Australian Bureau of Statistics

1351.0

Working Papers in Econometrics and Applied Statistics

Working Paper No. 2004/2

Mature Age Customers on Income Support: Duration, Transition and Flow Analyses Using the FaCS Longitudinal Data Set

1995 to 2000

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Mature Age Customers on Income Support: Duration, Transition and Flow Analyses Using the FaCS Longitudinal Data Set

Anil Kumar, John De Maio and Ruel Abello

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AUSTRALIAN BUREAU OF STATISTICS

EMBARGO: 11.30 AM (CANBERRA TIME) THURS 26 AUG 2004

ABS Catalogue no. 1351.0
ISSN 1320-5099

Produced by the Australian Bureau of Statistics

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Contents

1 Introduction

The aim of this paper is to illustrate a range of questions the Family and Community Services Longitudinal Data Set (FaCS LDS) is helpful in addressing and especially a range of analytical methods that can be brought to bear in addressing these questions. A sub-population of mature age customers on income support (MACIS) was selected as an example. The rest of this section provides some background about the analytical problem tackled and the data used in the study.

1.1 Background

The rising proportion of older workforce-age people who are out of work or having difficulty getting back into work quickly is a growing concern (VandenHeuvel 1999). Prolonged periods without jobs and earnings at an older age can result in loss of skills, increased financial stress, greater degree of social isolation and increased risks of low incomes and poor health in retirement.

However, while mature age unemployment and welfare dependency are clearly very important policy issues there is relatively little known about the welfare dynamics of mature age people, the time pattern of their welfare usage and their interactions between the welfare system and the labour market.

There are a number of Australian studies that have looked at the labour market experience of mature age persons. However, the majority of these studies are based on cross-sectional and/or time series data rather than on longitudinal data. These studies (VandenHeuvel 1999; FaCS 1999; House of Representatives 2000; Encel 2000; Perry 2001; Landt and Nicholls 2001) examined issues such as the labour market performance of older workers, barriers to reemployment and welfare dependence. They generally confirm that, relative to younger cohorts, older workers tend to have:

- longer duration on unemployment
- lower labour force participation rates, and
- higher rates of hidden unemployment, underemployment and long-term unemployment.

ABS (1999) took a longitudinal perspective when analysing the unemployment experiences of older jobseekers using longitudinal data from the 1994–1997 Survey of Employment and Unemployment Patterns. It found that older jobseekers are less successful in obtaining work than young jobseekers, are more likely to drop out of the labour market, are less likely to find a job as a result of a training course and the jobs they find are more likely to be part-time or casual, and low paid. A longitudinal study by Chalmers (2000) using FaCS longitudinal data only indirectly looked at older customers as the primary focus of this study was on customers who make a transition to Age Pension.

While these studies shed light on aspects of mature age workers, they are not able to capture the dynamic behaviour of this group nor their interactions with the welfare system and the labour market. Panel data collected over longer periods (e.g. at one year intervals) do not capture events taking place at shorter intervals. The availability of fortnightly longitudinal data as contained in the FaCS Longitudinal Data Set (LDS) enables a much richer analysis of time patterns of welfare customers than hitherto has been possible.

In October 2000, the Australian Bureau of Statistics (ABS) and Department of Family and Community Services (FaCS) signed a Memorandum of Understanding (MOU) relating to ABS analyses of FaCS-Centrelink databanks. Under this accord, among other things, the ABS agreed to examine the welfare dynamics of *mature age customers* using the FaCS LDS.

1.2 The data

The analysis is based on the FaCS LDS which is a one percent sample of Centrelink social security customers. The sample period covered is from 23 June 1995 to 10 March 2000 (i.e. 124 fortnights). The LDS contains a broad range of socioeconomic/demographic information on each customer on a fortnightly basis, such as age, sex, marital status, Indigenous status, country of birth, geographic location, number of dependent children, private income amounts, benefit payment types, and benefit amounts.

While the LDS contains detailed information on the interaction of FaCS customers with the social security system over successive fortnights, it has a number of limitations. For example, it does not contain information on individuals when they are not in receipt of income support, nor does it contain the reason for a customer's exit from income support. Details of occupation and hours worked for those who are working are not available. Data on some important variables such as level of education and duration of unemployment are also incomplete.

In this paper mature age customers are defined as those with an average age of 50–60 years over the sample period[1]. In the 1% sample used in this study, there are 7,433 individual mature age customers on income support. These account for 9.2% of total customers in the sample (81,016). This sample is not representative of the whole mature age population since it covers only those mature age customers who have been in receipt of welfare benefits over the sample period. Thus inferences from the analysis cannot be generalized to the mature age population as a whole.

For those explanatory variables that are time-varying (such as marital status or home ownership) there are several ways in which to construct an individuals' characteristics including:

- The characteristic of an individual the first time he or she is observed in FaCS LDS
- The characteristic of an individual the last time he or she is observed in FaCS LDS
- Average value of a characteristic over the entire sample period or
- The individual's characteristic at the time of a particular event (for example, at the time of exiting long term unemployment).

[1] The age at the first and last observation dates for each customer has been used to calculate the average age for the customer. While other researchers have defined mature age customers differently (ie 45–59 years, 50–64 years, 45+, 50+ etc.) we have decided to adopt 50–60 years as the appropriate range for this group as we are interested in the welfare experience of those customers who turn 50–60 years over the sample period and are likely to have interactions with the labour market. The 60 year cut-off is adopted to minimise the chances of inclusion of Age Pension (particularly females) recipients above this age during the sample period.

Using a customer's average characteristics over the entire data window captures information which is not available when only the first or last observation is used. The results reported in this paper are based on that method – using a customer's average characteristics over the entire sample. However the other three methods of estimating customers' characteristics are used to explore how sensitive modelling and other results are to the estimation of individuals' characteristics. Generally results are invariant to the method used to estimate characteristics of individuals in the LDS.

1.3 A map of analytical methods used and questions tackle.

The aim of this paper is to illustrate a range of questions the (FaCS LDS) is helpful in addressing and especially a range of analytical methods that can be brought to bear in addressing these questions. For illustrative purposes use is made of analyses of the welfare dynamics of FaCS mature age customers on income support. A wide range of questions are addressed including:

- Analyses of the socioeconomic characteristics, duration, spells and pathways of mature age customers on welfare during the sample period
- Comparisons of welfare experience among subgroups of mature age customers and between mature age customers and customers in younger age groups
- Exploration of the characteristics of individuals associated with a high or low tendency to have multiple spells on welfare and exit from welfare and
- An examination of the transition patterns of long-term unemployed customers.

The following table summarises the broad class of analytical techniques used in this study. A description of the specific techniques and the types of analytical questions that each answer are also included.

	Specific technique employed	Broad class of analytical technique
Descriptive Analyses	*a) Simple tabulations & cross tabulations*	• What are the demographic characteristics of MACIS in a "typical" fortnight of welfare receipt? • How common is churning (or experiencing multiple spells on welfare) for the MACIS caseload? • Are there differences in the welfare experience of MACIS compared to prime age customers (25—4yrs)?
	b) Flow analyses	• What welfare pathways (onto other payment programs and off-benefit) do MACIS experience?
Event-History Modelling	*a) Survival & hazard rate models* Technique to analyse the timing of welfare exit. The survival function (S_t) expresses the probability that a customer has not completed a welfare spell as a function of time. Hazard rates (H_t) give the probability that a spell is completed in the next short interval after duration t, given it has lasted until t.	• What is the probability of a MACIS remaining on welfare beyond a certain number of fortnights? • How do exit rates vary as spell length increases? • Are individuals with certain characteristics more likely to remain on a spell of welfare payments? (eg. males relative to females, indigenous compared to non-indigenous)? • Are there differences in survival times across groups (mature aged compared to prime aged, NSA compared to non-NSA customers)? The same techniques have been applied to analyse a specific sub-population - MACIS who experience a spell of long term unemployment. This allows us to answer: • Is there a tendency for MACIS to transfer to a specific payment type after leaving long term unemployment? • As the length of unemployment benefits increase are MACIS more likely to exit the welfare system? (or remain on some other form of income support?)
	b) Proportional hazards model The survival and hazard models described above do not allow personal characteristics to influence the expected length of time one spends on benefits. To overcome this limitation and allow for the effects of individual characteristics on the exit rate (or expected length of time on benefits) the proportional hazard duration model based on Cox's (1984) semi- parameteric model is estimated. *(Section 2.3)*	• What personal characteristics; - increase exit from welfare - decrease exit from welfare

Broad class of analytical technique	Specific technique employed	Analytical question addressed
Regression Modelling	*a) Logit modelling* When analysing the outcomes of MACIS, in some cases an event of interest can take on one of two values. For example a client experiences multiple welfare spells or just one spell. The logit or logistic model has been used to model binary dependent variables such as these. *(Section 2.4)*	• What socioeconomic and demographic factors are associated with MACIS being more likely to "churn" (or experience multiple spells of benefit)? The same technique has been used to analyse MACIS who experience a spell of long term unemployment payments: • What socioeconomic and demographic factors are associated with MACIS exiting long term unemployment by transferring to another payment program? • Are these factors different for those who leave long term unemployment by exiting the welfare system?
	b) Multinomial logit modelling This technique is an extension of the logistic model described above. In this case multinomial logistic regression is used to model dependent variables that contain multiple responses. *(Section 2.5)*	• What socioeconomic and demographic factors are associated with a MACIS experiencing a single long spell (greater than 6 months) on benefit? • Are these factors different for those who experience multiple long spells? (or multiple short spells?)
	c) Count models A Poisson type regression equation is used to model the number of spells of benefit receipt. It is assumed that the dependent variable (number of spells) has a Poisson distribution given the independent explanatory variables. The probability of the event (one spells, two spells...) is then estimated within this framework. *(Section 5.2)*	• What is the probability of a MACIS experiencing 1 spell? (or 2 spells? or 3 spells?) • Are these probabilities different for males relative to females?

The remainder of the paper is organised as follows. Section 2 discusses the methods that were used in the study. Section 3 presents the results from the descriptive analyses of the FaCS data. It gives the socioeconomic/demographic characteristics of mature age customers. Section 4 presents results to illustrate the application of survival and hazard analytical techniques on mature age customers on income support. In section 5 model results are discussed. Section 6 concludes the paper.

2 Methods used in the analysis

2.1 Descriptive analyses

Various descriptive techniques were applied on the data. These included simple tabulations, cross tabulations of the data and flow analysis. These techniques were part of exploratory data analysis prior to the application of more complex methods. Results from these analyses are summarised in section 3 of the paper.

2.2 Survival and hazard analysis techniques

2.2.1 Survival and hazard functions for all MACIS

Survival and hazard analysis techniques are used to explore the timing of exit from welfare by mature age customers. This analysis allows one to answer questions such as:

- What is the probability of a mature age customer remaining on a welfare spell beyond a certain number of fortnights?
- How do exit rates vary as spell lengths increase?
- Are individuals with particular characteristics more likely to exit welfare relative to other individuals?

The survival function S_t, expresses the probability that a customer has *not* yet experienced the event of interest (in this case, the completion of a spell) as a function of time *t*. It is formally defined as:

$$S_t = P\left(T > t\right) \tag{1}$$

where *P* represents the probability, and *T* is the survival time.

The above equation expresses the probability that a customer (or a spell) survives (or lasts) beyond time *T* (where *T* is larger than *t)*. The proportion of customers remaining in the sample after time *t* is often called the 'risk set' — that is, the *proportion* of the original sample that is still at risk of experiencing a particular event after time point *t* has elapsed.

The hazard rate h_t, can be (loosely) defined as the probability that the event of interest (once again, completion of a spell) occurs in the time interval $[t, t+\Delta t]$, provided that this event has not occurred before time *t* (that is, the duration T must be at least equal to *t)*.

More formally, the hazard rate can be expressed as:

$$h_t = \lim_{\Delta t \to 0} \frac{P\left(t \le T \le t + \Delta t \middle| T \ge t\right)}{\Delta t} \tag{2}$$

[1] The hazard rate is not really a probability, as it can be larger than 1; however most texts suggest that analysts should visualise the hazard rate as a chance (see Taris, 2000, page 99).

2.2.2 Survival and hazard functions for sub-populations

It is possible to estimate survival and hazard functions for various sub-populations of interest. For example, the outcomes of mature age customers who experience a spell of long term unemployment payments (Newstart Allowance or NSA) can be analysed within the survival and hazard model framework. A long term unemployed person is defined here as a customer who has received or has been receiving NSA payments for at least 26 consecutive fortnights.[2] A customer is deemed to have received a consecutive fortnight of NSA if he or she received a payment of NSA within two fortnights of their last NSA payment (with no other payment type received within this 2 fortnight interval).[3]

Let T_i be a random variable denoting time before exit from long term unemployment benefit receipt. Furthermore let J_i be a random variable denoting the type of exit that occurred to customer i. For example, $J_{6081} = 1$ indicates that customer number 6081 exited long term NSA receipt by transferring to the Disability Support Pension (or DSP) program. As explained in more detail in Section 4.5, there are five ways by which someone on NSA can leave the long term unemployed sub-population, namely:

i. One could move from NSA and start receiving the Disability Support Pension
ii. One could move from NSA and start receiving some other benefit other than NSA or the Disability Support Pension
iii. One could leave the welfare system for over 28 days and re-enter the welfare system receiving NSA
iv. One could leave the welfare system for over 28 days and re-enter the welfare system receiving some other benefit other than NSA
v. One could leave the welfare system.

Allison (1995) notes we can now define the hazard $h_{ij}(t)$ for exit type *j* at time *t* for customer *i* as:

$$h_{ij}(t) = \lim_{\Delta t \to 0} \frac{\Pr\left(t \le T_i < t + \Delta t,\ J_i = j \mid T_i \ge t\right)}{\Delta t} \qquad j = 1,\ \ldots 5 \tag{3}$$

In this case, *j* can take on one of five values corresponding to the five types of exit from long term unemployment defined above.

The conditional probability in equation (3) is the probability that exit from long term unemployment benefits occurs between time *t* and some interval $t + \Delta t$, and that the exit is of type j, given that the customer has not already exited from NSA by time *t*. (Where Δt is the change in *t*).

[2] The duration of unemployment variable (DUR_UNEM) on our version of the LDS was not used due to data quality concerns.

[3] The 28 day rule is consistent with our definition of spells. It should be noted, that it is different from break rules allowed by Centrelink (i.e. breaks of up to 6 weeks in the first 12 months and 13 weeks after 12 months of unemployment).

An additional approach to analysing the duration of mature age customers time on long term unemployment is provided by estimating survival functions.

In much the same way as type-specific hazard functions, type specific survival functions can also be defined (Allison, 1995):

$$S_{ij} = P\left(T_{ij} \geq t\right) \tag{4}$$

Where T_{ij} gives the time at which the *j*th event type either occurred to the *i*th person or would have occurred if other event types had not preceded it. To illustrate, we assume that a mature age customer who exits long term receipt of NSA by moving onto another program at time T_1, could have later exited through DSP at time T_2, if the earlier exit had not occurred. For a given set of T_{ij}'s the researcher can only observe the smallest one (the event which occurs first).

These type-specific hazards can be interpreted in much the same way as ordinary hazards: the hazard at any point in time t corresponds to the risk of an event occurring at time t. However, in the case of type-specific hazards, the events are now of a specific type.

For both sub-populations, ie. all mature age customers and the long term unemployed, the empirical survival and hazard functions are estimated non-parametrically using the life-table or actuarial method (this method is chosen over the Kaplan-Meier method as it is a superior method for datasets with a large number of observations or many unique event times). Under the life-table method, event times are grouped into appropriate intervals (four fortnights in this case) and the associated probabilities for each interval are then estimated.

The survival and hazard functions have been estimated using lengths of individual spells rather than total duration for each customer. Although the data contains multiple spells for the same person each spell has been treated as being independent, regardless of whether it was for the same person. Section 4 reports results from these analyses.

