C Unemployment duration analysis

Automotive manufacturing plant closures will result in job losses in the automotive manufacturing industry and its supply chain. The length of time taken by former automotive manufacturing employees to find re‑employment will be an important determinant of the magnitude of labour adjustment costs.

Dynamic simulations using the Monash Multi‑Regional Forecasting (MMRF) model allow for short‑term unemployment through a partial adjustment mechanism (described in the supplementary modelling report). Analysis of the time it is likely to take former automotive employees to find new work can be used to inform this mechanism in the MMRF model. The empirical analysis presented in this appendix was used as an input to calibrate the rate of labour adjustment in dynamic simulations.

The analysis presented in this appendix is not intended as a precise prediction of the level or duration of unemployment that will occur for retrenched automotive employees. Data limitations would make such a task impossible — in particular, there is a lack of time‑series data relating to the labour market outcomes of unemployed former automotive employees, which means that the analysis presented in this appendix is based on data for manufacturing employees more broadly. What the analysis does offer is an empirically‑informed estimate of the likely duration of unemployment that can be used for model calibration purposes. The analysis also provides insights into factors affecting the time taken to find re‑employment.

## C.1 Duration analysis and unemployment

The characteristics of affected employees and regions will influence the magnitude of adjustment costs (Borland 1998; PC 2001). In particular, the time between retrenchment and re‑employment is likely to be affected by differences in the ‘human capital’ of retrenched employees — the set of attributes that make it possible for people to work and contribute to production. Human capital encompasses skills, work experience, health and intangible characteristics such as motivation and work ethic. Higher levels of human capital, whether measured directly by skills or indirectly by educational attainment, have been found to be strongly associated with higher levels of productivity and workforce participation in a number of empirical studies (recent Australian studies include Forbes, Barker and Turner 2010; Kennedy, Stoney and Vance 2009; Lee and Coelli 2010; Leigh 2008; and Shomos 2010).

### Duration analysis

The time between retrenchment and re‑employment — the duration of unemployment — is typically examined using duration analysis.[[1]](#footnote-1) Duration analysis models focus on the concept of the *hazard function:* the risk — at a particular moment — that an individual who has not yet done so will experience an event of interest (Singer and Willett 2003).

In the context of unemployment duration, the hazard function is the risk that an unemployed person will find employment in a given time period, conditional on them not having found employment up to the beginning of that time period. The hazard function varies from zero (no risk of finding employment, or certainty of not finding employment) to infinity (certainty of finding employment). The hazard rate is closely linked to the duration of unemployment — a higher hazard rate is associated with a shorter likely duration of unemployment (and vice versa).

In duration analysis, ‘competing risks’ occur when a person is at risk of more than one type of event, but can actually experience only one of them. For example, an unemployed person might stop looking for work (exit the labour force), which prevents observation of an exit from unemployment to employment. Treating employment and exit from the labour force as separate ‘events’ that could complete a spell of unemployment means a person is at risk of two competing outcomes.

In the presence of competing risks, two important measures are the *subhazard rate* and the *cumulative incidence function*.

The subhazard rate is the hazard rate at a given time period, conditional on not having exited due to any of the competing risks. For example, the employment subhazard may be described as the risk of finding employment in a given time interval, conditional on not having found employment or exiting the labour force up to the beginning of that time interval. The subhazard rate can be estimated by treating the other competing risks as ‘censored’. Observations are considered censored when they are incomplete or where a person leaves the sample for a reason other than that under consideration. For example, people who are still unemployed at the end of the survey period are considered censored.

In terms of unemployment duration, the cumulative incidence of employment is the cumulative risk that a person will transition from unemployment to employment, in the presence of the competing risk of exiting the labour force. Similarly, the cumulative incidence of exiting the labour force, in the presence of the competing risk of exiting to employment, may also be estimated. Those who do not either exit to employment or exit the labour force will remain unemployed.

### Existing literature on the duration of unemployment

Recent analyses of the length of time taken for unemployed people to find re‑employment have emphasised that there are multiple routes that can be followed to conclude a period of unemployment (including re‑employment and exit from the labour force). A ‘competing risks’ model is the appropriate empirical approach to deal with multiple, mutually exclusive outcomes (for example, Addison and Portugal 2003; and Arranz, García-Serrano and Toharia 2010).

Recent Australian studies applying a competing risks model to analyse factors affecting unemployment duration include Borland and Johnston (2010) and Carroll (2006). Both studies use data from the Housing, Income, and Labour Dynamics of Australia (HILDA) survey, and are used as a basis for this analysis.

