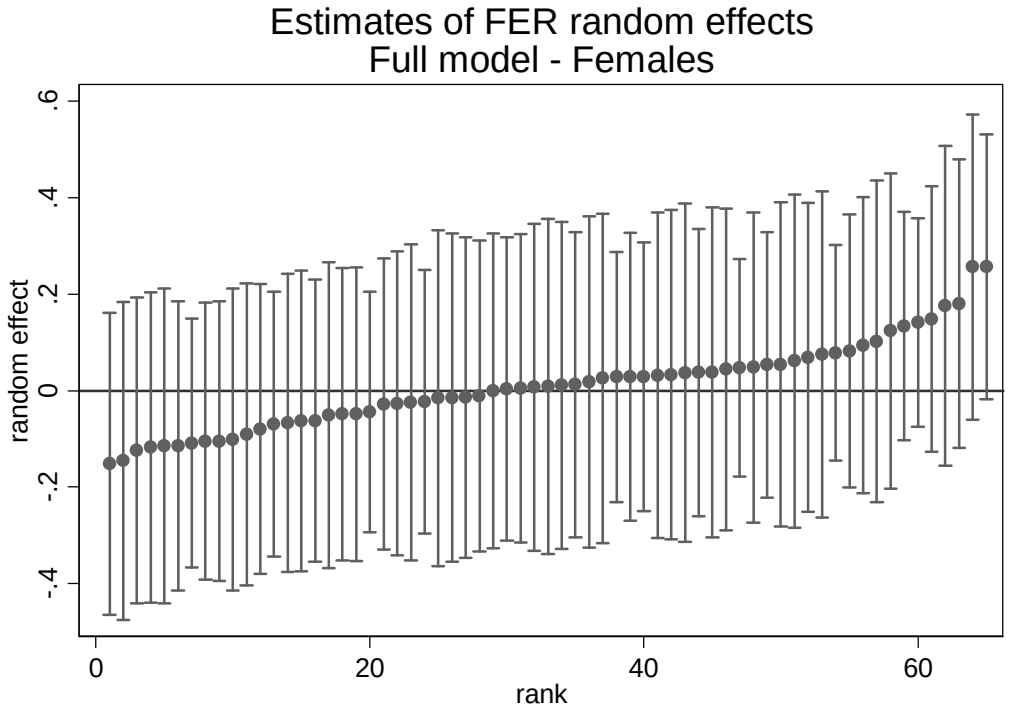

Figure 2: Estimates of Random intercepts for FER from Model 6, Women only

Table 9: Multilevel random effects model for duration of unemployment for men

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Log odds of transitioning from unemployment to employment					
Unemployment duration						
3 months or less (ref)	-	-	-	-	-	-
3 – 6 months	- 0.37***	- 0.34**	- 0.33**	- 0.35**	- 0.34**	- 0.34**
6 – 12 months	- 0.54***	- 0.47***	- 0.48***	- 0.51***	- 0.49***	- 0.49***
12 – 18 months	- 0.72***	- 0.76***	- 0.69**	- 0.75***	- 0.74***	- 0.72**
18 – 24 months	- 0.71**	- 0.73**	- 0.64*	- 0.72**	- 0.72**	- 0.68*
Over 24 months	- 1.66***	- 1.24***	- 1.17***	- 1.16***	- 1.14***	- 1.08***
Age at wave 1						
18 - 24		- 0.16	- 0.04	0.12	0.11	0.10
25 – 34 (ref)		-	-	-	-	-
35 - 44		- 0.21*	- 0.23*	- 0.20#	- 0.20#	- 0.20#
45 – 54		- 0.33*	- 0.44***	- 0.37**	- 0.37**	- 0.35**
55 - 64		- 0.61**	- 0.76***	- 0.68***	- 0.70***	- 0.72***
ATSI (1=yes)		- 0.29	- 0.27	- 0.29	- 0.22	- 0.25
Country of Birth						
Australia (ref)		-	-	-	-	-
Major English speaking		- 0.20	- 0.23#	- 0.28*	- 0.27*	- 0.30*
Other		- 0.37**	- 0.29*	- 0.31**	- 0.32*	- 0.33*
Nonfluent English (1=yes)		- 0.35	- 0.13	- 0.13	- 0.12	- 0.17
Limiting illness (1=yes)		- 0.38***	- 0.20*	- 0.17#	- 0.17#	- 0.18#
Education						
Year 12 (ref)			-	-	-	-
University			0.21	0.13	0.122	0.11
Diploma			0.11	0.10	0.09	0.10
Certificate			0.12	0.08	0.9	0.09
Under year 12			- 0.13	- 0.17	- 0.16	- 0.12
Proportion post-school unemployed			- 1.02***	- 0.92***	- 0.93***	- 0.89***
Proportion post-school NILF			- 0.78**	- 0.65**	- 0.65**	- 0.61**
Marital status						
Not partnered (ref)				-	-	-
Married				0.34***	0.33***	0.32**
Cohabiting				0.26*	0.27*	0.25*
Children under 5 (1=yes)				0.16	0.17#	0.19#
Section of State						
Major urban (ref)					-	-
Other urban					- 0.09	- 0.4
Bounded locality					- 0.32	- 0.28
Rural balance					- 0.02	0.03
Moved FER since unemployment (1=yes)					- 0.07	- 0.11
FER unemployment rate						- 7.77*
Constant	- 2.21***	- 1.89***	- 1.77***	- 2.00***	- 1.96***	- 1.57***
Number of observations	15949	13540	13090	13090	13090	13090
Number of individuals	622	567	551	551	551	551