2.3 Proportional hazards

A limitation of the empirical survival and hazard functions proposed above is that they treat the population as homogeneous and do not recognise the possible association between personal characteristics and the length of time one spends on benefits. To allow for the effects of individual characteristics on the exit rate (equivalently, the expected length of time on benefits) one can use a proportional hazard duration model based on Cox's (1984) semiparametric model.

Under this model the hazard function of the survival time can be specified as follows:

$$\lambda_i = \lambda_0\left(t\right)\exp\left(x_i'\beta\right) \tag{5}$$

where $\lambda_i(t)$ is the hazard for individual i at time t, $\lambda_o(t)$ is a baseline hazard function, x_i is a vector of individual characteristics (which may vary over time)and β is a parameter vector to be estimated.

The baseline hazard, $\lambda_o(t)$, is common to all individuals and can be regarded as the hazard function for an individual whose covariates all have values of 0 (Allison 1995).

To estimate the hazard function, we take the logs of both sides so that the log of the hazard now becomes a linear function of the covariates. The partial likelihood technique used to estimate the model cancels out the baseline hazard function. Results from this analysis are reported in section 4.

2.4 Logistic regression techniques

Given that we have chosen to examine only two possible outcomes for churning (i.e. whether a person has multiple spells on benefits or not) the variable of interest can be viewed as a dichotomous (0,1) variable.

The logistic model for estimating the likelihood of an event (e.g. churning) can be expressed as follows:

$$\log\left(\frac{P(Event)}{P(Non\ Event)}\right) = \alpha + \beta_1 X_1 + \ldots \beta_k X_k \qquad (6)$$

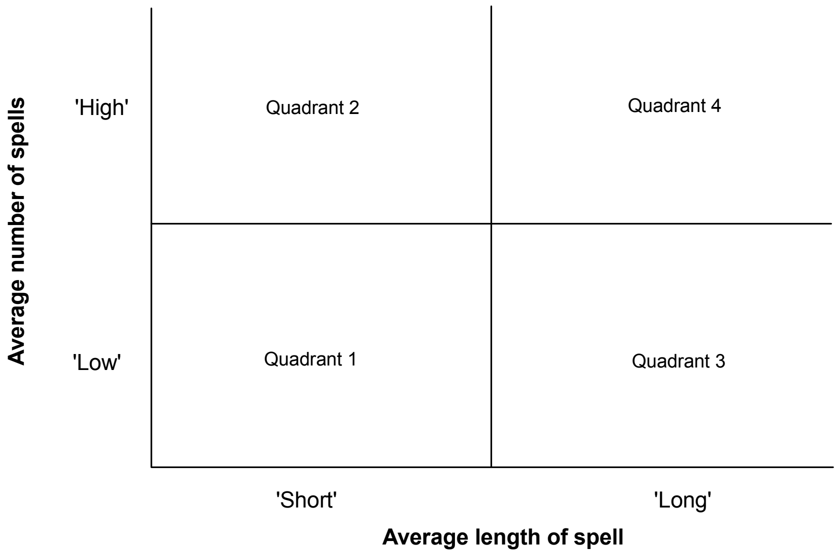
where α is the intercept parameter, the βs are k regression parameters, and the *Xs* are a set of k explanatory variables representing the individual's observed characteristics.

The model in (6) indicates that the log of the odds of an event occurring is a linear function of the explanatory variables. The parameters in β can be estimated using standard maximum likelihood techniques.

2.5 Multinomial logistic models

The model of churning given in equation (6) above focuses on spells only (i.e. single vs multiple spells), implicitly ignoring the length of welfare spells. In this section, we model different "types" of customers using information on both the number and average length of spells for each customer. This analysis divides customers into four groups. This allows one to examine whether customers with higher number of spells and/or longer average length of spells display characteristics different from those who experience fewer spells and shorter average stays on benefits. Following Dawkins et al (2000) we can use information on the number of spells and their average length to classify customers into certain "typologies". This is best explained by the use of a diagram as shown below.

The diagram is split into 4 quadrants with the vertical axis representing the average number of spells and the horizontal axis representing the average length of spell.



Quadrant 1 has those individuals with a "low" number of "short" spells. Quadrant 2 has those individuals with a high number of short spells, Quadrant 3 has those individuals with a low number of long spells and Quadrant 4 has those individuals with a high number of long spells. The cut-offs chosen to distinguish low and high number of spells and short and long lengths of spells are discussed in Section 5.3.

To analyse a typology or category of customers where there are multiple responses a Multinomial Logistic regression (MNL) model is the most appropriate method. Given that in the above case the responses have no essential ordering a generalised logistic regression model can be used to estimate the log of the odds of other responses relative to the reference or baseline category as a linear function of the explanatory variables. The model to be fitted can then be expressed as

$$\log(P_{ij}/P_{ik}) = \alpha_j + x'_i\beta_j \qquad (7)$$

where P_{ij} is the probability that customer i falls in category j, $j \neq k$ and k is the reference category, α_j are separate sets of intercept parameters, x_i is the set of explanatory variables for the ith customer, and β_j are separate sets of regression parameters for each logistic regression.

Given the four response categories we make one of the responses as the reference category (which in this case is single-spelled customers with less than 26 fortnights on benefits) and estimate the logistic regressions for the remaining three responses relative to the reference category.

Section 5.3 reports results from the multinomial logistic models.

3 Results from the descriptive analyses

Given the data underlying the analysis of mature age customers spans almost five years, there are various ways in which the mature age caseload can be described. Section 3.1 reports customer characteristics in terms of their average values over the entire sample period while section 3.2 reports customer characteristics at a particular point in time (for example, their time of entry into the sample). The episodes or spells mature age customers spend on welfare are described in section 3.3. Section 3.4 tracks a particular cohort of customers and trace their movements onto other payment programs and off-benefit over the data window. In sections 3.5, mature age customers on Newstart Allowance (NSA) are compared against those mature age customers on non-NSA benefits. Section 3.6 describes the welfare experience of mature age customers vis-a-vis prime age customers.

3.1 Average characteristics of mature age customers over the entire sample

Table 1 shows selected characteristics of mature age customers on income support. The averages for the variables are calculated over the entire observation window and as such refer to the characteristics of mature age customers in a typical or average fortnight.

The sample means show that in a typical fortnight 58% of mature age customers were females[4]. The average age of a mature age customer in an average fortnight was 55 years. Australian born customers[5] accounted for 63% of the total; slightly over 1% identified themselves as Indigenous; and 59% were married. Around 10% of customers had dependent children[6], with an average of 1.5 children per customer for those who had children (over all observations the average number of children was 0.15). The average age of the youngest child was 11 years for customers with children.

In a typical fortnight a majority of mature age customers were home owners (around 58%). Around a third of mature age customers were renters, while 4% paid no rent. Almost 18% of mature age customers received rent assistance, with an average rent allowance of $52 per fortnight for those who received such assistance ($9 per fortnight over all observations)[7].

The largest fraction of the mature age customers resided in NSW (32%), while the Northern Territory had the smallest fraction with 0.8%. The state distribution of mature age customers were broadly in line with state population shares of total persons.

Around 10% earned income in a typical fortnight, with average earnings amounting to $324 per fortnight for those with positive income. Approximately 46% received some unearned income (in the form of interest, dividends, compensation, superannuation etc). The average fortnightly program payment received by mature age customers was $286.

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[4] Females account for 58% of total observations though they are 54% of customers. The higher share of females in total observations is because females spent more time on welfare compared to males.

[5] Customers with missing records for country of birth were assumed to be Australian born.

[6] Throughout this paper, the number of dependent children refer to only those children who would be eligible for Family Payments.

[7] For some 'coupled' customers, all rent assistance may be paid to one of the couple rather than shared between both. Thus the percentage of customers who are recorded as receiving Rent Assistance does not exactly equate with the number who benefit from Rent Assistance.

Mature age customers spent almost two-thirds of their time over the sample period on two main payment types — Disability Support Pension (DSP) (39%) and Newstart Allowance (NSA) (20%). Recipients of Wife Pension and Partner Allowances accounted for 25% of all sample observations.

Table 1: Mature Age customers on income support – selected characteristics

	Sample average
Demographic Characteristics	
Male (%)	42.0
Average age (years)	55.4
Australian born (%)	63.1
Identifies as Indigenous (%)	1.1
Married (%)	59.0
Presence of children (%)	9.8
Average no. of children for those with children	1.5
Average age of youngest child for those with children (yrs)	11.3
Home Ownership and Rental Type (%)	
Home owner	40.8
Purchasing own home	2.1
Other home owner	15.4
Private rental	17.4
Govt rental	10.8
Other rental	5.8
No rent paid	4.2
Missing/unknown	3.5
State of Residence (%)	
NSW	32.4
VIC	24.9
QLD	18.1
SA	9.4
WA	8.7
TAS	3.4
NT	0.8
ACT	1.0
Overseas/unknown	1.3
Financial Variables	
Received earned income (%)	10.0
Average earned income (positive earnings) ($/fortnight)	324.52
Received unearned income (%)	46.5
Average unearned income (positive earnings) ($/fortnight)	62.78
Basic payment entitlement ($/fortnight)	286.83
Received rent assistance (%)	17.8
Rent assistance ($/fortnight)	9.31
Program Payment Type (%)	
Disability support pension	39.3
Newstart allowance	20.3
Wife pension/partner allowances[a]	25.7
Older payments[b]	6.3
Carer payments[c]	6.1
Age pension	0.9
Sickness allowance	0.9
Others	0.5
Total Number of Fortnightly Observations	611 644

(a) Includes Wife Pension - Age and DSP,Partner Allowances (PA/PTA) and Mature Age Partner Allowance (MPA).
(b)Includes Mature Age Allowance, Newstart Mature Age Allowance and Widow Allowance/Pension.
(c) Includes Carer Pension, Sole Parent Pension (SPP/PPS) and Parenting Payments.

3.2 Characteristics of mature age customers at a particular point in time

Table 2 presents the characteristics and distribution of mature age customers on income support by total time on benefits[8].

In the table below, mature age customers on income support are divided into seven groups according to their total time on welfare benefits. The first group are those customers who receive between 1–20 fortnights of welfare payments. The seventh group consists of those who had been observed in all of the fortnights within the observation window (i.e. 124 fortnights). The second last row in the table gives the total number of clients in each group. The last row shows the percentage share of each group in the whole sample of MACIS.

In this analysis, customer characteristics refer to the characteristics observed at the time of first entry into the observation window. The averages are over the individuals in the group at time of entry into the window. The first column of Table 2 lists the customer characteristics used to compare the different groups.

On average, mature age customers were on income support for 82 of the 124 fortnights of the sample period. Around 16% of mature age customers spent 20 fortnights or less on welfare payments. Slightly over one-half experienced at least 100 fortnights of welfare, and over a third spent their entire time (124 fortnights) on benefits.

Female customers comprise a larger proportion of the mature age customers as total time on benefits lengthens. They make up:

- 44% of the group who receive between 1 and 20 welfare payments
- 54% of those who receive between 101 and 123 payments and
- 63% of those who spend their entire time in the sample (124 fortnights).

The majority of the mature age customers are Australian born (65%) and 62% are married (at entry in the LDS). A little under 1% of mature age customers identify as Indigenous.

Customers who spend less than 20 fortnights on benefit are most likely to be receiving unemployment benefits upon entering the welfare system. Almost half (47%) of the customers who were on welfare for the entire duration of the observation window (124 fortnights) were on DSP in fortnight number one of the window. There is also an association between payment amounts and length of welfare receipt, with average basic payment (at entry) higher for those with longer durations in the welfare system.

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[8] This analysis the calculation of total time on benefits (or benefit duration) is based on a count of fortnights the customer is observed in the LDS. As such this duration count is different from the duration measure contained in the LDS denoted by *duration on income support* (ISS_ST_D) variable. This variable could not be used due to incomplete or inconsistent data for a large number of customers. In our dataset there are some records with zero basic payments and to the extent these records are included in the duration count for the customer it may overstate their duration on benefit. However, our analysis of this issue reveals the number of customers with zero payments is extremely small and they do not significantly In alter the descriptive statistics or model results.

Caution should be exercised when interpreting Table 2. The table groups customers by characteristics at first point of entry in the window and by total time on welfare benefits while in the window. The pattern of welfare usage for customers outside the data window is unobservable to the researcher. For example, a customer who is present in the sample at the first extract date and then permanently exits welfare, may have received 10 years of payments prior to 23 June 1995 (the first observed fortnight in the window). However we can not observe these welfare payments and for this reason care should be taken when interpreting the table.

Table 2: The distribution of mature age customers by total time on benefits

	Total time on benefits (fortnights)							All
Characteristic	1–20	21–40	41–60	61–80	81–100	101–123	124	Clients
Average Age (years)	54.3	54.0	53.6	53.5	53.3	53.0	53.2	53.5
Total time on benefits (fortnights)	9.7	30.1	50.2	70.5	90.8	116.4	124.0	82.3
Male (%)	56.5	53.4	50.4	47.7	45.0	46.1	36.9	45.8
Married (%)	64.0	66.8	64.8	65.1	62.5	56.1	60.6	61.9
Australian born (%)	66.8	67.7	68.4	68.5	63.9	62.0	63.5	65.0
Identifies as Indigenous (%)	0.2	1.0	1.1	0.9	0.8	1.4	0.9	0.9
Home Ownership Status (%)								
Home owner	58.5	55.7	55.1	57.3	49.1	43.2	31.5	45.4
Purchasing own home	5.3	4.3	3.0	3.4	3.5	1.8	1.7	2.9
Other home owner	5.1	4.1	6.3	5.9	5.3	9.2	24.0	12.4
Private rental	16.3	15.9	17.1	16.0	20.1	20.6	15.8	17.1
Govt rental	1.9	3.7	2.8	4.6	6.3	7.6	12.8	7.3
Other rental	4.0	3.6	4.5	4.8	6.1	7.1	6.4	5.6
No rent paid	5.4	4.8	5.0	5.9	6.1	6.3	6.6	6.0
Missing/unknown	3.5	7.9	6.3	2.1	3.6	4.2	1.3	3.4
Payment Types (%)								
Carer	7.2	6.9	9.4	7.5	7.7	8.3	4.4	6.6
Wife pension/ partner allowances	13.9	17.2	22.9	21.2	21.1	22.6	34.2	24.4
Unemployed	56.6	53.5	47.9	47.5	49.7	44.0	7.5	35.4
Disability	8.9	13.1	11.6	15.1	14.6	13.8	47.4	24.4
Sickness	9.1	5.0	4.2	4.6	3.3	6.9	1.0	4.4
Older	2.8	1.7	1.9	2.3	2.0	3.0	5.3	3.4
Other	1.6	2.6	2.2	1.8	1.6	1.3	0.3	1.3
Average Basic Payment	175.1	202.5	227.0	229.6	236.8	253.9	279.4	239.5
Number of Spells	1.2	1.6	1.7	1.7	1.8	1.5	1.0	1.3
Individual MACIS (No.)	1,215	725	639	562	493	1,246	2,553	7,433
Share of MACIS population (%)	16.4	9.8	8.6	7.6	6.6	16.8	34.4	100.0

3.3 Number of spells spent on welfare

Table 3 presents information on spells on welfare by mature age customers. In this paper spells have been defined as continuous fortnights on benefits including up to two fortnights (28 days) off welfare. Thus a customer who leaves benefits for one or two fortnights and returns to welfare is considered to continue on the same spell. If they go off benefits for more than two consecutive fortnights and return to welfare then they are considered to commence a new spell[9].

An issue of particular interest in the study of welfare experience of income support customers is the extent of "churning" or multiple spells on benefits. Churning on welfare, among other things, reflects a closer attachment to the labour market and as such the extent of churning by mature age customers may indicate the degree of interaction between work and welfare.