Borland and Johnston (2010) focus on the importance of recent labour market history as a determinant of labour market outcomes, while Carroll (2006) uses a competing risks model to empirically examine a job search framework. The job search framework relates the likelihood of exit from unemployment to the minimum amount a jobseeker will accept to work (reservation wage), the frequency at which they receive job offers and the wage levels that accompany these job offers. Individuals accept offers above, and decline those below, the reservation wage. Neither Borland and Johnston (2010) nor Carroll (2006) examine differences in the likely duration of unemployment across industries, limiting the application of results from these studies to the automotive industry.

These and other studies are useful to identify key factors affecting the duration of unemployment in Australia. Both Borland and Johnston (2010) and Carroll (2006) support the summary conclusion in PC (2003b) that age, education and English ability are key drivers of the duration of unemployment. Older people have a lower likelihood of finding re‑employment, as do those with poor English (in Borland and Johnston (2010) and Carroll (2006), immigrants from non‑English speaking countries are found have a lower likelihood of finding re‑employment). Higher levels of education are associated with an increased likelihood of finding re‑employment.

Surveys of Mitsubishi employees who were retrenched following the announced closure of Mitsubishi’s Lonsdale engine manufacturing plant in 2004 (Beer et al. 2006) give an indication of the duration of unemployment of former automotive employees. These surveys found that approximately 60 per cent of those surveyed had found work between zero and six months after retrenchment, 69 per cent had found work approximately 12 to 18 months after retrenchment and 74 per cent had found work approximately 24 to 30 months after retrenchment (Pieters 2013). The job characteristics of those who were re‑employed changed substantially, with many respondents reporting that they struggled to find full‑time employment and had to settle for casual or part time contract positions.

## C.2 Data and descriptive statistics

The sample used for the Commission’s analysis is drawn from calendar data included in the first eleven waves of the HILDA panel dataset. HILDA is a household‑based longitudinal study that began in 2001 with a survey of 13 969 people from 7682 households. Each year since 2001, interviews of all willing members of each household over the age of 15 have been conducted. The HILDA survey is nationally‑representative, with the exception of under‑sampling people living in more remote areas of Australia, and an under‑representation of recent migrants to Australia due to sample attrition.

Each survey involves a series of questions relating to current labour force status, household composition, income, health, education and demographics. In the event that a respondent’s job has changed since the last interview, they are also asked a series of questions about their most recently terminated job.

Respondents are also requested to report their labour force status in a calendar that spans the previous 18 months. The different states that are recorded in the calendar include being:

* enrolled in school or education
* employed
* not employed, but looking for work
* not employed and not looking for work.

The HILDA calendar data includes information for each third of a month over the 18 months preceding the survey interview. The calendar data was combined to form a monthly record of employment data using the approach outlined in Fry and Boulton (2013).[[2]](#footnote-2) This calendar allows the identification of periods of employment and unemployment that last at least one month.[[3]](#footnote-3)

### Employment prior to a spell of unemployment

The Commission’s analysis focuses on factors affecting the prospect of re‑employment of retrenched employees, and so the sample is limited to those who have been employed prior to experiencing a spell of unemployment. A spell of unemployment is defined as a continuous period of unemployment that is observed to last for at least one month. Unemployment spellslasting less than onemonth are discarded to ensure that the sample includes only significant spells of unemployment and to minimise measurement error arising from factors such as recall bias.[[4]](#footnote-4) Thismeans that an unemployment spell must have a minimum duration of one month to beincluded in the sample, and only ends when the person is in employment or has exited the labour force for at least one month. Uncompleted (right‑censored) spells of unemployment are included in the sample for analysis.

Sample restrictions follow the approach of Borland and Johnston (2010), in that the sample used is restricted to people who are aged between 25 and 65, are observed to have a valid spell of unemployment, and are not missing information required to undertake the competing risks regression, such as their marital status, country of birth or level of educational attainment. The sample is restricted to those aged between 25 and 65 at the beginning of their spell of unemployment in order to focus on a population that is less likely to be engaged in full‑time study and more likely to be fully engaged in the labour market. Sample restrictions differ from Borland and Johnston (2010) in that only spells of unemployment immediately preceded by employment are included for analysis.

Where multiple spells are identified, subsequent spells of unemployment for the same person are not independent, and are excluded from the analysis. Only the first observed spell of unemployment for each person is included in the sample for analysis. Spells do not necessarily begin in the same month or year for each person.

### Sample description

There are 1507 people in the HILDA dataset who experienced spells of unemployment that meet the criteria for inclusion in the analysis, with 73.3 per cent of these spells ending in employment, 18.8 per cent concluding with exit from the labour force, and 7.9 per cent of all spells right‑censored (table C.1). Spells ending in employment are typically shorter than spells ending in labour market exit or that have not concluded.