Number of FERs	66	64	64	64	64	64
Between-FER variance	.0086	.0049	.0130	. 0265	.0236	.0151
Std Error	(.0152)	(.0186)	(.0186)	(.0201)	(.0200)	(.0181)
Between-person variance	.1461	.1549	.1000	.0368	.0413	.0508
Std Error	(.0549)	(.0645)	(.0591)	(.0532)	(.0548)	(.0562)
LR test vs Logistic regression	13.53**	10.57**	6.00*	4.15	3.57	2.82
AIC statistic	7773	6751	6536	6522	6527	6523
BIC statistic	7834	6878	6708	6716	6752	6755

#p<0.10, *p<.05, **p<.01, ***p<.001

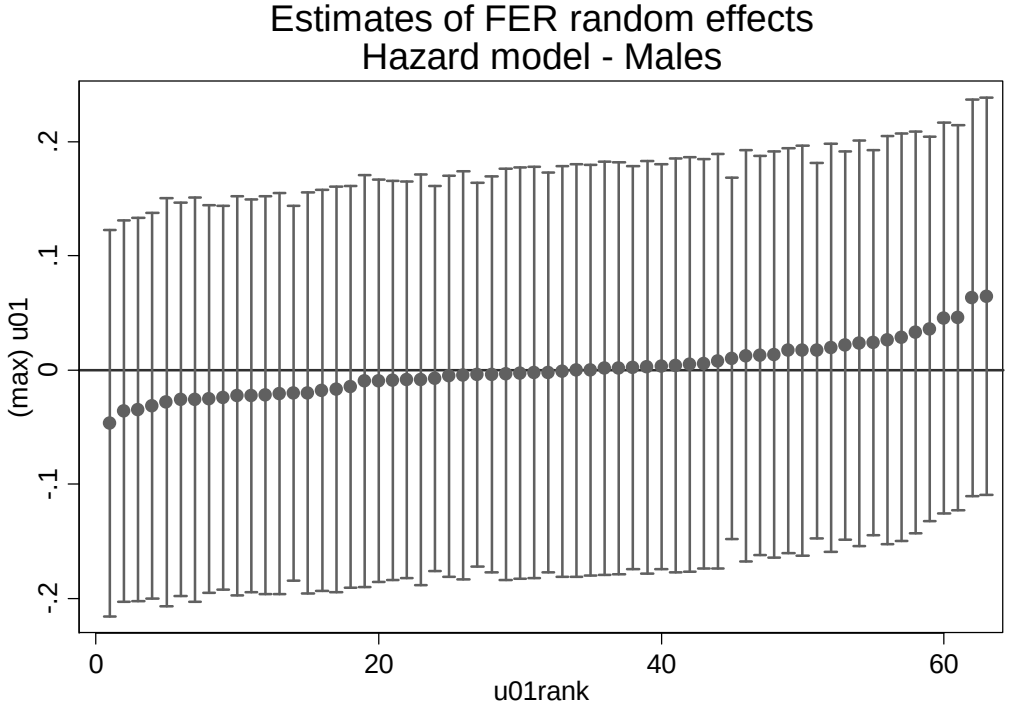

Figure 3: Estimates of Random intercepts for FER from Model 1, Men only

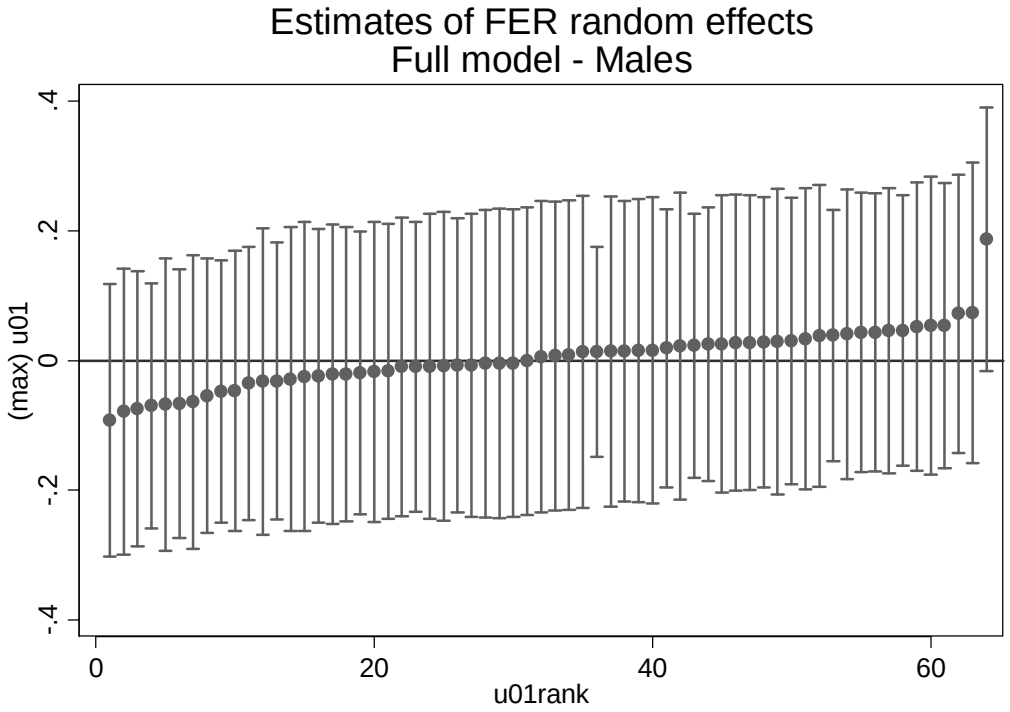

Figure 4: Estimates of Random intercepts for FER from Model 6, Men only

Table 10: Estimates and rank order of random intercept value for FERs with the ten highest and ten lowest ranked random intercepts from Model 6, Women only. (Lower ranking has more negative effect on hazard of leaving unemployment for employment)

FER name	Unemp. rate	Rank	Random intercept
Muswellbrook-Upper Hunter	0.0495	1	-0.1522
Adelaide Hills-Murray Bridge and surrounds	0.0436	2	-0.1457
Yorke Peninsula-Barossa	0.0478	3	-0.1235
Mackay and surrounds	0.0352	4	-0.1180
Shepparton-Deniliquin	0.0514	5	-0.1152
North-Eastern Melbourne	0.0519	6	-0.1150
Sydney North	0.0338	7	-0.1090
Newcastle-Singleton	0.0689	8	-0.1051
Gosford-Wyong	0.0711	9	-0.1050
North-Eastern Perth	0.0353	10	-0.1017
ACT and surrounds	0.0329	55	0.0820
Toowoomba-Central Darling Downs	0.0461	56	0.0937