An analysis of welfare spells of mature age customers suggests that the pattern of welfare usage among mature age customers is characterised by single long continuous spells of benefit receipt. Over three quarters (77.2%) of mature age customers had only one spell on welfare. The remainder (22.8%) were multi-spellers thus indicating that the incidence of churning on benefit among mature age customers is low.

Males were more likely to have multiple spells than females (27% vs 19%). Single spellers averaged 86 fortnights on welfare compared to 69 fortnights for churners.

Table 3: Percentage Distribution of Mature Age Customers by Number of Welfare Spells

Spells	Number of Spells								
	1	2	3	4	5+	*Total*	Single Spellers	Churners	*Total*
All Customers (%)	77.2	16.1	4.7	1.5	0.6	*100*	77.2	22.8	*100*
Males (%)	72.8	18.3	6.0	1.8	1.1	*100*	72.8	27.2	*100*
Females (%)	80.8	14.2	3.6	1.2	0.2	*100*	80.8	19.2	*100*
Ave. duration of spell (no. of fortnights)	*86.3*	*70.0*	*65.4*	*62.5*	*74.3*		*86.3*	*68.7*	

4 Flow analysis of mature age customers pathways on welfare

Table 4 presents the results of a flow analysis of mature age customers tracing the paths they follow over the sample period. It tracks mature age customers (totalling 4,159 individuals) who were in receipt of benefits at the first observation date (23 June 1995), and examines the payment types this cohort moves onto at yearly intervals (March of each year). It also examines the extent to which this original group of mature age customers exit the welfare system.

Of the 4,159 mature age customers who were on income support on the first observation date, the bulk (87%) were split across three payment categories: DSP, NSA and WifePension/Partner Allowances.

[9] The spell definition is based on what other researchers have used. It is a reasonable assumption to make as it minimises the appearance of false transitions if shorter duratioins (e.g. > 14 days) are adopted. Sensitivity analysis done to test model results under alternative definitions (14, 28, 42, 56 days) yields similar conclusions. It is noted that our definition of spells may be different from the break rules allowed by Centrelink.

The proportion of mature age customers who remain on NSA and Wife Pension/Partner Allowances tapers off in later years, with a much larger decline in the share of NSA customers. Between the first and last observation dates the proportion of mature age customers on NSA falls from 22.2% to 7.5% while the proportion of customers on Wife Pension/Partner Allowances falls from 29.9% to 19.0%. Over the same period, the proportion of customers on DSP increases from 35.2% to 40.1% while the proportion receiving "Older" payments increases over the sample period.

The proportion of the original cohort who move off benefits rises over time. Of the original customers, 8.1% did not receive a payment in March 1996, 14.0% no longer received payments in March 1998 and by March 2000 around 16.3% were no longer on benefit. However given that after almost 5 years less than a fifth of mature age customers go off benefits confirms a slow exit from welfare by mature age customers once they enter the welfare system. This compares with around two-fifths of prime age customers exiting welfare over the same period.

From Table 4, a greater percentage of males are no longer receiving payments in the March 2000 fortnight (20.5% compared to 13.1% for females). For both males and females the percentage receiving DSP increases over time. Around 59% of males and 26% of females were on DSP in March 2000. The proportion receiving NSA and Wife Pension/Partner Allowances falls over time for both males and females.

Table 4: Mature Age Customers - Pathways on welfare for customers who were on welfare on 23 June 1995 (percentage distribution)

Payment Category	Jun 1995	Mar 1996	Mar 1997	Mar 1998	Mar 1999	Mar 2000
	All customers who were on welfare at 23 June 1995 (%)					
Age	0.0	0.0	0.0	0.0	2.2	5.4
Carer	5.3	5.9	5.1	4.2	3.9	3.5
WifePension/Partner Allowances	29.9	27.0	25.2	23.5	21.9	19.0
Unemployed	22.2	15.8	14.2	11.5	9.5	7.5
Disability Support	35.2	37.1	38.8	40.1	40.3	40.1
Sickness	2.3	1.4	0.2	0.1	0.1	0.1
Older	4.3	4.3	4.7	6.5	7.4	8.0
Other	0.7	0.5	0.3	0.1	0.1	0.1
Off-Benefit	0.0	8.1	11.4	14.0	14.5	16.3
Total	100.0	100.0	100.0	100.0	100.0	100.0
	Male customers who were on welfare at 23 June 1995 (%)					
Age	0.0	0.0	0.0	0.0	0.0	0.0
Carer	3.6	3.9	3.7	3.2	3.0	2.4
WifePension/Partner Allowances	2.5	1.5	1.1	1.0	1.1	0.8
Unemployed	37.7	26.3	22.3	18.9	15.9	12.4
Disability Support	51.4	54.0	56.2	57.6	58.5	58.9
Sickness	3.5	2.0	0.3	0.1	0.1	0.2
Older	0.0	0.0	0.2	0.7	2.9	4.6
Other	1.2	1.1	0.6	0.2	0.1	0.1
Off-Benefit	0.0	11.1	15.5	18.3	18.3	20.5
Total	100.0	100.0	100.0	100.0	100.0	100.0
	Female customers who were on welfare at 23 June 1995 (%)					
Age	0.0	0.0	0.0	0.0	3.8	9.4
Carer	6.5	7.4	6.2	4.9	4.6	4.3
WifePension/Partner Allowances	50.2	45.8	43.1	40.3	37.2	32.4
Unemployed	10.8	8.1	8.2	6.1	4.8	4.0
Disability Support	23.2	24.5	25.9	27.1	26.9	26.2
Sickness	1.5	0.9	0.1	0.0	0.0	0.0
Older	7.5	7.5	8.0	10.7	10.8	10.4
Other	0.4	0.1	0.1	0.0	0.1	0.1
Off-Benefit	0.0	5.8	8.4	10.9	11.8	13.1
Total	100.0	100.0	100.0	100.0	100.0	100.0

3.5 Mature age customers on NSA versus those on Non-NSA: a comparative analysis

3.5.1 Mature Age Customers on NSA versus those on DSP

Table 4 in the previous section shows that over time (for customers who were on welfare at 23 June 1995) there is an increase in the relative share of the DSP and a corresponding decline in the share of NSA[10]. Further analysis was undertaken to examine the relationship and the interactions between the two pay types to see whether there is an outflow from one to the other.

Table 5 presents the results of the flow analysis for mature age customers by NSA and DSP payment types only by first and last dates of the period covered by the data file. Note this analysis only looks at the flow analysis at the beginning and end periods and therefore ignores any outflows and inflows that may be occurring in the intervening period.

Of the 924 NSA customers present at 23 June 1995, 28% were still present on this program by 10 March 2000, 24% moved to DSP, 19% moved to other programs while the remaining 28% had moved off benefits. Of the 1,464 DSP customers present on 23 June 1995, 86% were still present on this program by the end of the period, around 11% moved off benefits and very few moved to NSA (3 customers only) or other payments. As expected, this analysis confirms that a much smaller proportion of initial DSP customers go off their initial program (to some other program or off welfare altogether) compared to NSA customers.

Table 5: Mature Age customers – NSA DSP Flow Analysis

	NSA	DSP
Number of Customers at 23 June 1995	924	1464
% of Customers on NSA at 10 March 2000	28.4	0.2
% of Customers on DSP at 10 March 2000	24.0	86.3
% of Customers on OTHERS at 10 March 2000	19.2	2.9
% of Customers OFF-BENEFIT at 10 March 2000	28.5	10.6

3.5.2 Mature Age Customers on NSA versus those on non-NSA

Mature age customers are not a homogeneous group and significant differences in welfare experience exist between sub-groups. An analysis was undertaken to compare the welfare dependence and labour market experience of NSA and non-NSA customers within the mature age group. Mature age customers on unemployment benefit type payments (mainly NSA) are subject to activity tests (i.e. required to actively look for work or partake in training etc.) compared to other payment type customers who are exempt from such activity tests. While activity testing may account for some of the differences in welfare duration, it should be noted that the circumstances of mature age customers which determine what payment they are on. These circumstances include main activity (such as caring, parenting, and looking for work), work capacity and recent workforce experience.

[10] The share of DSP rose from 35.2% at 23 June 1995 to 40.1% at 10 March 2000 while the share of NSA over the same period fell from 22.2% to 7.5% (From Table 4).

Since a customer can move across several benefit programs (e.g. NSA, SPP, DSP) during his or her time on welfare it is not possible to uniquely identify NSA customers and non-NSA customers. However, for ease of analysis, this paper defines NSA customers as those mature age customers who spend half or more of their total time on NSA. Non-NSA customers are all the remaining customers who spend less than half of their time on NSA (i.e. spend majority of their time on other payments).

Table 6 presents the results of this analysis, showing that around 30% of mature age customers can be classified as NSA, while the remaining 70% can be considered as non-NSA customers. NSA customers were more likely to be males (72%) while non-NSA customers were more likely to be females (65%). NSA customers are also likely to be slightly younger than non-NSA customers (54.5 years vs 55.4 years).

NSA customers had a lower average duration on welfare (55 fortnights vs. 94 fortnights) and were multi-spellers (42% vs. 15%). They were more likely to be attached to the labour market as reflected by their higher incidence of earned income (51% vs. 19%) and higher average levels of earned income.

Thus NSA customers generally spend a shorter time on welfare and have a greater attachment to the labour market vis-a-vis non-NSA customers. However, caution should be exercised in interpreting these results. As noted earlier, the different circumstances of mature age customers (for example, caring responsibilities, work capacity and recent work experience), along with different eligibility conditions, income testing rules and payment rates across programs, play a role in determining the payment types mature age customers are on. The analysis in this section may simply be reflecting these differences rather than the impact of activity testing itself.

Table 6: Comparison Between NSA and Non–NSA Customers

	NSA(a)	Non-NSA(b)
Customers (no.)	2191	5242
% Share of total	29.5	70.5
Male (%)	71.9	34.8
Average age (yrs)	54.5	55.4
Avg duration (fortnights)	55.3	93.6
Multi spellers (%)	41.9	14.9
Avg no. of spells	1.6	1.2
Spell range	1–7	1–7
% Earned income	51.4	18.7
Avg non-zero earned income ($/fnt)	90.4	24.3

(a) Mature age customers who spend half or more of their total time on NSA.

(b) Mature age customers who spend over half of their total time on non-NSA type payments.

3.6 Welfare experience of mature age and prime age customers by selected indicators

This section compares the welfare experience of mature age customers (50–60 years) with prime age customers (25–44 years). Table 7 presents the comparative statistics for these two groups. (Note the sample averages for the two groups have been calculated over the entire observation window and as such they represent customer characteristics in a typical fortnight).

From table 7, there were 7,433 mature age customers and 21,104 prime age customers representing 9% and 26% respectively of the total number of customers on the 1% sample (i.e. 81,016). The average age of mature age customers was 55 years compared to 34 years for prime age customers (with average age at entry being 54 years and 33 years respectively).

The share of males in total observations of MACIS is 42% and 41% among prime age customers. Around three-fifths of mature age customers were married compared to around a third of prime age customers. There were more non-Australian born customers in the mature age group compared to the prime age group, with over a third of mature age customers born overseas compared to only a quarter of prime age customers. A much smaller proportion of mature age group were of Indigenous origin compared to prime age customers (1.1% vs 3.4%). Mature age customers had a lower incidence of earned income (9%) compared to prime age customers (18%). Mature age customers spent a much larger proportion of their time on DSP compared to prime age (39% vs 14%) while prime age customers spent a much larger proportion of their time on NSA compared to mature age customers (37% vs 20%).

On average, mature age customers stayed longer on benefits compared to prime age customers (i.e. 82 fortnights vs 56 fortnights), and slightly over a third of mature age customers stayed on the benefit program for the entire 124 fortnights (covered by the dataset) compared to only a tenth of prime age customers. A large part of the difference in average duration between mature age and prime age customers could be explained with reference to the type of payments these two groups of customers receive while on welfare. Given a much higher proportion of mature age customers on non-NSA type payments, which are generally associated with longer duration on welfare, this explains the large disparity in duration between these two groups. However, even after controlling for payment types, mature age NSA customers have higher durations on payment (55.3 fortnights) than their prime age counterparts. The application of the activitiy test may vary with age, to take account of the different circumstances of mature age customers, so this different application may still have effects on duration. All the same, this result does suggest that other factors apart from activity testing are also having some effect on average duration on benefits.

Mature age customers had an average of 1.3 spells compared to 1.8 spells for prime age customers. The distribution of the spells for mature age customers was more skewed towards lower number of spells compared to prime age customers. Slightly over three-quarters of mature age customers were single-spellers compared to less than half of prime age customers. Thus a much smaller proportion of mature age customers are churners or multi-spellers compared to prime age customers (22.8% vs 56.3%).

Table 7: A Comparison of Welfare Experience Between Mature Age and Prime Age Customers Selected Indicators

	MACIS (50–60 yrs)[(a)]	PRIME AGE (25–44 yrs)[(a)]
Total observations (no.)	611 644	1 190 319
Number of individuals (no.)	7 433	21 104
Share of total 1% sample (81016) (%)	9.2	26.0
Average age (years)	55.4	34.2
Average age at entry (years)	53.5	32.5
Males (%)	42.0	41.2
Married (%)	59.0	36.2
Australian born (%)	63.1	76.0
Indigenous (%)	1.1	3.4
Proportion with earned income (%)	9.2	18.1
Pay type – DSP (%)	39.3	13.5
Pay type – NSA (%)	20.3	37.3
Average duration (fortnights)	82.3	56.4
NSA customers (fortnights)	55.3	42.9
Non-NSA customers (fortnights)	93.6	69.1
Average no. of spells (no.)	1.33	1.75
Spell range (no.)	1–7	1–10
Multi-spellers (%)	22.8	56.3
Proportion of customers with 124 fortnights duration	34.4	9.9

(a) Age calculated as average of first and last observation age for each customer.
Note the averages for the selected indicators are calculated over the whole observation period.

4 Results from survival and hazard analyses

This section reports illustrative results to demonstrate the applicability of survival and hazard analysis methods to the FaCS LDS. These techniques are applied to various sub-populations of FaCS customers in order to address the following style of questions:

- What is the probability of a MACIS remaining on welfare beyond a certain number of fortnights?
- How do exit rates vary as spell length increases?
- Are there differences in the probability of remaining on a spell of welfare between various sub-populations (mature aged compared to prime aged, NSA customers relative to non-NSA customers)?
- Is there a tendency for MACIS to transfer to a specific payment type after leaving long term unemployment?

4.1 Survival and hazard functions – Mature Age vs Prime Age customers

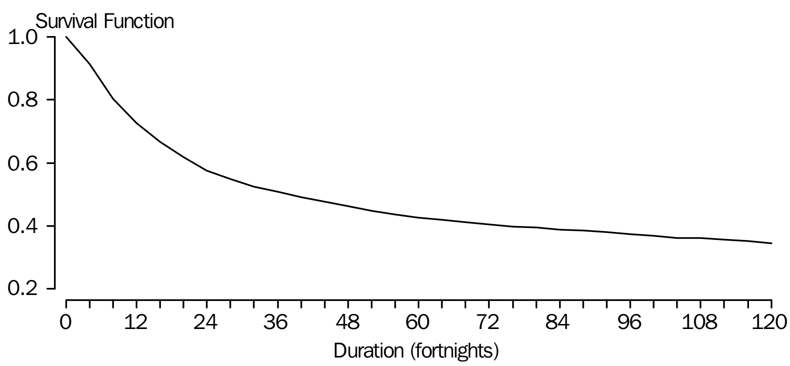
The 7,433 mature age customers in the sub-group considered for analysis experienced 9,853 spells of benefit receipt. Of these spells – 4,159 (or 42.2%) are *left-censored* and 5,602 (or 56.9%) are *right censored*. Left censored spells refer to those spells which begin prior to or on the first extract date (23 June 1995). Right censored spells are those spells that are still ongoing at the end of the observation window (10 March 2000).