Table C.1 Duration of unemployment spells, by subsequent labour force status

First spell, people aged 25‑65 at beginning of spell

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Labour force status after unemployment spell |  | Mean duration | Median duration | Maximum duration | Mean duration in Borland and Johnston (2010) |
|  | Per cent | Months | Months | Months | Months |
| Employment | 73.3 | 4.15 | 3 | 68 | 3.58 |
| Not in the labour force (NILF) | 18.8 | 6.81 | 5 | 48 | 6.27 |
| Censored | 7.9 | 6.42 | 4 | 34 | 6.91 |
| All labour force states | 100.0 | 4.83 | 3 | 68 | 4.48 |
| People previously employed in manufacturing | 14.0 | 5.96 | 4 | 42 | - |
| Number of observations | 1507 | - | - | - | 1859 |

*Sources*: Borland and Johnston (2010); Productivity Commission estimates using HILDA waves 1 to 11.

Most spells of unemployment in the sample are short, with a median duration of three months (four months for people whose previous job was in manufacturing). However, a minority of unemployment spells are much longer: the longest spell of unemployment in the sample was 68 months (42 months for former manufacturing employees). Mean spell lengths are slightly longer than those reported by Borland and Johnston (2010). It is likely that these differences are attributable to differences in sample inclusion criteria, in particular the inclusion of more recent data covering a relatively weaker labour market between 2008‑09 and 2011‑12.[[5]](#footnote-5) The characteristics of people in the sample are summarised in table C.2.

Table C.2 Descriptive statistics

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Measure | Value | SD |
| Length of spell (months) | Mean | 4.83 | 5.66 |
| *Age at commencement of spell (years)*a |  |  |  |
| 25-34 | Proportion | 0.34 |  |
| 35-44 | Proportion | 0.32 |  |
| 45-54 | Proportion | 0.24 |  |
| 55-65 | Proportion | 0.11 |  |
| Female | Proportion | 0.48 |  |
| *Marital status* |  |  |  |
| Not married or de facto | Proportion | 0.20 |  |
| Married/de facto | Proportion | 0.64 |  |
| Divorced/separated/widowed | Proportion | 0.16 |  |
| Number of children aged less than 14 | Mean | 0.74 | 1.06 |
| Living outside a major city | Proportion | 0.38 |  |
| *Country of birth* |  |  |  |
| Australia | Proportion | 0.75 |  |
| Main English speaking | Proportion | 0.11 |  |
| Non-English speaking | Proportion | 0.14 |  |
| Own home/ currently paying off mortgage | Proportion | 0.57 |  |
| *Highest level of education* |  |  |  |
| Year 11 | Proportion | 0.30 |  |
| Year 12 | Proportion | 0.12 |  |
| Diploma or certificate | Proportion | 0.37 |  |
| Bachelor degree or higher | Proportion | 0.21 |  |
| Illness restricting ability to work | Proportion | 0.16 |  |
| *Industry of previous employment* |  |  |  |
| Business services | Proportion | 0.16 |  |
| Primary industries | Proportion | 0.06 |  |
| Manufacturing | Proportion | 0.14 |  |
| Construction and utilities | Proportion | 0.09 |  |
| Distribution services | Proportion | 0.21 |  |
| Public administration, education, health & community services | Proportion | 0.19 |  |
| Other services | Proportion | 0.15 |  |
| State/territory unemployment rate at commencement of spell (per cent) | Mean | 5.57 | 1.16 |

SD – standard deviation. a Total is greater than 1 due to rounding. b ‘Primary industries’ is an aggregation of ANZSIC 2006 industries ‘agriculture, forestry and fishing’ and ‘mining’. ‘Construction and utilities’ includes ‘electricity, gas, water and waste services’ and ‘construction’. ‘Distribution services’ includes ‘wholesale trade’, ‘retail trade’, ‘transport, postal and warehousing’ and ‘information media and telecommunications’. ‘Business services’ includes ‘financial and insurance services’ ‘rental, hiring and real estate services’, ‘professional, scientific and technical services’ and ‘administrative and support services’. ‘Public administration, education, health and community services’ includes ‘public administration and safety’, ‘education and training’ and ‘health care and social assistance. ‘Other Services’ includes ‘accommodation and food service’, ‘health care and social assistance’ and ‘other services’.

*Source*: Productivity Commission estimates using HILDA, waves 1 to 11.

## C.3 Method

The empirical approach used in the Commission’s analysis follows Arranz, García‑Serrano and Toharia (2010), Borland and Johnston (2010) and Carroll (2006) in applying a competing risks model to analyse factors affecting unemployment duration. This framework allows for two possible conclusions to a period of unemployment: finding re‑employment, or exit from the labour force. Individuals that remain unemployed are treated as ‘censored’ observations — their period of unemployment remains incomplete.