Latrobe Valley-South Gippsland	0.0632	57	0.1019
South-Eastern SA - West Wimmera	0.0476	58	0.1235
Kew-Camberwell-Yarra Ranges	0.0415	59	0.1340
Brisbane South - Beaudesert	0.0456	60	0.1409
Inner Melbourne	0.0574	61	0.1484
Inner West Sydney - Canterbury-Bankstown	0.0653	62	0.1756
Outer South Western Sydney	0.0764	63	0.1803
Rockhampton-Emerald	0.0434	64	0.2566
Monash-Casey-Cardinia	0.0611	65	0.2570

Table 11: Estimates and rank order of random intercept value for FERs with the ten highest and ten lowest ranked random intercepts from Model 6, Men only. (Lower ranking has more negative effect on hazard of leaving unemployment for employment)

FER name	Unemp. rate	Rank	Random intercept
Sydney North	0.0338	1	-0.0920
Mackay and surrounds	0.0352	2	-0.0787
Newcastle-Singleton	0.0689	3	-0.0745
Kew-Camberwell-Yarra Ranges	0.0415	4	-0.0699
Bathurst-Orange	0.0565	5	-0.0678
North-Eastern Melbourne	0.0519	6	-0.0669
North-Eastern Perth	0.0353	7	-0.0636
Sunshine Coast	0.0575	8	-0.0544
West Melbourne-Ballan-Macedon	0.0653	9	-0.0478
Cairns-Cook	0.0443	10	-0.0469
Far North Coast NSW and Hinterland	0.0854	55	0.0435
Gosford-Wyong	0.0711	56	0.0435
Caulfield - South-Eastern Suburbs	0.0419	57	0.0460
Monash-Casey-Cardinia	0.0611	58	0.0464
North Perth-Joondalup	0.0342	59	0.0520
Kingaroy-Gympie	0.0674	60	0.0536
ACT and surrounds	0.0329	61	0.0537
Inner and South Sydney-Eastern Suburbs	0.0434	62	0.0723
Albury-Wangaratta	0.0505	63	0.0741
Brisbane North – Caboolture	0.041	64	0.1871