Given that the observation window in a longitudinal dataset like LDS usually covers a fixed period it is not possible to obtain full information on the commencement and completion times of individual spells for all customers. The inclusion of censored spells in the analysis may lead to biased estimates and potentially misleading inferences (Barrett 2002). Inclusion of left-censored spells (by calculating the duration of such spells from the start of the observation window) is likely to bias the analysis towards shorter spells. To avoid length-based bias, all left-censored spells were removed from the estimation procedure (leaving 5,694 spells out of the original 9,853 spells).

In the mature age dataset, all the right censored spells are of “Type 1” censoring - that is all the observations have the same censoring time – (10 March 2000). Allison (1995) notes that the survival analysis techniques employed in this part of the analysis handle “Type 1” censoring with no appreciable bias.[11]

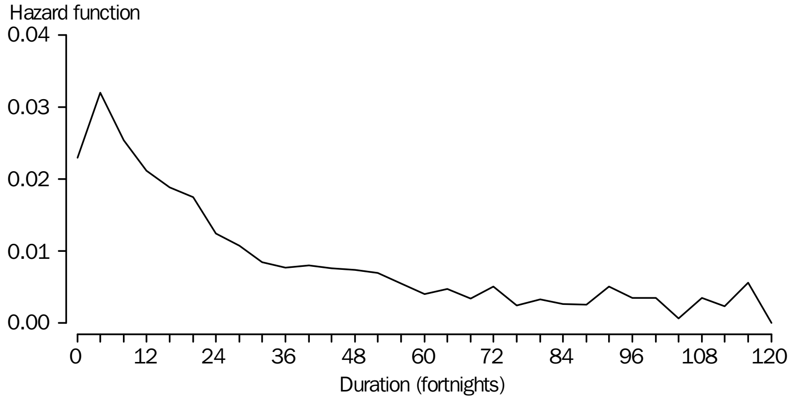
Graph 1 and Graph 2 present the survival and hazard curves, respectively, of mature age customers' duration of non-left-censored welfare spells. The survival curve traces the probability that a mature age person remains on their current spell of welfare benefits past a certain length of time. An examination of the survival curve for mature age customers shows that the survival rate declines over time. For example the probability of a spell lasting at least 26 fortnights is 0.5760. Similarly, the probability of remaining on welfare beyond a spell duration of 114 fortnights is 0.3565.

Graph 1 SURVIVAL CURVE: ALL MATURE AGE CLIENTS



[11] In the models to account for right censored observations only observed (uncensored) exit times feature in the numerator, while censored observations are still counted as part of the risk set and hence appear in the denominator where appropriate.

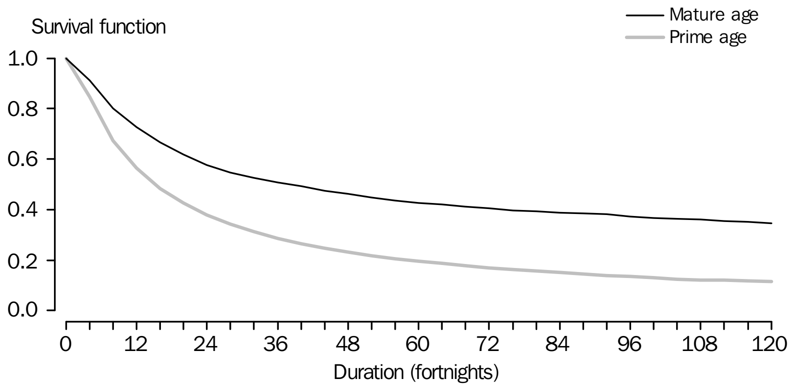
Graph 2 HAZARD FUNCTION: ALL MATURE AGE CLIENTS



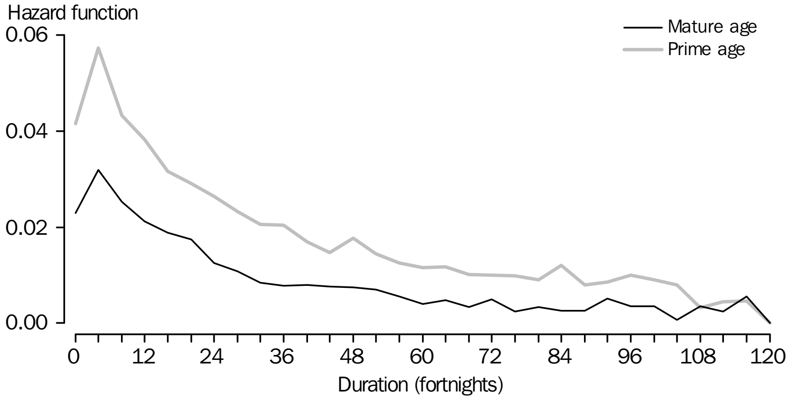
The examination of the hazard function (Graph 2) shows that customers' probability of exiting their current welfare spell, peaks at relatively short spell durations (between 4–8 fortnights of payments with an associated hazard estimate of 0.03198). Exit rates then generally decline as the duration of current spell lengthens. (The apparent erratic hazard at very long spell lengths, is possibly explained by the small sample sizes at these spell lengths). This finding shows that as the length of a mature age customers' welfare spell increases, it becomes less likely that the spell will end. This may suggest that there is a *negative duration dependence* — the likelihood of a mature age person exiting from welfare declines the longer he/she remains on welfare. The difficulty in re-entering employment, may reflect a decay in skills, increased screening by employers and lower morale or motivation. It might also represent a group who were more likely to remain on welfare for other reasons such as physical disability.

A comparison of the survival and hazard functions between mature age customers and prime age customers was undertaken to see if there were differences in their survival and exit patterns from welfare. The survival and hazard curves for each group are plotted in Graph 3 and 4. The survival curves show that at all spell durations, mature age customers exhibit a higher survival rate, reflecting that they experience a longer stay on benefits compared to prime age customers. Moreover, the gap between these two groups appears to increase with time, such that at the end of the data window, only around 12% of spells of prime age customers are still in progress compared to around 35% of spells of mature age customers.

Graph 3 SURVIVAL FUNCTION: MATURE AGE VS PRIME AGE CLIENTS



Graph 4 HAZARD FUNCTION: MATURE AGE VS PRIME AGE CLIENTS



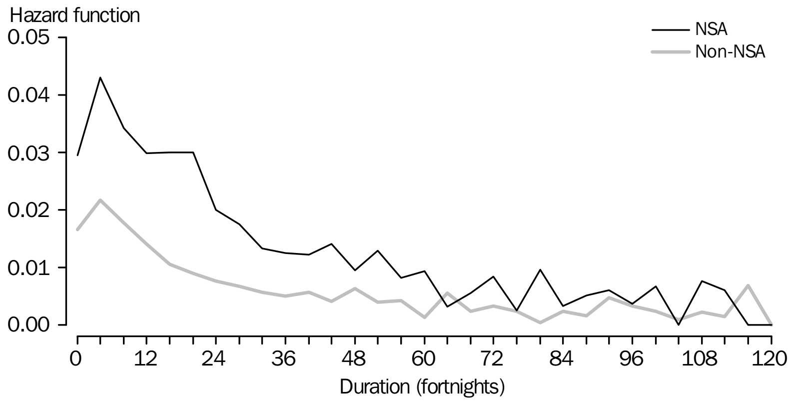
The fact that mature age customers' durations are likely to be longer, is confirmed by reference to Figure 4, which contains an alternative description of the duration data — the hazard functions. The hazard rate for mature age customers appears to be much lower (ranging from 0–3.2%) compared to prime age customers (0–5.7%) at all durations (except towards the end of the sample period) indicating a lower probability of exit from a welfare spell by mature age customers relative to prime age customers. The hazard rates for both mature age and prime age customers peak in the 4–8 fortnight interval. Both hazards decline as duration lengthens and exhibit the same general shape. Although the exit rate pattern for mature age customers is similar to that of prime age customers the decline in the former is from a much lower base than the latter.

4.2 Hazard Functions - NSA vs non-NSA mature age customers

A comparison of hazard functions between NSA and non-NSA mature age customers has also been undertaken. The results are presented in Graph 5. As might be expected, exit rates are higher for NSA customers relative to non-NSA customers, at least over the first 2½ years of spell duration. At very short spell durations, the probability of exiting from welfare by both the groups initially increases but the rise is much sharper for NSA customers and their rate of exit is almost twice that of non-NSA customers (4% vs 2%).

The decline in the hazard rate for NSA customers (after 2½ years of spell duration) may partly be explained by the way we have defined NSA customers (i.e. those customers who spend at least half of their time on NSA payments). Therefore the longer the spell duration of a NSA customer the more likely that some of his/her time will be spent on non-NSA type benefits. Such payments are generally associated with a lower propensity to exit. The decline in the hazard rate for both types of customers over time may indicate 'negative duration dependence'— the longer they stay on benefits, the lower the likelihood of exit from welfare.

Graph 5 HAZARD FUNCTION: NSA VS NON-NSA CLIENTS



4.3 Survival analysis of mature age customers by selected customer characteristics

Survival distribution functions can also be separately calculated for different sub-groups of interest (for example, whether a customer is a male or female, foreign born or not, or various age groupings). Allison (1995) notes that the survival functions calculated in this way give a complete accounting of the survival experience of each group, and so it is possible to test whether survival functions are statistically the same across groups.

Differences in survival curves for seven sub-groups of customers are tested for: sex, marital status, country of birth, Indigenous status, age, home ownership and rental status. The Log-Rank and Wilcoxon statistical tests (see Appendix 1 for details) are used to determine if differences in survival curves across customer characteristics exist.

Table 8, summarises the results of the Log-Rank and Wilcoxon tests of equality of survival curves. Based on these tests, we can conclude that there is evidence that individual characteristics are important in explaining the timing of mature age customers' exit from a spell of welfare receipt. There are statistically significant differences in survival rates for mature age customers by sex, country of birth and age.

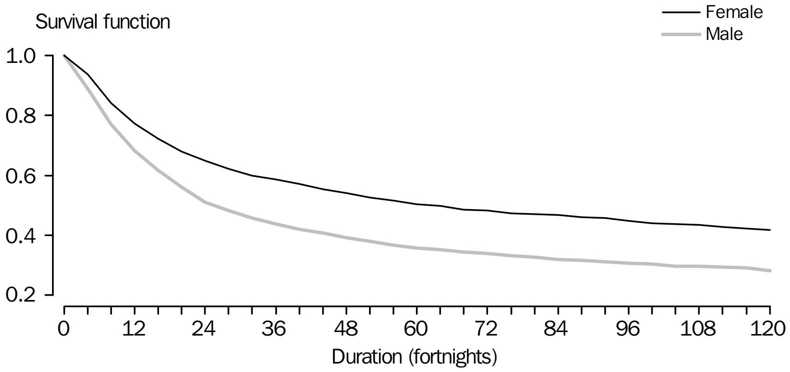
Table 8: Test results of equality of survival functions across strata

Customer Characteristic	Is the Log Rank Test[a] significant?	Is the Wilcoxon Test[a] significant?
Sex	Yes	Yes
Marital status	No	Yes
Country of birth	Yes	Yes
Indigenous status	No	No
Home ownership	Yes	No
Rental status	No	No
Age group	Yes	Yes

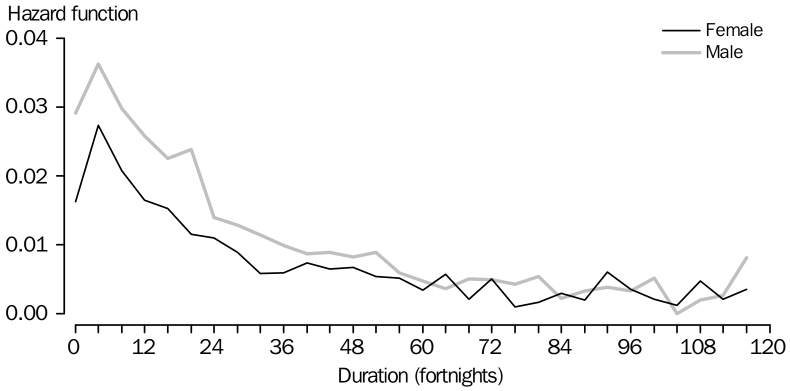
(a) A "Yes" indicates a Statistically significant difference in survival rate (at the 5% confidence level)

Graph 6a to 6f show the survival and hazard curves for the three sub-groups found to be statistically significant (by both test statistics) in Table 8.

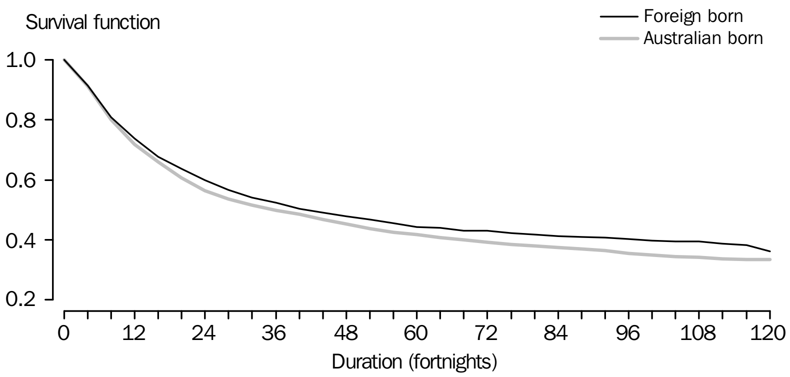
Graph 6a SURVIVAL FUNCTION: ALL MATURE AGE CLIENTS, By sex



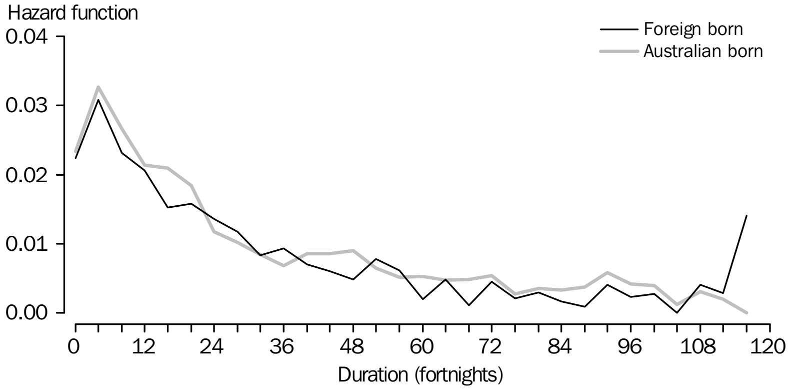
Graph 6b HAZARD FUNCTION: ALL MATURE AGE CLIENTS, By sex



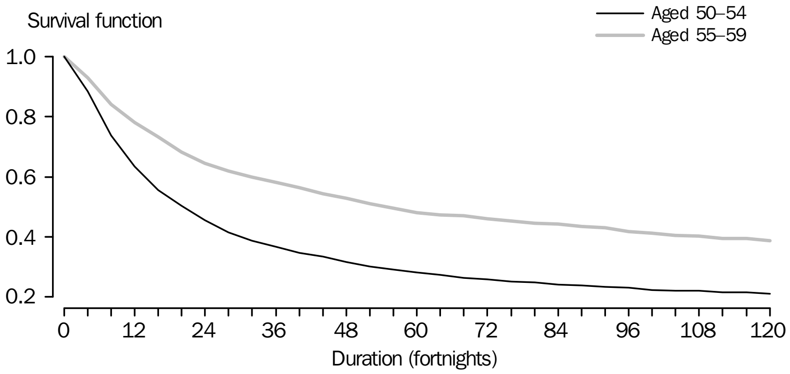
Grapgh 6c SURVIVAL FUNCTION: ALL MATURE AGE CLIENTS, By country of birth



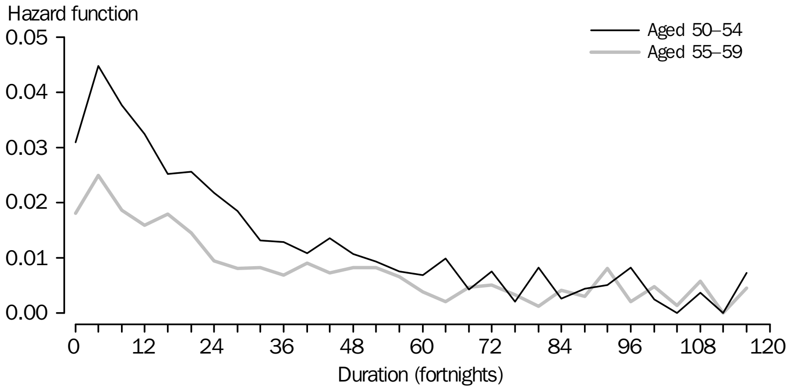
Graph 6d HAZARD FUNCTION: ALL MATURE AGE CLIENTS,
By country of birth



Graph 6e SURVIVAL FUNCTION: ALL MATURE AGE CLIENTS,
By age group



Graph 6f HAZARD FUNCTION: ALL MATURE AGE CLIENTS,
By age group



The hazard functions for these sub-groups reveal the same general trend as was found for all mature age customers. The probability of exit from a welfare spell peaks within the initial four to twelve fortnights of a customer's spell and then declines as spell durations lengthen.