There are two key steps in estimating the likely duration of unemployment for unemployed manufacturing employees:

* competing risks regression analysis of the factors affecting unemployment duration
* estimating baseline hazard rates.

### Competing risks analysis of the factors affecting unemployment duration

For the two possible conclusions to a period of unemployment, the risk of ending a spell of unemployment is estimated using the approach of Fine and Gray (1999). For example, the employment subhazard — the instantaneous risk of exiting unemployment for employment — is estimated as below (a corresponding model is also estimated for the competing risk of exit from the labour force).

Where:

* is the subhazard of finding re‑employment (denoted by the subscript ‘1’; exit from the labour force would be denoted by subscript ‘2’) at time *t* for individual *i*
* is the baseline subhazard (for )
* is a vector of control variables representing the characteristics of each individual *i*experiencing a spell of unemployment
* is a vector of coefficient estimates
* is a vector of coefficient estimates for control variables where the effect of that variable on the subhazard of finding employment is found to vary over the length of spell
* is an error term.

This framework is similar to the Cox proportional hazards model (Cox 1972) in that the effects of the control variables () on the hazard rate (or, in the case of competing risks, the subhazard rate) are assumed to be proportional. As per the equation above, this means that the effect of a one unit increase in a variable is assumed to have the same (multiplicative) effect on the subhazard rate irrespective of the baseline hazard at time *t*.

The key divergence from the Cox proportional hazards model in the Commission’s analysis is the assumption of two alternative conclusions to a period of unemployment under the competing risks model. Under the competing risks model, the competing risks of employment and exiting the labour force are assumed to be independent (for any fixed set of personal characteristics represented by the control variables). Previous research has indicated that the risks of finding employment and exiting the labour force tend to be independent (see Carroll 2006 for a review of relevant studies).

### Estimating baseline subhazard rates

The baseline subhazard rates and ) are not directly parameterised as part of the competing risks regression. Only relative changes in the probability of finding employment or exiting the labour force caused by changes in control variables are estimated. For example, the regression estimates the difference in the probability of a person finding re‑employment if they have completed year 12, compared to not having completed year 12. The absolute probability of finding re‑employment is not estimated as part of the competing risks regression.

In order to consider the likely duration of unemployment for retrenched automotive employees, the baseline subhazards need to be specified for the probability of both finding re‑employment and exiting the labour force. This is achieved by summarising the data on when people find re‑employment or exit from the labour force, without making any distributional assumptions (referred to as a ‘nonparametric’ approach).

#### Applying the Nelson‑Aalen estimator

Baseline hazard functions are estimated based on the Nelson–Aalen estimator (Aalen 1978; Nelson 1972). The Nelson‑Aalen estimator calculates the probability of finding re‑employment (or exit from the labour force) based on the ratio between the number of people finding re‑employment up to a point in time, and the number of people still unemployed up to that point (thus adjusting for people who have exited the labour force or left the sample for other reasons) (Cleves et al. 2008).

The baseline cumulative subhazard up to a specific time (the number of expected re‑employments if re‑employment was a repeatable process) can be calculated using the Nelson‑Aalen estimator by summing the hazard rate over all the events where someone finds employment up to that time. For example, the cumulative subhazard of finding re‑employment would be estimated as follows.

Where:

* is the cumulative employment subhazard up until time *t*
* is the time at which people find re‑employment (that is, *j* indicates the time at which people exit from unemployment)
* is the number of people that are re‑employed at time
* is the number of people remaining unemployed and thus looking for re‑employment at time .

The Nelson‑Aalen estimator can then be used to calculate the cumulative incidence of re‑employment, according to the cumulative incidence function:

Where:

* is the cumulative incidence function of the probability of finding re‑employment by time *t.*

Following the competing risks regression, baseline subhazard rates and cumulative incidence functions (as reported below) also take into account the characteristics of each person in the sample, using the regression results (Kalbfleisch and Prentice 2002; StataCorp 2013).

### Selection of control variables

Multivariate competing risks studies typically include a range of demographic, human capital, previous employment and job search factors as control variables in regressions. This is based on job search theory, as these factors can influence the probability of receiving a job offer and/or the probability of accepting it (Arranz, García-Serrano and Toharia 2010; Carroll 2006).