Table 8, along with a visual inspection of the survival curves suggests the following:

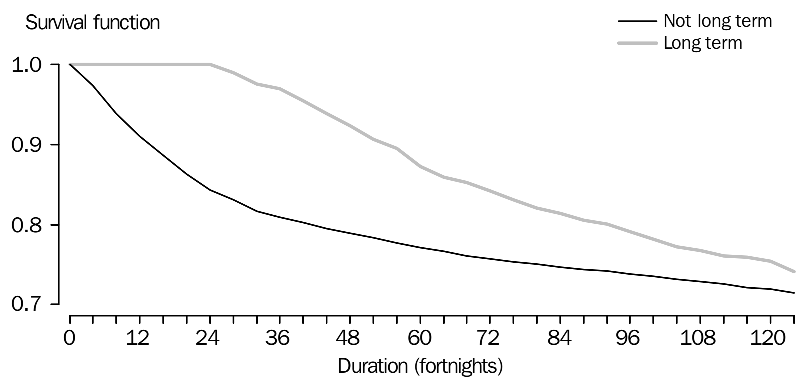
- Females tend to exhibit higher survival rates on welfare relative to males.
- Foreign born customers have higher survival rates on welfare relative to Australian born recipients.
- Older customers have higher survival rates on their current spell of welfare payments, when compared to younger customers. To illustrate, the survival rate of an individual aged 55–59[12], experiencing a welfare spell lasting 120 fortnights is 0.387. For those aged between 50–54 the corresponding survival rate is around 0.2108.

4.4 Survival analysis of mature age customers by long term unemployment receipt

Earlier sections of this paper presented results on survival and hazard functions for all mature age customers. In much the same way, separate hazard functions can also be calculated depending on whether or not a customer is a long term recipient of unemployment benefits.

The survival curve plotted in Graph 7a analyses the length of time before a mature age customer exits the welfare system[13]. Separate survival curves are calculated for those who experience a spell of long term unemployment and for those who have no such experience.

Graph 7a SURVIVAL FUNCTION: ALL MATURE AGE CLIENTS, By long-term receipt of NSA



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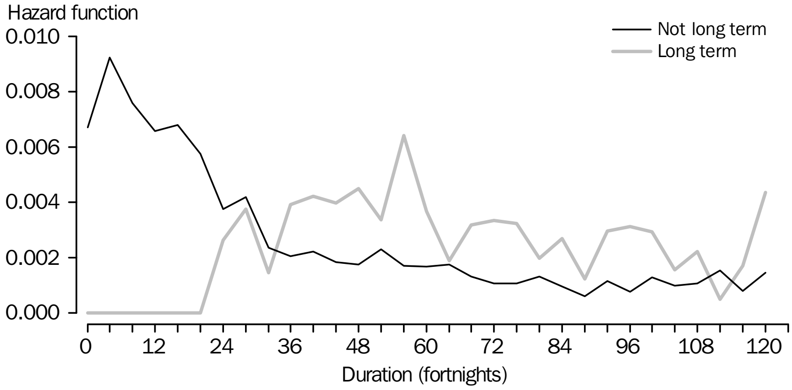
[12]Age refers to age at the end of a customer's spell.

[13] This particular analysis examines all mature age customers, it includes left censored spells as the event of interest is time on benefits before exit from welfare. It distinguishes those who experience a spell of long term unemployment with those customers who do not.

The curves plotted above suggests that mature age customers who experience a spell of long term unemployment have a higher probability of remaining on welfare receipt relative to those who have never received long term unemployment benefits. It can also be observed that the survival curves converge for the two groups as total time on benefits lengthens. This implies that for all mature age customers, the probability of remaining on welfare for the duration of the data window is similar regardless of whether a mature age customer records a spell of long term unemployment payments.

The hazard functions for the two groups are plotted in Graph 7b. The hazard functions provide the probability that an exit occurs within the next small time interval, given that an individual has not exited welfare before the start of this time interval. Graph 7b indicates that the exit rates for those who do not experience a spell of long term unemployment peak within 4–8 fortnights of welfare payments and generally decline with total time on benefits (solid line). For those mature age customers who experience a spell of long term unemployment, their hazard rate peaks in the interval of 56–60 fortnights (0.00641) and then trends down as time on benefits increases.

Graph 7b HAZARD FUNCTION: ALL MATURE AGE CLIENTS,
By long-term receipt of NSA



These results have quite clear implications for the experience of people on welfare. For those who do not experience a spell of long term unemployment, the longer they remain on benefit the less likely that they will exit the welfare system. In contrast, exit rates for the long term unemployed increase as total time on welfare lengthens. The hazard rate for this group reaches a maximum value after 60 fortnights of payments and then trends lower over time. After 60 fortnights of payments, the long term unemployed are not substantially more likely to exit welfare relative to those who have not had a spell of long term unemployment benefits.

Note that by definition, no customers defined as receiving a spell of long term unemployment exit the welfare system within 26 fortnights. Therefore the probability of exit for this group is equal to zero over this time frame.

In the analysis above, all exits from welfare are treated as though they are identical. While this approach sheds light on the broad differences between the two groups considered, in exploring survival times it may be more helpful to distinguish between different kinds of exit events. For example, mature age customers can exit the pool of long term unemployed in multiple ways. From a policy perspective, exiting the welfare system after a spell of long term unemployment has different implications compared to exiting onto another payment program such as Disability Support. This classification of events into different types can be handled by computing type-specific hazard functions which are discussed next.

4.5 Survival and Hazard rate analysis of the long term unemployed by different types of exit from welfare

A long-term unemployed is defined as a customer who has received or has been receiving NSA payments for at least 26 consecutive fortnights. Of the total mature age customers (7,433 customers), almost 1 in 5, (1,442 individuals) experience at least one spell of long term unemployment. These 1,442 mature age customers experience 1,553 spells of long term unemployment.

Using survival analysis techniques, this section addresses the following types of questions:

- How many MACIS eventually exit their spell of long term unemployment payments?
- What factors affect their probability of exiting long term NSA?
- Is there a tendency for MACIS to transfer to a specific payment type after leaving long term unemployment?

Table 9 details the five competing events that can be identified for mature age customers' exits from the pool of long term beneficiaries of NSA. The five competing events are:

- exit by transferring to Disability Support Pension (DSP)
- exit by temporarily leaving welfare and re-entering unemployment benefits
- exit by entering a program other than NSA or DSP
- exit by temporarily leaving welfare and entering a program other than NSA; and
- exiting the welfare system.

Of those long-term unemployment spells that are finalised within the data window, only one in five involve a customer exiting the welfare system[14]. The remainder involve a mature age customer completing a spell of unemployment benefits by transferring to another form of income support (such as DSP or another payment program). Around one-third of the long-term unemployment spells are still ongoing at the last observation available in our sample. (534 out of 1,553 exits)

[14] Exit from welfare in this context refers to those customers who do not reappear in the data window after completing a spell of long term unemployment payments.

Table 9: Frequency distribution of exits from long term receipt of NSA[a]

Type of exit	Number	Percent
By entering the Disability Support Pension (DSP)	237	15.3
By leaving welfare for over 28 days and re-entering NSA	277	17.8
By entering a program other than NSA or DSP	243	15.6
By leaving welfare for over 28 days and entering a program other than NSA	43	2.8
By exiting the welfare system	219	14.1
Sub-Total	*1,019*	*65.6*
Long term unemployment spells ongoing at last observation	534	34.4
Total	1 553	100.00

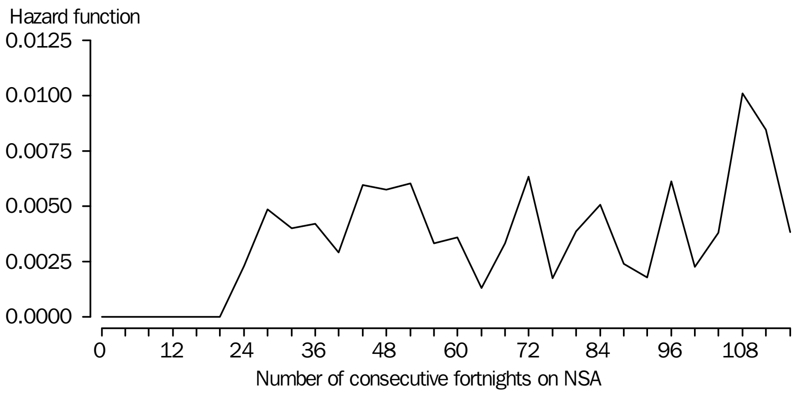
(a) Based on 1,442 customers with 1,553 "spells" of long term unemployment

For each type of exit from long term receipt of NSA outlined in Table 9, we define a separate hazard function called a type-specific or cause-specific hazard.

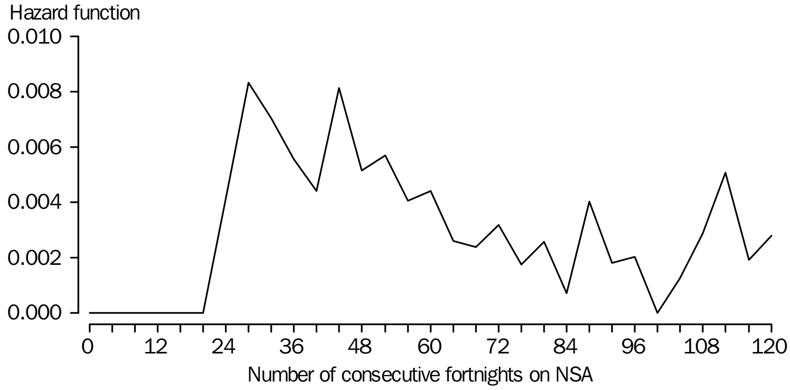
The *population* to be analysed is the group of long term recipients of NSA (26 fortnights or more). The *event of interest* is exiting the NSA program stream, with five *competing events* outlined previously.

The type-specific hazard functions for each type of exit from long term receipt of NSA are plotted in Graphs 8a–8e. The duration variable in this case is the number of consecutive fortnights of NSA a mature age customer receives before exiting unemployment benefits. The focus of this analysis is exit from long-term unemployment (defined as a customer receiving at least 26 consecutive fortnights of NSA payments). For this reason the hazard rate equals zero for the first 6 intervals of 0–24 fortnights — as by definition no customers have exited the pool of long term unemployed within this time frame.

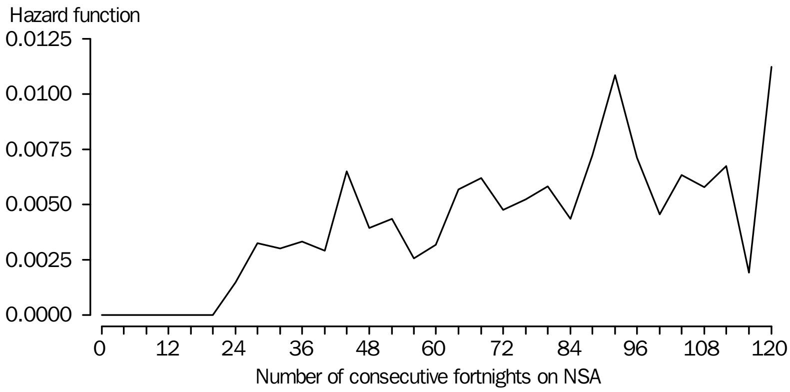
Graph 8a TYPE-SPECIFIC HAZARD FUNCTION, Exit from long term unemployment by transferring to DSP



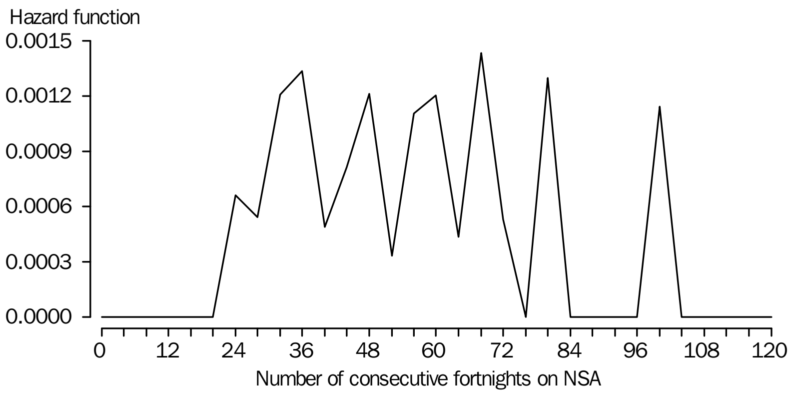
Graph 8b TYPE-SPECIFIC HAZARD FUNCTION,
Exit from long term unemployment but later returning to NSA



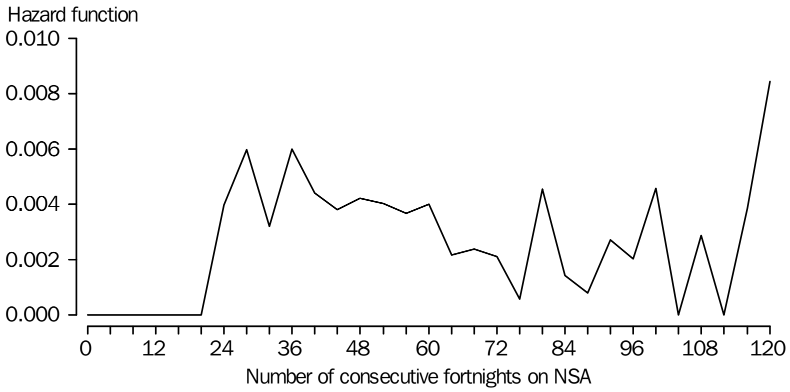
Graph 8c TYPE-SPECIFIC HAZARD FUNCTION: EXIT FROM LTU,
By transferring to other payments



Graph 8d TYPE-SPECIFIC HAZARD FUNCTION: EXIT FROM LTU,
And later returning to another payment type



Graph 8e TYPE-SPECIFIC HAZARD FUNCTION, Exit from welfare



The hazard rate estimates indicate the following:

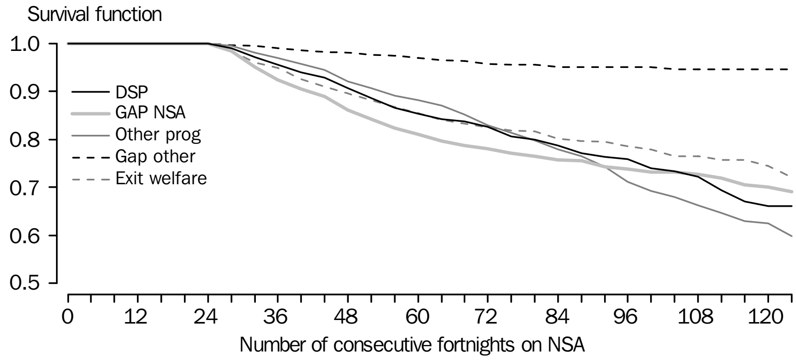
- For those customers who exit by transferring to disability payments or other payment programs, the trend is for exit rates to generally increase with duration on unemployment benefits. The exit rate for mature age customers who exit long-term unemployment by transferring to disability support, begins at 0.233 in the interval of 24–28 fortnights. For the 60–64 and 116–120 fortnight intervals, the hazard estimate is 0.361 and 0.386 respectively.