The choice of demographic and human capital control variables (table C.3) follows closely those chosen in multivariate competing risk analysis using HILDA data by Borland and Johnston (2010) and Carroll (2006). Prior labour market experience was a key focus of Borland and Johnston (2010), so labour force history factors were important control variables in that study. By contrast, the focus of this study is former automotive industry employees, so the industry of employment prior to an unemployment spell was included as a control variable. The state or territory unemployment rate at the time a spell commences was used as a proxy for the effect of local labour market conditions on the probability of receiving job offers.

Table C.3 Control variables included in the competing risk models

|  |  |
| --- | --- |
| Group of variables | Variable list |
| Demographic | Gender, age, marital status, number of children of different ages, home ownership |
| Human capital | Highest level of educational attainment, illness restricting ability to work |
| Previous employment | Industry of employment prior to spell |
| Job search | State unemployment rate at time spell commences. |

There are other factors likely to affect the duration of unemployment that are not accounted for in this study due to data limitations. For example, a longer list of variables is used by the Department of Employment (DEEWR 2012b) to allocate access to labour market assistance programs (box C.1). This list covers the key factors identified in the academic literature, but also includes a broader range of factors such as indigenous status, access to transport, ability to be contacted by telephone and living circumstances. These factors have been found to be statistically significant in explaining whether a person continues to receive unemployment benefits.

|  |
| --- |
| Box C.1 Risk of long‑term unemployment as measured by the Job Seeker Classification Instrument |
| Unemployment benefit recipients are assessed by Centrelink using a profiling instrument — the Job Seeker Classification Instrument (JSCI) — to assess their risk of prolonged unemployment. Job seekers assessed as being at high risk of prolonged unemployment are provided access to greater levels of labour market assistance. The JSCI is designed to provide a relative, rather than absolute, measure of job seeker disadvantage in the labour market.  The JSCI assigns each of the 18 identified risk factors (personal characteristics or employment barriers) a numerical weight or point score. The JSCI is based on regression analysis of administrative data for job seekers to identify factors that have a statistically significant impact on whether a person remains a job seeker for an additional year.  Table JSCI factors   |  |  | | --- | --- | | * Age and gender | * Geographic location | | * Work experience | * Proximity to a labour market | | * Job seeker history | * Access to transport | | * Educational attainment | * Contactability | | * Vocational qualifications | * Disability/medical conditions | | * English proficiency | * Stability of residence | | * Country of birth | * Living circumstances | | * Indigenous status | * Criminal convictions | | * Indigenous location | * Personal factors | |
| *Source*: DEEWR (2012b). |
|  |
|  |

## C.4 Drawing inferences about retrenched automotive employees

There is insufficient data to analyse the duration of unemployment of former automotive manufacturing industry employees directly. The sample size of the HILDA survey is not large enough to give an adequate sample of automotive employees who have become unemployed: in the HILDA dataset, only 62 people were employed in the automotive industry in 2001 (of 873 people employed in the entire manufacturing division) and the number of unemployment spells for automotive industry employees is even lower. Other datasets, such as the Census, provide more observations but do not contain the longitudinal detail required to undertake duration analysis.

Instead, the experience of unemployed manufacturing employees is used as a proxy for retrenched automotive employees. This is a key limitation of the Commission’s analysis, and requires three assumptions.

1. The duration of unemployment for people who are made redundant by plant closures or other structural adjustment is similar to that of people who become unemployed for other reasons, such as voluntary resignation or termination for other reasons
2. The duration of unemployment for former manufacturing employees more broadly is a reasonable guide to that for former automotive manufacturing employees specifically.
3. The ‘re-absorption’ of employees into employment following the closure of the motor vehicle manufacturing industry is similar to that observed when a single firm makes retrenchments due to plant closure or other structural adjustment.

The first assumption requires that once a person has become unemployed, the challenges they face in finding re‑employment (after adjusting for control variables such as age and education) will not be any different whether unemployment arises due to structural adjustment or for other reasons. There is limited empirical data available on this issue for Australia. However, international evidence suggests that workers laid off as a result of plant closure or downsizing tend to suffer shorter spells of unemployment relative to those who are laid off for other reasons (Gibbons and Katz 1991; Margolis 2002; Okatenko 2010; Rodriguez-Planas 2003).

This is a logical consequence of employers regarding retrenchments that are unrelated to plant closure as a signal of low ability. In contrast, employees displaced by plant closure ‘suffer from no such adverse inference and so receive (relatively) higher re‑employment wages from the market’ (Gibbons and Katz 1991, p. 353). The offer of higher wages is associated with a higher likelihood of job offer acceptance and therefore a shorter duration of unemployment.

If this is true for Australia, it suggests that using the experience of all unemployed manufacturing employees as in the Commission’s analysis would tend to overestimate the likely duration of unemployment for retrenched manufacturing employees.

The second assumption is supported by the similarities between the automotive manufacturing workforce and the manufacturing workforce more broadly, in terms of the key factors affecting the duration of unemployment. These similarities suggest that results for manufacturing employees provide a reasonable approximation of re‑employment prospects for automotive manufacturing employees. As noted above, age, education and English proficiency have been identified as key determinants of the likely duration of unemployment. The automotive workforce is broadly similar to the manufacturing workforce in terms of age profile, educational attainment and English proficiency (chapter 6).

Studies of labour market outcomes for retrenched automotive employees in Australia (in particular, surveys of retrenched Mitsubishi employees) do not provide the same frequency of observation to allow such a detailed analysis of duration of unemployment as using the HILDA dataset. However, point estimates of re‑employment and exit from the labour force from the Mitsubishi surveys are drawn on in the results section below to consider whether the analysis of unemployed manufacturing employees provides a useful guide to the experience of retrenched automotive employees.

The third assumption means that, to the extent that automotive manufacturing employees would be dependent upon the automotive industry for their future employment, the results of this analysis would tend to understate the duration of unemployment for retrenched employees. Of the 133 former manufacturing employees included in the sample who were re‑employed, over 70 per cent found employment outside the manufacturing division.

This is consistent with evidence that automotive manufacturing employees commonly transition to employment in other industries. Recent analysis of longitudinally‑linked Census data shows that, of those employed in automotive manufacturing in 2006 and employed in 2011, most had transitioned to employment in another industry (Department of Industry 2014).

On the other hand, the restriction of the sample to unemployment spells of greater than one month in duration (as noted above) was applied partly to minimise measurement error arising from factors such as recall bias, but is also useful to avoid including shorter spells that could yield an inappropriately optimistic view of the time that will be taken by retrenched automotive employees to find re‑employment.

This approach ensures that the analysis is conservative about the time it is likely to take for retrenched automotive employees to return to work. In reality, some automotive manufacturing employees might not experience any period of time out of work. Where retrenchments are announced in advance (as is the case with Ford, Holden and Toyota plant closures), some people may be able to obtain new employment positions and to shift jobs prior to the retrenchment date. This group of people will not spend any time out of employment (Borland 1998), which has been shown empirically to reduce the *average* length of time spent out of employment by people given advance notice of retrenchment (Addison and Blackburn 1997; Fallick 1996; Friesen 1997).

## C.5 Results

Results from the competing risks regressions are presented in table C.4 as estimates of hazard ratios for finding re‑employment and exiting from the labour force. For each of the categorical control variables included in the competing risks regression, the hazard ratios provide an estimate of the subhazard of ending a period of unemployment for those in a given category, relative to those in the default category. (For each categorical variable representing the share of the sample in various categories — such as age categories — regression analysis requires one ‘default category’ to be excluded from the regression, so that parameter estimates are interpreted relative to that default category.)

Where the hazard ratio is greater (less) than one, people in that category are more (less) likely to end a period of unemployment. Separate hazard ratios are estimated for movement to employment and out of the labour force. For example, someone aged 55‑65 around 40 per cent less likely to move from unemployment to employment than someone aged 25‑34 (the default category) and more than twice as likely to move from unemployment out of the labour force.

Statistically significant results reported in table C.4 show that:

* Consistent with Borland and Johnston (2010), Carroll (2006) and PC (2003b), age, education and English proficiency were found to be key drivers of the duration of unemployment.
* As noted above, people aged 55 years and over are significantly less likely to be re‑employed, and more likely to exit the labour force.
* Higher education levels have a strong and positive relationship with re‑employment. People with a bachelor degree or higher were found to be around 60 per cent more likely to find re‑employment than those who have not completed high‑school (although this effect was found to decline with the duration of an unemployment spell).
* Being born in a non‑English speaking country was found to reduce the probability of being re‑employed (relative to being born in Australia), but this effect was also found to decrease with the duration of an unemployment spell.[[6]](#footnote-6)

Table C.4 Competing risks regressions for factors affecting unemployment durationa