- The hazard rate associated with exit from long-term unemployment by leaving welfare and returning to another payment program, displays no discernible trend over the 124 fortnight interval considered.

- There is a general decline in the hazard rate for those who leave welfare altogether or leave welfare and then return to NSA.

These results suggest that long-term unemployed mature age customers found it more difficult to exit the welfare system as their duration on unemployment benefits (NSA) increased. If they leave the NSA spell at all, it will be because of transferring to another welfare program (either disability support or another payment program).

Graph 9 TYPE-SPECIFIC SURVIVAL CURVES: EXIT FROM LTU,
Exit from long- term unemployment, by five competing risks



The type-specific survival curves for each of the five types of exit from long term unemployment are plotted in Graph 9.

In Graph 9 and Table 10 the five ways by which a customer on NSA can leave the long term unemployed sub-population, are notated as follows:

i. DSP- One could move from NSA and start receiving the Disability Support Pension;
ii. Other Prog- One could move from NSA and start receiving some other benefit other than NSA or the Disability Support Pension;
iii. GAP NSA- One could leave the welfare system for over 28 days and re-enter the welfare system receiving NSA
iv. GAP Other- One could leave the welfare system for over 28 days and re-enter the welfare system receiving some other benefit other than NSA or DSP
v. Exit welfare- One could leave the welfare system permanently

Table 10 outlines the survival probabilities associated with each type of exit from long term unemployment for selected fortnightly intervals.

Table 10: Survival rates for long-term NSA recipients, by type of exit

	Type of Exit				
Duration (fortnights)	DSP	GAP NSA	Other Prog	GAP Other	Exit Welfare
28–31	0.9907	0.9835	0.9940	0.9973	0.9842
44–47	0.9290	0.8887	0.9454	0.9832	0.9100
60–63	0.8539	0.8105	0.8818	0.9697	0.8544
76–79	0.8054	0.7706	0.8145	0.9558	0.8186
92–95	0.7642	0.7431	0.7438	0.9508	0.7948
108–111	0.7225	0.7280	0.6625	0.9465	0.7657
120–124	0.6605	0.6998	0.6252	0.9465	0.7453

Table 10 and Graph 9 reveal that:

- The lowest survival rates (or highest rates of exit) are experienced by those who transfer to other payment programs after a spell of long-term unemployment. (The probability of remaining on long-term unemployment for at least 120 fortnights for this group is 0.6252).
- Those who exit by leaving welfare and returning to another payment program exhibit the highest survival rates (or highest probability of remaining on unemployment benefits after 120 fortnights).
- In analysing exits from long term NSA by mature age customers, an important test to consider is whether the survival functions are the same for groups with different characteristics. The Log-Rank and Wilcoxon statistics are used to test for differences in survival functions between groups (results not shown). Based on these statistical tests, the following customer characteristics seem to have a role to play in explaining the timing and method of exit from long term unemployment:

- Indigenous (relative to non-indigenous) and foreign born customers (relative to Australian born) are more likely to exit long term unemployment by transferring to Disability Support Pension.

- For the group who exit a spell of long-term unemployment payments by temporarily leaving welfare and returning to NSA, males, foreign born, non home owners and renters are all more likely to exit in this manner.

- In contrast, females, and customers residing in South Australia are more likely to exit long term unemployment by transferring to another payment program.

- Females are more likely to exit unemployment payments by temporarily leaving welfare and returning to another payment program.

4.6 Estimates of a regression model of proportional hazards

This section reports results of a proportional hazards regression model. For the proportional hazards model a positive coefficient for a particular variable implies that the hazard is high (i.e. the events occur quickly and survival times are therefore short) while a negative sign implies the hazard is low (i.e. the events occur slowly and therefore the survival times are long).

The regression results for the proportional hazard model are presented in Table 11. The results suggest that Australian-born, males, those with higher levels of earned and unearned income and those living in Queensland or Western Australia have a higher hazard or likelihood of exit from welfare (i.e. experience a shorter time on welfare). On the other hand older customers, those renting, those identifying as Indigenous, those with more children and those with presence of earned and unearned income have a lower hazard or likelihood of exit from welfare (i.e. they experience a longer time on welfare)[15].

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[15]An analysis by gender shows that for males being married, value of earned and unearned income and living in QLD/WA increase the exit from welfare spells while being older, ATSI origin and presence of earned and unearned income reduce the exit from welfare spells. For females being Australian-born, value of earned income and living in WA increase the exit from welfare spells while being older, renting and presence of earned and unearned income reduce the exit from welfare spells.

The opposite results for the value and presence of the income variables may suggest that only when income (earned or unearned) reach sufficiently high levels, are customers likely to leave benefits. The mere presence of some income may not be a sufficient condition and it may actually reduce the likelihood of getting off benefits.

The significance of the two state variables may either reflect the labour market conditions in these two states or it may simply reflect a random effect resulting from the small sample numbers.

Table 11: Mature age customers - Regression Results of Proportional Hazards Model

Parameter	Coefficient	Pr > ChiSq	Hazard Ratio
Australian x1	0.07821*	0.0489	1.081
Age	–0.11118*	<0.0001	0.895
Male x1	0.36466*	<0.0001	1.44
Indigenous x1	–0.47851*	0.0152	0.62
Own home x1	0.03051	0.6822	1.031
Renting x1	–0.14045**	0.0645	0.869
Married x1	0.02713	0.5292	1.027
Age of youngest child	0.00436	0.5357	1.004
No. of children	–0.08769**	0.063	0.916
Earned income	0.0006383*	<0.0001	1.001
Earned income x1	–0.07596**	0.0631	0.927
Unearned income	0.0001482**	0.0506	1
Unearned income x1	–0.32835*	<0.0001	0.72
Victoria x1	0.02369	0.6408	1.024
Queensland x1	0.12025*	0.0202	1.128
South Australia x1	–0.02593	0.7277	0.974
Western Australia x1	0.34451*	<0.0001	1.411
Tasmania/NT x1	0.01528	0.8843	1.015
N	5694		
Likelihood Ratio	701*		

* Significant at 5%.
** Significant at 10%.
Note variables with a x1 sign beside them indicate they are dichotomous variables with the variable taking a value of 1 if that condition is satisfied otherwise it takes a value of 0. For example Malex1 implies a value of 1 if the person is a male and 0 if the person is a female.

5 Results from regression models

This section reports illustrative results to demonstrate the applicability of various regression techniques (logit, multinomial logit and count modelling) to the FaCS LDS data. These techniques have been applied to address the following style of analytical questions:

- What socioeconomic and demographic characteristics are associated with MACIS being more likely to churn (experience multiple spells of benefit)?
- What factors are associated with MACIS exiting long term unemployment by transferring to another payment program?
- What personal characteristics influence a MACIS experiencing a single long spell (greater than 6 months) of welfare benefits?
- What is the probability of a MACIS experiencing 1 spell? (or 2 spells?).

5.1 Churning on Welfare by Mature Age Customers

Around a quarter of mature age customers are churners (multiple spellers, see table 3). This section presents models of the probability of churning and identifies the socioeconomic/demographic factors that influence it.

Churning on benefits may be preferred to spending one long continuous stay on welfare. Churning may indicate that the individual goes off benefits, and hopefully into employment, even if for short periods. On the other hand more frequent churning on and off benefits ("classic" churners) may raise questions about why the person is not able to hold on to a job for longer periods. Classic churning (i.e. multiple short spells) among mature age customers is relatively rare. Churners, on average, are found to spend a shorter time on welfare compared to non-churners. A higher incidence of churning implies reduced total time on welfare.

5.1.1 Baseline Regression Model

Table 12 presents the results of a logistic regression model of churning. The factors that appear to increase the likelihood of churning by mature age customers are the presence of earned income, being a male, presence of unearned income and living in Queensland. The odds ratios[16] for these variables (as given in the last column of table 12) indicate that those with earned income are 3.7 times more likely to churn than those without such income, males are 1.5 times more likely to churn than females and those with unearned income are 1.3 times more likely to churn than those without such income.

On the other hand home-owners, Australian-born, married and older customers are less likely to experience multiple claims on benefit, i.e. they are associated with lower odds of churning. An odds ratio of 0.96 for age implies that for each year increase in age the odds of churning declines by 4%[17].

The positive effect for the earned income variable may suggest that those benefit recipients who have some degree of attachment to the labour market (through part-time or casual paid employment) are more likely to be churners. However, the results could also be regarded as being purely definitional or simply reflecting administrative procedures, as those with some earned income may become ineligible for benefits and thus exit benefits only to return later when their income level declines. Further analysis, including obtaining data about churners' labour market experience (including earnings) is required to gain a clearer picture of the effects of earnings on churning.

A number of potentially important variables, for example education levels, previous work experience, have been omitted from this analysis due to the poor quality or unavailability of such data on the LDS. The omission of these variables may be limiting the model results and the implications that follow from the analysis**.**

[16] The odds ratio (calculated as e^b) provide the relative hazards or percent change for each unit increase in the variable of interest. For indicator (dummy) variables with values of 1 and 0, we can interpret the hazard ratio as the ratio of the estimated hazard for those with a value of 1 to the estimated hazard for those with a value of 0 (controlling for other covariates). For continuous covariates, the estimated percent change in the hazard for a one unit increase in the covariate is obtained by subtracting 1 from the hazard ratio and multiplying by 100, namely $(e^b - 1)100$.

[17]An analysis by gender shows that for males presence of earned income and being of ATSI origin increase the odds of churning while being Australian-born, older and married reduce the likelihood of churning. For females value of unearned income and the presence of earned and unearned income increase the odds of churning while home-ownership reduces the odds of churning.

Table 12: Mature age customers - Logistic regression Model Results of Churning

Parameter	Coefficient	*p*-value	Odds Ratio
Constant	0.4806	0.4037	
Australian x1	–0.2021*	0.0011	0.817
Age	–0.0403*	<0.0001	0.961
Male x1	0.4236*	<0.0001	1.527
Indigenous x1	0.1778	0.5538	1.195
Own home x1	–0.233**	0.0501	0.792
Renting x1	-0.0782	0.5231	0.925
Married x1	-0.142*	0.0346	0.868
Age of youngest child	0.00196	0.8708	1.002
No. of children	0.0444	0.5689	1.045
Earned income	–1.77E-006	0.9935	1
Earned income x1	1.3024*	<0.0001	3.678
Unearned income	0.000301	0.2885	1
Unearned income x1	0.2287*	0.0006	1.257
Victoria x1	0.0774	0.3264	1.08
Queensland x1	0.1718*	0.0394	1.187
South Australia x1	0.0542	0.6271	1.056
Western Australia x1	0.1407	0.1884	1.151
Tasmania/NT x1	–0.1672	0.3021	0.846
N	7433		
Likelihood Ratio	639		
Hosmer-Lemeshow GOF *p-value*	0.7838		

* Significant at 5%,
** Significant at 10%

5.1.2 Other Models of Churning

In addition to the baseline model discussed above a number of other models of churning have been estimated. These models are a variation on the main model involving either dropping or adding a few variables or testing for the effects of a number of covariates. Table 13 presents a comparison the regression results of these different models along with Model 1.

In Model 2 the age variable is broken down into 2 subgroups (ie those aged over 55 vs those aged 50–55 which is the reference group). The same 7 variables as in Model 1 are found to be significant (with the same sign and more or less similar order of magnitude). With regards to the age variable (greater than 55 years) the negative coefficient suggests that "older" customers (within the MACIS age band) are less likely to be churners than "younger" customers which is as expected.

In Model 3 the stepwise selection procedure is used to select significant variables (a *p*-value = 0.3 is used for both entry and stay rule). A total of 11 variables are selected by this procedure. The same 8 variables as in Model 1 are found to be significant..

In Model 4 a number of interaction terms are incorporated in addition to the main covariates in Model 1. Given a large number of independent variables it is difficult to decide which interaction terms to incorporate in the model as a large number of possibilities exist. Based on a priori reasoning three interaction terms are included in this model: age*sex (to examine the effect of older males on churning); mstatus*child (to test the effect of whether being married with children influences the odds of churning); and mstatus*age (to test whether being married and older impacts on churning). Of the 21 variables in this model 12 are found to be significant — all 8 variables from Model 1, age of the youngest child and all three interaction terms. The negative coefficient for the age of the youngest child variable is contrary to expectations as it implies the older the youngest child gets the less the likelihood of churning by customers.

The interaction term age*sex has a negative coefficient which may imply that the odds of churning for males declines as they get older i.e the differences in the probability of churning between the sexes becomes less significant for older age groups. The interaction term mstatus*child has a positive coefficient which appears to be a perverse result ie it implies that if you are married and have children then there is a greater likelihood of churning. This result may, however, imply a need for an income, and a family structure where child-care barrier may be lower for at least one of the parents. The interaction term age*mstatus has a positive effect. Given that from Model 1 both marital status and age have a negative effect it is difficult to interpret this result.

In Model 5 paytype variables are included to explore whether being on a particular payment type also influences the incidence of churning. Since the two major payment types associated with mature age customers are DSP and NSA only these two paytype variables are included in the analysis. We can use either the proportion of time on a particular benefit or the first payment type through which a customer enters the welfare program. The latter formulation of the variable is considered more appropriate as it is more amenable for policy purposes as we can for each customer easily identify what benefit type he/she first enters the benefit program unlike the proportion of time on benefits where at any point in time we will not know how much time that particular customer will spend on a particular benefit. Regardless, either formulation of the paytype variable appears to produce similar results.

Using information on the payment type via which they first make an entry onto the benefit program we can create two dummy variables called DSP_first and NSA_first. DSP_first is assigned a value of 1 if the first payment type of the customer is DSP and a value of 0 if the first paytype is anything other than DSP. NSA_first is assigned a value of 1 if the first payment type of the customer is NSA and a value of 0 if the first paytype is anything other than NSA. As can be seen from the results of this analysis in Model 6 customers who enter the benefit system via the DSP program are more likely to be single spellers while customers entering the benefit system via the NSA program are more likely to be multi-spellers.

From table 12 and table 13 one can now draw the following conclusions about the extent and nature of churning by mature age customers. Those customers with some earned or unearned income, males, younger, single, overseas-born, non-homeowners and those living in Queensland are more likely to experience multiple spells on benefits. Those with no earned or unearned income, females, older, married, Australian-born and home-owners are more likely to experience a single spell on benefit. Older males are less likely to churn than their younger male counterparts and females. Customers who enter the welfare program via DSP are more likely to be single-spellers while customers who enter the benefit program via NSA are more likely to be multi-spellers.

Some attachment to the labour market increases the chances of mature age customers going off benefits, albeit for short periods. Further analysis, including obtaining data about churners labour market experience (including earnings) when they are off benefits is needed to get a better picture of what may actually be happening in relation to earned income.