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Unemployment →Employment | | |  | Unemployment → Not in the labour force | | |
|  | Subhazard ratio | | SE |  | Subhazard ratio | | SE |
| *Age* (default: 25-34) |  |  |  |  |  |  |  |
| 35-44 | 0.96 |  | 0.07 |  | 1.08 |  | 0.17 |
| 45-54 | 0.95 |  | 0.07 |  | 1.00 |  | 0.19 |
| 55-65 | 0.59 | \*\*\* | 0.07 |  | 2.42 | \*\*\* | 0.50 |
| Female | 0.78 | \*\*\* | 0.05 |  | 1.79 | \*\*\* | 0.24 |
| *Marital status* (default: single) |  |  |  |  |  |  |  |
| Married/de facto | 1.31 | \*\*\* | 0.10 |  | 0.78 |  | 0.13 |
| Divorced/separated/widowed | 1.22 | \*\* | 0.12 |  | 0.79 |  | 0.17 |
| Number of children aged less than 14 | 0.91 | \*\*\* | 0.03 |  | 1.13 | \* | 0.07 |
| Living outside a major city | 0.88 | \*\* | 0.05 |  | 1.04 |  | 0.14 |
| *Country of birth* (default: Australia) |  |  |  |  |  |  |  |
| Main English speaking | 0.87 |  | 0.08 |  | 1.27 |  | 0.23 |
| Non-English speaking | 0.73 | \*\*\* | 0.07 |  | 1.24 |  | 0.30 |
| Own home/ currently paying off mortgage | 1.20 | \*\* | 0.09 |  | 1.02 |  | 0.18 |
| *Highest level of education* (default: Year 11 or below) |  |  |  |  |  |  |  |
| Year 12 | 1.42 | \*\*\* | 0.13 |  | 0.63 | \*\* | 0.14 |
| Diploma or certificate | 1.18 | \*\* | 0.09 |  | 0.79 | \* | 0.11 |
| Bachelor degree or higher | 1.57 | \*\*\* | 0.16 |  | 0.97 |  | 0.27 |
| Illness restricting ability to work | 0.66 | \*\*\* | 0.06 |  | 1.87 | \*\*\* | 0.26 |
| *Industry of previous employment* (default: business services) |  |  |  |  |  |  |  |
| Primary industries | 0.96 |  | 0.14 |  | 1.43 |  | 0.42 |
| Manufacturing | 0.79 | \*\* | 0.08 |  | 1.44 |  | 0.33 |
| Construction and utilities | 0.87 |  | 0.10 |  | 1.41 |  | 0.39 |
| Distribution services | 1.00 |  | 0.09 |  | 1.24 |  | 0.27 |
| Public administration, education health & community services | 0.95 |  | 0.09 |  | 1.18 |  | 0.25 |
| Other services | 0.98 |  | 0.10 |  | 1.22 |  | 0.28 |
| State/territory unemployment rate at commencement of spell | 0.93 | \*\*\* | 0.02 |  | 1.12 | \*\* | 0.05 |
| *Time varying impacts (variables interacted with spell length)* | | | | | | | |
| Non-English speaking country of birth | 1.03 | \*\* | 0.01 |  | 0.98 |  | 0.03 |
| Own home/ currently paying off mortgage | 0.97 | \*\* | 0.01 |  | 0.94 | \* | 0.03 |
| Bachelor degree or higher | 0.98 | \*\* | 0.01 |  | 0.98 |  | 0.02 |

SE – standard error. a The subhazard ratio indicates the ‘subhazard’ or instantaneous risk of ending a period of unemployment for those in a given category, relative to those in the default category. For some variables this ratio is found to vary over time. The subhazard ratio for these variables is split into time‑varying and time‑invariant components by interacting the variable with spell length.

\*\*\* significant at 1 per cent level \*\* significant at 5 per cent level \* significant at 10 per cent level.

*Source*: Productivity Commission estimates using HILDA, waves 1 to 11.

* Results confirm Carroll (2006)and Borland and Johnston’s (2010) findings that marriage is associated with an increased likelihood of finding re‑employment, while having young children is associated with a decreased likelihood of finding re‑employment. The finding that people living outside a major city are less likely to find re‑employment is also consistent with Borland and Johnston (2010). In contrast to these studies, unemployed women are found to be statistically significantly less likely to find re‑employment and more likely to leave the labour force.
* Home owners are found to be more likely to find re‑employment, but this effect was found to decrease over time, to the extent that home owners are less likely to find re‑employment than non‑home owners after approximately six months of unemployment.
* People who enter unemployment after previously being employed in manufacturing are less likely to find re‑employment than those who were employed in other industries. As a result they are expected to have unemployment spells of a longer duration. This finding is statistically significant at the 10 per cent level, and takes into account differences in a range of demographic characteristics, human capital variables and state unemployment rates.

### Transitions from unemployment over time

Although people who enter unemployment after being employed in manufacturing can be expected to experience longer spells of unemployment than those entering unemployment from other industries, about two thirds are expected to be re‑employed within 12 months (figure C.1). After two years, less than ten per cent of unemployed manufacturing employees are expected to remain unemployed.

Figure C.1 Transitions from unemployment over time

Cumulative incidence of re‑employment, exit from the labour force and survival in unemployment, by industry of previous employmenta

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a Covariates are set at mean values for each industry grouping shown.