Table 13: A Comparison of Alternative Models of Churning by Mature age customers

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.4806	–1.6333	0.555	1.0771	–0.1089
Australian x1	–0.2021*	–0.1992*	–0.2031*	–0.1987*	–0.1808*
Age	–0.0403*		–0.042*	–0.0507*	–0.0271*
Age > 55		–0.1991*			
Male x1	0.4236*	0.4207*	0.4278*	3.1527*	0.3467*
Indigenous x1	0.1778	0.1682		0.1935	0.2877
Own home x1	–0.233**	–0.2335*	–0.1725*	–0.2271**	–0.2857*
Renting x1	–0.0782	–0.0779		–0.0845	–0.0668
Married x1	–0.142*	–0.1485*	–0.1317*	–4.0328*	–0.1685*
Age of youngest child	0.00196	0.00275		–0.0303*	0.00941
No. of children	0.0444	0.0526		–0.1014	0.00794
Earned income	–1.77E-006	3.58E-006	1.3048*	4E-005	–0.0002
Earned income x1	1.3024*	1.3102*		1.3179*	0.9642*
Unearned income	0.0003	0.0003	0.0003	0.0003	0.0006*
Unearned income x1	0.2287*	0.223*	0.2287*	0.233*	0.2694*
Victoria x1	0.0774	0.0805		0.0861	0.0265
Queensland x1	0.1718*	0.171*	0.1365**	0.1774*	0.1358
South Australia x1	0.0542	0.0534		0.072	0.0691
Western Australia x1	0.1407	0.1397	0.1063	0.1502	0.1647
Tasmania/NT x1	–0.1672	–0.1688	–0.1951	–0.1749	–0.1678
Age*Sex				–0.0503*	
Age*Mstatus				0.069*	
Mstatus*Child				0.8016*	
DSP_first					–1.4454*
NSA_first					0.5963*
N	7433	7433	7433	7433	7433
Hosmer-Lemesshow GOF p-value	0.7838	0.0826	0.5046	0.7801	0.8094

* Significant at 5%,
** Significant at 10%

5.2 A count model of churning

While the logistic regression model discussed in the previous section is appropriate for modelling the probability of a dichotomous event (e.g. churning versus non-churning), the use of such a dichotomous response variable leads to a loss of information on both the number and duration of the various spells. Therefore a natural extension of the logistic regression analysis is to define churning as simply the number of spells of benefit an individual incurs during the data window. A Poisson–type regression model is considered more appropriate for modelling the number of spells.

In Poisson regression it is assumed that the dependent variable Y, number of occurrences of an event (e.g. number of spells on benefit), has a Poisson distribution given the independent variables $x_1, x_2, \ldots, x_k$.

The probability of that event then can be specified as:

$$P(Y=y|\ x_i) = (e^{-\mu}\mu^y) / y!, \qquad y=0, 1, 2, \ldots\ldots, \tag{5}$$

where $\log(\mu) = \alpha + \beta_1 x_1 + \ldots + \beta_k x_k$ (i.e. log of μ is a linear function of the independent variables).

Such Poisson models have been criticised for their implied restriction that μ_i is both the mean and the variance of y_i. In many applications count data may be "overdispersed", with conditional variance exceeding conditional mean. To overcome such problems a *negative binomial regression model* (NBN) is proposed as an extension to the Poisson regression model where now

$$\log(\mu) = \alpha + \beta_1 x_1 + \ldots + \beta_k x_k + \varepsilon_i \tag{6}$$

and where $\exp(\varepsilon_i)$ follows a Gamma distribution with unity mean and variance α. That allows us to relax the assumption about equality of mean and variance (Poisson distribution property), since the variance of NBN is equal to $\mu + k\mu^2$, where $k \geq 0$ is a dispersion parameter.

The results for the negative binomial regression model for mature age customers are reported in Table 14[18]. The results of this count model largely confirm the results of the logistic regression model of churning as the same 8 variables as in the logistic regression model of churning (i.e. country of birth, age, sex, home-ownership, marital status, presence of earned income, presence of unearned income, living in Queensland) are also significant here. Two additional variables (being of Indigenous origin and living in WA) are now being picked up in the count model.

From this count model it can be interpreted that the average number of spells is higher for those with some earned or unearned income, males, those of Indigenous origin and those living in QLD or WA. The average number of spells is lower for homeowners, Australian-born, married and older customers.

The parameter estimates given in table 14 can be used to predict the mean number of spells for different categories of the dichotomous variables (e.g. sex, country of birth, marital status) and for different values of the continuous variables (e.g. age, amount of earned income) as well as the probabilities for different number of spells for different groups of customers (e.g. male vs female, Australian-born vs overseas born customers etc). Table 15 presents predicted probabilities of spells by all customers and by sex while Graph 10 presents the same information by sex only.

[18]Note the dependent variable in this model is the number of spells which for scaling reasons is defined as number of spells minus one, as all individuals have at least one spell.

Table 14: Negative Binomial Model Regression Results

Parameter	Coefficient	p-value
Intercept	0.3388	0.4763
Australian x1	–0.1879*	0.0002
Age	–0.0367*	<0.0001
Male x1	0.3830*	<0.0001
Indigenous x1	0.4309**	0.0601
Own home x1	–0.2158*	0.0302
Renting x1	–0.0259	0.7994
Married x1	–0.0989**	0.0766
Age of youngest child	0.0093	0.3367
No. of children	0.0055	0.9294
Earned income	0.0000	0.8066
Earned income x1	1.1142*	<0.0001
Unearned income	0.0002	0.484
Unearned income x1	0.2168*	<0.0001
Victoria x1	0.0285	0.665
Queensland x1	0.1150**	0.0951
South Australia x1	0.0136	0.8827
Western Australia x1	0.1797*	0.0367
Tasmania/NT x1	–0.1182	0.3757
Dispersion[19]	0.8637*	<0.0001
N	7433	
Likelihood Ratio	–4513	

* Significant at 5% level.
** Significant at 10% level.

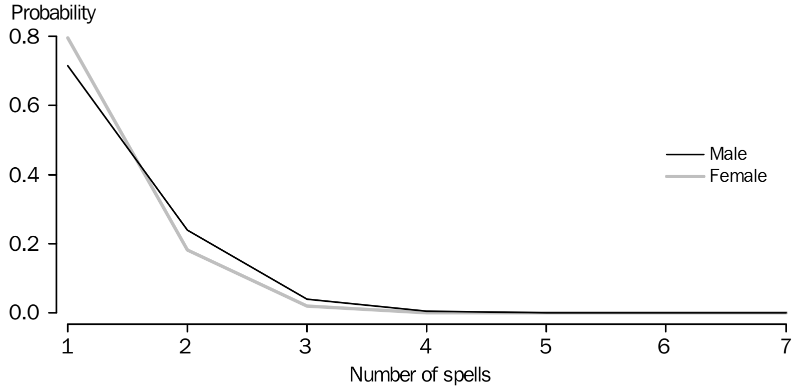
Table 15: Predicted Probabilities of Spells by sex

No of spells	All customers	Male	Female
1	0.7614298	0.7145912	0.7952334
2	0.2075333	0.2401346	0.1822036
3	0.0282824	0.0403480	0.0208732
4	0.0025695	0.0045196	0.0015942
5	0.0001751	0.0003797	0.0000913
6	0.0000095	0.0000255	0.0000042
7	0.0000004	0.0000014	0.0000002

As can be seen from Graph 10, males are less likely to have single spells (71% probability compared to 80% probability for females), but are more likely to have multiple spells up to 4 spells, beyond which the probabilities become similar for both the sexes.

[19]The strong significance of the dispersion term clearly indicates that there is over-dispersion in the data. As such a simple Poisson regression would have under specified the model and hence a Negative Binomial model is more suitable.

Graph 10 PREDICTED PROBABILITIES OF SPELLS, By sex



A comparison of the average number of spells for males and females at age 50 and age 60 is presented in Table 16. From the results it appears that younger males and females have on average more spells than their older counterparts. At age 50 males on average have 10% (1.41/1.28) more spells than females of the same age while at age 60 they have around 8% more spells than females.

Table 16: Average Number of Spells by Sex and Selected Age

	Avg No. of Spells
Males aged 50 years	1.41
Males aged 60 years	1.28
Females aged 50 years	1.28
Females aged 60 years	1.19

5.3 Multinomial logistic models of the number of spells versus average duration of a spell

There are a number of ways in which we can categorise a customer's dependence on welfare. For example, using information on their average length of spell such as the mean or median, or by using arbitrary cut-offs — short-term (6 months) or long-term (12 months). We chose to adopt 1 year as a cut-off point to distinguish between short and long-term. This was considered more appropriate as categorising customers based on their mean and median length of spell resulted in a much higher cut-off point of 74 fortnights and 72 fortnights respectively, and this also resulted in an empty cell for one of the categories selected for analysis.

In this section customers fall in four categories:

- a majority (61%) of customers experienced one single long spell on benefits
- (i.e. LONG-LOW group in Table 17)
- 12% had multiple long spells (LONG-HIGH group in Table 17)
- 11% had multiple short spells (SHORT-HIGH group in Table 17) and
- around 16% experienced single short spell (SHORT-LOW is a reference group and does not appear in table 17).

The results of the multinomial logistic (MNL) regression model are reported in Table 17. Given a large number of coefficients and their magnitude and effect differing across the alternatives it is difficult to interpret or identify any clear-cut or dominant factors that may influence customers to fall in any of these groups. However, it does appear that the more common significant explanatory variables include presence of earned and unearned income, value of earned income, home-ownership, being Australian-born, age, gender, Indigenous origin and residing in Western Australia.

Based on the significance and relative magnitude of the coefficients it appears that Australian-born, home-owners and those with no earned or unearned income or higher amounts of earned income are more likely to experience single short spells on benefit. Overseas born, Indigenous, non-homeowners, singles, those with more children and those with some earned income are more likely to experience more frequent long spells on benefit. Females are more likely to experience single long spells on benefit while older customers are more likely to experience single or multiple long spells on benefit. Customers with low amounts of earned income or those with some earned or unearned income and those residing in Western Australia are more likely to experience multiple number of short spells.

Table 17: Mature Age Customers MNL Model Results - Customer Types Based on Spells and Average Length of Spells

	LONG-HIGH (ALS>=26 fnts SPELLS>1)		LONG-LOW (ALS>=26 fnts SPELLS=1)		SHORT-HIGH (ALS<26 fnts SPELLS>1)	
Parameter	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	–3.083	0.0008	–2.9467	<0.0001	1.3095	0.1578
Australian x1	–0.3383*	0.0006	–0.1477*	0.0447	–0.2941*	0.0034
Age	0.0709*	<0.0001	0.087*	<0.0001	–0.0212	0.2018
Male x1	–0.1541*	0.001	–0.3414*	<0.0001	0.0602	0.2069
Indigenous x1	1.5583*	0.0095	1.1215*	0.0378	0.4302	0.559
Own home x1	–0.6001*	0.0015	–0.3198*	0.0259	–0.3486**	0.0781
Renting x1	0.1714	0.3829	0.3248*	0.0321	0.1925	0.3527
Married x1	–0.22*	0.04	–0.0458	0.5659	–0.1272	0.2434
Age of youngest child	–0.0179	0.3626	–0.0223	0.1414	–0.0133	0.4872
No. of children	0.2224**	0.0949	0.1819**	0.0976	0.1547	0.2485
Earned income	–0.00416*	<0.0001	–0.00366*	<0.0001	–0.001*	0.0003
Earned income x1	0.8217*	<0.0001	0.1704*	0.0007	0.7222*	<0.0001
Unearned income	–0.00055	0.2302	–0.00104*	0.0012	–0.00019	0.6035
Unearned income x1	0.1648*	0.0019	0.0905*	0.0198	0.2004*	0.0002
Victoria x1	0.128	0.3012	0.0792	0.3849	0.1537	0.2299
Queensland x1	0.00938	0.9426	–0.1357	0.1587	0.1353	0.3098
South Australia x1	0.2976**	0.0923	0.2	0.1393	0.1054	0.5777
Western Australia x1	–0.4145*	0.0193	–0.2601*	0.0356	0.267**	0.0984
Tasmania/NT x1	–0.1685	0.5482	0.3411**	0.0768	0.3325	0.1885
N	7433					
Likelihood Ratio	14945					

* Significant at 5% level.

** Significant at 10% level.

5.4 A multinomial logistic regression analysis of MACIS based on time spent on and off unemployment benefits

In the above analysis we have identified different types or groups of customers using information on the number and duration of spells while on benefits. We can also identify different types of customers based on the time they spend both on and off benefits. Such an analysis could provide an added insight to customer behaviour while on and off benefits over the observation window. For example it could help to explore the question as to whether customers who spend a long time on benefits and a short time off benefits display characteristics different from those who spend short time on benefits and long time off benefits, or from those who spend short times both on and off benefits. Can we detect patterns which distinguish long-term customers compared to short-term customers?

Using information on average spell duration (ASD) and average non-spell duration (ANSD) for each customer and taking 26 fortnights (i.e. long-term) as a cut-off point we can identify four groups of customers:

- "long-long" (i.e. customers who spend long time on and long time off benefits – ASD 26 fnts and ANSD 26 fortnights);
- "long-short" (i.e. customers who spend long time on benefits and short time off benefits - ASD 26 fortnights ANSD< 26 fortnights);
- "short-long" (i.e. customers who spend short time on benefits and long time off benefits - ASD< 26 fortnights ANSD 26 fortnights); and
- "short-short" (i.e. customers who spend short time on benefits and short time off benefits - ASD< 26 fortnights ANSD<26 fortnights).

Note that in this analysis only multi-spellers (1,698 customers out of 7,433 customers) are considered. Based on this analysis, we find that two types of customers are dominant. Around 45% of customers experience long periods on benefits and short periods off benefits and around 36% of customers experience short periods on and off benefits. Around 13% of customers experience short time on benefits and long time off benefits while only around 6% of customers experience long periods on and off benefits. In the subsequent analysis we take the "short-short" group as a reference group and model the probabilities of the other three groups to this reference group using the MNL framework.

The MNL regression results for this analysis are presented in table 18. From the results it is again difficult to ascertain any clear cut patterns associated with any particular group of customers. However, it does appear that significant explanatory variables include age, value of earned income and number of children.

Older customers, those with more children, those with some earned income or lower amounts of such income are more likely to experience long periods on and off benefits (i.e. fall into the “long-long” category). On the other hand, females, those of Indigenous origin and those residing in SA are more likely to experience long periods on benefits and short periods off benefits (ie “long-short”). Customers residing in Victoria are more likely to experience short periods on benefits and long periods off benefits.

Table 18: Mature Age Customers MNL Model Results-Customer Types Based on Average Duration On and Off Benefits

(Reference: ASD<26fnts, ANSD<26fnts)

Parameter	LONG-LONG (ASD 26 fnts and ANSD 26 fnts) Coefficient	p-value	LONG-SHORT (ASD 26 fnts ANSD< 26 fnts) Coefficient	p-value	SHORT-LONG (ASD< 26 fnts ANSD 26 fnts) Coefficient	p-value
Constant	–11.5111	<0.0001	–4.2047	0.0003	–2.7116	0.0917
Australian x1	0.3417	0.1509	–0.0491	0.688	0.0561	0.744
Age	0.186*	<0.0001	0.0906*	<0.0001	0.027	0.3457
Male x1	–0.1381	0.2053	–0.2255*	0.0001	–0.085	0.2988
Indigenous x1	0.1179	0.9307	1.0617**	0.0881	–16.9435#	
Own home x1	–0.3775	0.3865	–0.1718	0.4935	0.1993	0.5966
Renting x1	–0.3907	0.3907	0.0872	0.7359	0.1675	0.6687
Married x1	–0.0587	0.8184	–0.1874	0.1627	–0.0968	0.6094
Age of youngest child	–0.0597	0.1922	–0.0154	0.5005	–0.0823*	0.017
No. of children	0.4178**	0.0781	0.1311	0.3891	0.3482**	0.0745
Earned income	–0.00506*	0.0002	–0.00295*	<0.0001	–0.00028	0.546
Earned income x1	0.3448*	0.0055	0.0344	0.6086	–0.0727	0.4339
Unearned income	–0.00049	0.7231	–0.00019	0.694	0.000122	0.8342
Unearned income x1	–0.0729	0.5677	–0.0374	0.5722	0.00343	0.9705
Victoria x1	0.3945	0.1708	0.0689	0.6599	0.4245**	0.0541
Queensland x1	0.0899	0.7681	–0.1078	0.5056	0.1475	0.531
South Australia x1	0.5557	0.1751	0.3989**	0.0782	0.1385	0.6824
Western Australia x1	–0.7204	0.1155	–0.6748*	0.0011	0.1231	0.6522
Tasmania/NT x1	–0.3401	0.5881	–0.6144**	0.0685	–0.0873	0.8487
N	1698					
Likelihood Ratio	3778					

* Significant at 5%.

** Significant at 10%.

NOTE : Parameters marked with '#' are regarded to be infinite.

5.5 A logistic regression analysis of MACIS exit from a spell of long term unemployment benefits

The focus of this section is mature age customers who have experienced a spell of long term unemployment benefits (NSA payments). This analysis explores the welfare pathways taken by the long term unemployed after their spell of Newstart Allowance (NSA) payments has ceased. A long-term unemployed person is defined here as a customer who has received or has been receiving unemployment benefits (NSA) for at least 26 consecutive fortnights[20] (a break of up to 28 days between payments is allowed).[21] Using logistic modelling techniques, this section answers the following types of questions:

[20] The duration of unemployment variable (DUR_UNEM) on our version of the LDS was not used, due to data quality concerns from May 1998.

[21] The 28 day rule is consistent with our definition of spells. It should be noted, that it is different from break rules allowed by Centrelink (ie breaks of up to 6 weeks in the first 12 months and 13 weeks after 12 months of unemployment).

- What factors affect their probability of exiting long term NSA?
- Is there a tendency for MACIS to transfer to a specific payment type after leaving long term unemployment?

Answers to the questions above are provided within the framework of competing risks models. Competing risks are defined as the situations in which the occurrence of one type of event removes the individual or customer from the risk of all the other event types.

This analysis distinguishes between different types of events for the long-term unemployed. In this section, the event of interest is a mature age customer's exit from a spell of long term unemployment payments. However, unlike the analysis conducted in previous sections, exit from a particular payment type (NSA) can mean several things for the same customer. It can mean total exit from the welfare system; or a transfer to another payment type. The term 'competing events' or 'competing risks' is used to describe this complication.

One strength of the competing risks framework is that it allows the researcher to distinguish between separate event types and treat them differently when analysing the event of interest. In many cases this may be desirable.

In this part of the paper, the competing risks framework is used to analyse separately mature age customers who exit long term unemployment by leaving welfare, and distinguish these with those who complete a spell of unemployment benefits by remaining on some other form of income support (such as DSP).

In examining the outcome of interest, which is exit from long term receipt of NSA, the phenomenon we seek to model is discrete rather than continuous. A customer either exits long term NSA in a particular manner or does not. Therefore, the dependent variable in each of these cases can take on one of two possible values.

Here, the logistic technique is applied to long term unemployment recipients, in order to identify and explore the customer characteristics that influence different types of exit. In this section we report modelling results for three types of exit from long term unemployment:

1. Transfer to Disability Support Pension (DSP)
2. Transfer to another payment program other than NSA or DSP
3. Exit from the welfare system.

Table 19 presents a frequency distribution of the length of long term unemployment spells experienced by mature age customers. It can be observed that around six-tenths (59.2%) of the long term unemployment spells experienced by MACIS last for 60 fortnights or less. One-in-four spells (or 25.4%) of long term unemployment involve at least 80 consecutive fortnights of unemployment benefit receipt. The last column in table 19 provides an indication of how many of these spells are still ongoing at the last observation date available in our version of the LDS (10 March 2000). For example, of the 414 spells of long term unemployment which are observed to have a duration between 41 and 60 fortnights — 21.3% (or 88 spells) have not been completed by 10 March 2000 and are still ongoing. The percentage of long term unemployment spells still ongoing at the last observation date increases as duration on long term NSA increases.

Table 19: Frequency distribution of duration on long term unemployment

Consecutive fortnights on NSA	Count	%	% of these spells ongoing at the last observation date
26–40	505	32.5	19.8
41–60	414	26.7	21.3
61–80	240	15.5	40.8
81–100	168	10.8	45.2
101–123	170	11.0	67.3
124	56	3.6	100.0
Total	1 553	100.0	

Intuition would also suggest that a range of socio-demographic factors such as age, marital status, Indigenous status or country of birth, along with economic variables such as earned and unearned income may also be relevant in explaining how a customer exits long term unemployment. Location may also be a factor, thus a variable called ARIA (Accessibility and Remoteness Index of Australia) is included in modelling the outcomes of the long term unemployed. ARIA is an index that may indicate the degree of advantage/disadvantage of a particular locality based on its distance to four categories of service centres (DHAC 1999)[22]. The logistic regression model results for the three transition states of exit from long term unemployment are presented in table 20.

[22] This variable is a 12 point index, where a value of zero represents a highly accessible area which is defined as relatively unrestricted accessibility to a wide range of goods and services and opportunities for social interaction while an ARIA value of 12 indicates very remote areas with very little accessibility of goods, services and opportunities for social interaction.

Table 20: Logistic regression Model Results of exit from long term unemployment

	Transfer to DSP			Transfer to Other Program			Exit Welfare		
Parameter	Co-eff	P-Value	Odds Ratio	Co-eff	P- Value	Odds Ratio	Co-eff	P-Value	Odds Ratio
Constant	–1.3177	0.4286		–25.9355*	<0.0001		7.5031*	0.0002	
Age	–0.0241	0.3893	0.976	0.4101*	<0.0001	1.507	–0.1120*	0.0011	0.894
Male x1	0.4037*	0.0266	1.497	–1.6622*	<0.0001	0.190	0.1710	0.4087	1.186
Married x1	0.0688	0.7215	1.071	0.0212	0.9158	1.021	0.4501*	0.0462	1.568
Non-Indigenous x1	–0.9984**	0.0897	0.368	–0.2849	0.7510	0.752	–0.5696	0.4677	0.566
Age of youngest child	0.0305	0.4266	1.031	–0.0093	0.8455	0.991	0.0317	0.3665	1.032
No. of children	–0.4458**	0.0953	0.640	–0.0214	0.9454	0.979	–0.2165	0.2236	0.805
Churner x1	–0.8922*	<0.0001	0.410	–0.4136*	0.0232	0.661	–0.8279*	<0.0001	0.437
Australian born x1	–0.2386	0.1632	0.788	0.1759	0.3490	1.192	0.4847*	0.0162	1.624
Total duration on welfare	0.0258*	<0.0001	1.026	0.0259*	<0.0001	1.026	–0.0423*	<0.0001	0.959
Earned Income ($)	–0.0061*	0.0035	0.994	–0.0018**	0.0776	0.998	0.0013**	0.0529	1.001
Earned Income x1	–0.4827*	0.0118	0.617	0.0792	0.6807	1.082	0.9177*	<0.0001	2.503
Unearned income($)	0.0004	0.7822	1.000	–0.0048*	0.0240	0.995	0.00077	0.4376	1.001
Unearned Income x1	0.1066	0.5753	1.113	0.5373*	0.0090	1.711	–0.5810*	0.0043	0.559
Victoria x1	0.0179	0.9310	1.018	0.2845	0.2075	1.329	0.0404	0.8675	1.041
Queensland x1	0.1079	0.6347	1.114	0.1587	0.5333	1.172	0.2421	0.3186	1.274
South Australia x1	0.2669	0.3682	1.306	1.1069*	0.0001	3.025	–0.3132	0.4193	0.731
Western Australia x1	0.6534*	0.0342	1.922	0.0457	0.9019	1.047	0.1933	0.5717	1.213
Tasmania/NT x1	–1.1663**	0.0585	0.312	0.6041	0.1693	1.830	–0.8660	0.1464	0.421
Home owner x1	–0.2824	0.3799	0.754	0.0029	0.9935	1.003	–0.1272	0.7506	0.881
Renter x1	–0.0894	0.7760	0.914	–0.1362	0.7092	0.873	0.0682	0.8622	1.071
ARIA	0.0508	0.3623	1.052	–0.0514	0.4429	0.950	–0.1015	0.1262	0.903
Likelihood Ratio	226			371			373		
Hosmer-Lemeshow GOF *p-value*	0.1562			0.6205			0.1050		

* Significant at 5%

** Significant at 10%

Exit long-term unemployment by transferring to DSP

The following variables are found to increase the odds of a mature age customer exiting long term NSA receipt by moving onto DSP:

- Being male (males are 1.5 times more likely to transfer to DSP relative to females)
- Total time on benefits — a longer duration on welfare increases the probability of exiting through the DSP payment stream (each 1% increase in time a customer spends on welfare increases the odds of this type of exit by 2.6%)
- Residing in Western Australia (those residing in WA are 1.9 times more likely to transfer to DSP relative to those residing in NSW/ACT).

The following variables are found to reduce the probability of exit through disability support:

- Non-Indigenous customers (are 63.2% less likely to exit long term unemployment by transferring to DSP relative to Indigenous customers)
- Number of dependent children (an additional child is associated with a 36% reduction in the odds of exiting onto DSP)
- Customers with multiple spells of benefit receipt are 59% less likely to transfer to DSP relative to single spellers.
- Both the presence and amount of earned income lessen the likelihood of transition onto DSP.

The significance of the earned income variables may reflect the possible link between a customer's health status and ability to maintain employment, with those who are in good health better able to work and earn income and therefore less likely to move onto the DSP program. Furthermore, for customers aged over 55, eligibility for DSP takes into account the availability of work in the local labour market. Therefore, it is not surprising that the amount of earned income reduces the likelihood of transfer to DSP. The presence and amount of earnings may be associated with strong local labour market conditions, and therefore disqualify a customer from the DSP program.

Exit long term unemployment by transferring to another payment program

The following variables are found to increase the odds of a mature age customer exiting long term NSA receipt by transferring to another payment program:

- Age (an increase in age by 1 year is associated with a 50.7% increase in the likelihood of transferring to another payment program)
- Total time on benefits — a longer duration on welfare increases the probability of exiting through another payment program (each 1% increase in time a customer spends on welfare increases the odds of exiting in this manner by 2.6%)
- The presence of unearned income.
- Those residing in South Australia are over 3 times more likely to transfer to another payment program relative to those living in NSW/ACT.

The following variables are found to reduce the probability of exiting long term unemployment by transferring to another payment program:

- Being a male (Males are 81% less likely to exit in this manner relative to females)
- Customers with multiple spells of benefit receipt are 34% less likely to transfer to another payment program relative to single spellers.
- The amount of both earned and unearned income lessen the likelihood of transition onto another payment program.

Exit long-term NSA by exiting the welfare system

The variables that increase the probability of exiting long term unemployment by leaving the welfare system include:

- Marital status (those who are married are 56.8% more likely to exit long term unemployment by leaving welfare relative to single customers)
- Australian born customers are 62.4% more likely to exit in this manner relative to foreign born customers.
- Both the presence and amount of earned income.

The following variables decrease the likelihood of exiting long term unemployment by leaving welfare:

- Age (an increase in age by 1 year is associated with a 10.6% reduction in the likelihood of exit from a spell of long term unemployment by leaving welfare)
- Customers who experience multiple spells of benefit receipt are 56.3% less likely to exit in this manner relative to single spellers.
- Total time on benefits (a one unit increase in benefit duration is associated with a 4.1% decrease in the likelihood of welfare exit)
- The presence of unearned income.

The significance of the total duration on welfare variable agrees with prior expectations. Norris (1996) argues that employers may use the duration of unemployment as a screening device, therefore those customers with longer durations on welfare may face greater hurdles in re-entering the workforce relative to those who have shorter spells on welfare. He also identifies a further factor of ineffective job search by demoralised job searchers who experience long spells of unemployment. Clearly, these two effects predict that increases in the total duration on welfare decrease the likelihood of a customer securing employment and exiting the welfare system.

The two earned income variables may reflect other factors such as a customer's motivation level which may play a role in explaining a customer's propensity to exit the welfare system.

The ARIA variable was not significant in any of the three transition states modelled above.

6 Conclusions

This paper analyses a one percent sample of Centrelink customers on a current income support payment. As with other datasets built from administrative data, the LDS has its own limitations. One of the most critical limitations of the LDS is that data is limited in scope to the information that is collected or generated in the process of administration. For this reason, it is difficult to talk comprehensively about customers destinations at the end of a spell of welfare payments, or analyse the characteristics of persons when they are not present in the welfare system.

Despite these limitations, the LDS still provides a very valuable source of information about welfare recipients. The LDS allows longitudinal analysis, and so helps to fill some of the gaps in our understanding of the dynamics of welfare usage.

In this paper, we have applied a wide range of statistical and modelling tools to explore the welfare dependency, dynamics and transitions of mature age customers on income support.

Based on the application of various descriptive techniques such as one way tabulations, cross tabulations and flow analysis, the study finds that:

- Mature age customers welfare experience is characterised by a long continuous spell of benefit receipt. Mature age customers spend a longer time on benefit and have lower rates of exit from welfare compared to prime age customers. They also have a much lower incidence of churning and less interaction with the labour market in terms of earned income through employment while on welfare.

- Considerable differences exist in terms of welfare experience and labour market participation across the mature age caseload. Customers on unemployment benefits (NSA) average shorter stays on benefit receipt and have higher incidence of churning compared to non-activity tested customers.

Event-history modelling techniques were also applied to the FaCS data. These analytical methods included:

- Survival and hazard rate models which were used to analyse the timing of exit from a welfare spell for all mature age customers and other sub-populations (the long term unemployed, prime aged customers and NSA customers).

- Proportional hazard models which were used to examine the personal characteristics associated with length of time on benefit.

Based on these model results, the study concludes that:

- There is some evidence of negative duration dependence for mature age customers - the longer an individual remains on their current spell of welfare, the less likely it is that the spell will end.

- As the length of unemployment benefits increase, the more likely it is that this spell of unemployment payments will end by a customer transferring to some other form of income support (such as Disability Support Pension) rather than by movement off the welfare system.

- Individual characteristics have a role to play in explaining exit from welfare. Australian born customers, males, those with higher levels of earned and unearned income, and those residing in WA or QLD display higher rates of exit from welfare.

A number of regression techniques have also been applied in this study to analyse the outcomes of mature age customers with different characteristics. These regression techniques include:

- Logit regression models were used to model binary dependent variables such as whether a customer is a "churner" (multiple speller) or not.

- Multinomial logit models were used to model dependent variables with more than two responses.

- Count models (Poisson type regression) were used to analyse the probability of a mature age customer experiencing a discrete number of welfare spells.

Based on these regression estimates, the study concludes the following:

- Attachment to the labour market in terms of presence of earned income is found to significantly increase the likelihood of churning by mature age customers. Being male, presence of unearned income and residing in Queensland are characteristics of customers associated with higher likelihood of churning. Those born in Australia, older, married and home owners are less likely to experience multiple spells of benefit receipt.

- An analysis of customers based on the number of spells and average length of spells shows that around three-fifths of customers experience single spells lasting over a year. Overseas born, Indigenous, non-home owners, singles, additional children, and those with some earned income are more likely to experience more frequent long spells on benefit. Females are more likely to experience single long spells on benefit, while older customers are more likely to experience single or multiple long spells on benefit.

- The average number of welfare spells is higher for those with some earned or unearned income, males, those of Indigenous origin, and those living in Queensland or Western Australia. The average number of spells is lower for homeowners, Australian born, married and older customers.

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ISSN 1320-5099

Produced by the Australian Bureau of Statistics