*Source*: Productivity Commission estimates using HILDA, waves 1 to 11.

Older people are far less likely to find re‑employment (figure C.2). After two years, only around half of unemployed 55-65 year olds who previously worked in manufacturing are expected to find re‑employment. The majority of those who do not find re‑employment are expected to exit from the labour force.

Figure C.2 Transitions from unemployment over time, people aged 55‑65

Cumulative incidence of re‑employment, exit from the labour force and survival in unemployment, by industry of previous employment a

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a Covariates are set at mean values for each industry grouping shown.

*Source*: Productivity Commission estimates using HILDA, waves 1 to 11.

After 12 months or more following retrenchment, the results for manufacturing employees are broadly consistent with the surveys of retrenched Mitsubishi employees mentioned above (figure C.3). This lends support to the approach of using the experience of unemployed manufacturing employees as a proxy for retrenched automotive employees, at least for analysis of periods of 12 months or longer.

The results are inconsistent within the first six months of retrenchment, when a far greater proportion of former Mitsubishi employees had found re‑employment or exited from the labour force than would be predicted by the Commission’s analysis of the experience of unemployed manufacturing employees. Possible reasons for this inconsistency include:

* Mitsubishi employees would have been given some advance notice of their redundancy, so some might have been able to begin seeking alternative employment before they finished at Mitsubishi. As noted above, this has been shown to increase the likelihood of moving directly into new employment without any period out of employment.
* Mitsubishi employees received involuntary redundancy payouts of five weeks pay for every year of service up to 20 years and one week for every year after that. Employees who took voluntary redundancy packages from Mitsubishi left with three weeks’ pay for every year of service (Beer et al. 2006). These relatively large redundancy payouts might have allowed a greater proportion of Mitsubishi employees to immediately retire from the labour force.

Figure C.3 Transitions from unemployment over time

Comparison of duration analysis results for manufacturing employees with Mitsubishi survey data following plant closures announced in 2004a,b

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a Duration analysis covariates are set at the mean values for former manufacturing employees in the HILDA subsample used in this analysis. The comparison does not take into account differences in characteristics between manufacturing employees in the HILDA sample and the Mitsubishi employees. b In 2004, Mitsubishi Australia announced the closure of its Lonsdale engine manufacturing plant and a reduction in capacity at its Tonsley Park assembly plant, resulting in 700 involuntary retrenchments at Lonsdale and 400 voluntary retrenchments at Tonsley Park. Following the restructure and plant closure, researchers surveyed a sample of retrenched employees in three ‘waves’. Wave 1 took place within 6 months of retrenchment, wave 2 took place approximately a year after wave 1, and wave 3 took place approximately a year after wave 2. Midpoints are used to represent the range of timing for each wave, but the nature of the survey data does not allow for precise identification of exactly how long it took for each person to find re‑employment or to exit from the labour force.

*Sources*: Productivity Commission estimates using HILDA, waves 1 to 11; Pieters (2013).

1. More common statistical approaches such as ordinary least squares regression are not appropriate for examining ‘time-to-event’ situations, as the assumption of a normal distribution of spell length is inappropriate. [↑](#footnote-ref-1)
2. Stata code provided by Fry and Boulton (2013) was used to construct calendar panels. [↑](#footnote-ref-2)
3. Strictly, following the approach outlined in Fry and Boulton (2013), spells of unemployment of at least one *calendar* month are identified. The distribution and average duration of spells of unemployment in the sample was found not to be sensitive to whether only calendar month spells were included or also spells of three successive thirds of a month over different calendar months. [↑](#footnote-ref-3)
4. Recall bias is a form of measurement error that arises where people do not accurately recall their past experiences. For example, Borland and Johnston (2010) note that overlapping calendar data from HILDA shows that respondents often redefine a period of unemployment (as recorded in an earlier interview) as being out of the labour force, which can bias estimates of the rate of movement from unemployment to not in the labour force. Borland and Johnston focus on employment and unemployment spells of at least one month as a means to minimise recall bias. [↑](#footnote-ref-4)
5. Borland and Johnston (2010) use the first seven waves of HILDA, and include people who were not in the labour force and people who were at school immediately prior to a spell of unemployment. People in employment prior to the commencement of a spell of unemployment comprise 56.4 per cent (about 1048) of their total sample of 1859 spells. The analysis presented here includes 1507 spells of unemployment, 1027 of which occurred in the first seven waves of HILDA. [↑](#footnote-ref-5)
6. Being born in a non-English speaking country was used as an indicator of poor English. However, this variable might also capture cultural difficulties or discrimination (Carroll 2006). [↑](#footnote-ref-6)