An Analysis of Durations on the Disability Support Pension (DSP) Program*

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Abstract

The paper examines the factors that determine the duration on the Disability Support Pension (DSP) program using administrative data. We estimate two models based on two competing assumptions: the first model takes the standard assumption in duration models that all recipients will eventually leave the program. The second one takes into account the possibility that there may be some recipients who will never recover from their disabilities and hence not leave the program. Although there are differences in the results, both models indicate that female recipients, recipients who enter DSP at a young or old age, and recipients who transfer from unemployment benefits have the potential of a longer DSP duration.

I. Introduction

The Disability Support Pension (DSP) is the payment for people of working age with an illness or injury for a prolonged period of time that prevents them from undertaking full-time employment. In 2001, there were 624,000 DSP recipients in Australia. In the financial year 2000-01, the expenditure on the program was over $45.8 billions. Among all the income support payment programs administrated by the federal government, the DSP program is the second largest in terms of recipients and expenditure. Despite the importance of the program, little is known about the dynamics of the recipients.

Duration on the DSP program is also of great policy interest. Firstly, the number of DSP recipients is not only determined by inflows of new recipients, but also by durations on the program. Understanding duration will thus help enhance understanding the growth of the program (Cai and Gregory, 2003, 2004). Secondly, projections of future expenditures on the DSP program depend on estimates of expected durations on the program. Thirdly, when comparing costs among recipients with different characteristics, duration differences among them become relevant. For example, if a 20 years old new recipient is expected to stay on the program for 10 years, this person's cost is equivalent to five 60 year old new recipients if the latter are expected to stay for only two years. In addition, policy makers may also be interested in how the duration varies with subgroup characteristics, such as age and gender.

The objective of this paper is to provide an empirical analysis on the determinants of durations on the DSP program, using the administrative Longitudinal Data Set (LDS) available from the Department of Family and Community Services (FaCS). The analysis is undertaken in the framework of duration models. The duration models have a history of extensive implementation in economics and related areas[1]. However, the application of the models to disability benefit

[1] Duration studies include length of marriage (Lillard, 1993), length of time until return migration (Lindstrom, 1996), length of time in employment (Keane and Wolpin, 1995), length of time until childbirth (Heckman and Walker, 1990), length of strike (Kennan, 1985), length of time until a purchase (Jain and Vilcassim, 1997), length of business cycles (Diebold and Rudebush, 1990),

programs is limited. There appear to be only two studies: Hennessey and Dykacz (1989) and Holmes and Lynch (1990). Hennessey and Dykacz applied a competing risk duration model to a random sample of Social Security disability beneficiaries in the US who were first entitled to disabled-worker benefits in 1972. Their study estimated the coefficients of the factors that determined the probability of leaving the benefit and used these coefficients to project the expected destinations and length of stay of the beneficiaries. The Holmes and Lynch study examined the factors that impacted on durations on the Invalid Benefit (IVB) program for males in Britain.

The main reason for the few studies in this area may be the lack of available data. Duration on the disability benefit program is normally long compared with other benefit programs, such as unemployment or sickness benefits. Consequently, not only are longitudinal data required, but also the required period of data is generally long.

The currently available FaCS LDS data are most suitable for the study of disability benefit duration, although a longer data period would of course be better. The LDS data are derived from the fortnightly administrative records of one percent of individuals who received FaCS payments during the period from 6th January 1995 to 16th June 2000. The longitudinal nature of the data allows the duration on the program to be derived, the key variable in duration analyses. In addition, because the data contain fortnightly recorded information on DSP participation, the time pattern of program participation and the precise length of stay can be determined accurately. This is a great advantage over survey data which are often subject to the problems of systematic non-response or recall error (Berrett, 2002). However, the data suffer several limitations. Firstly, the data contain only limited socio-economic information. Information on human capital and labour market activity, such as recipients' education, employment history and market wage, which may be important in explaining the dynamics of DSP participation, are not included in the data. Secondly, The LDS data do not record

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length of unemployment (Devine and Kiefer, 1991), and length of stay on the US Aid to Families with Dependent Children (AFDC) program (Blank, 1989; and O'Neill, Bassi and Wolf, 1987).

information if a recipient moves off the income support system. This means that for recipients who exit DSP, their destinations cannot be distinguished unless they transfer to other income support payments.

Barrett (2002) used the LDS data to examine the dynamics of sole parent pension recipients, employing duration model techniques. It is a natural extension to apply these techniques to DSP recipients. Dawkins, Harris and Loundes (2000) also used this data set to examine the length distribution of spells of DSP recipients, but they did not examine the determinants of the duration of DSP spells.

The paper is organized as follows: Section 2 provides a brief discussion on the theoretical and empirical model and the estimation method. Section 3 describes the data. The estimation results are reported in section 4. Section 5 sets out the conclusion.

II. The theoretical and empirical model

The application of duration models in labour economics, such as the studies on the durations of unemployment and other benefit payments, is often motivated by modelling individual choice in the context of utility maximization. A stylized model for durations on welfare programs is as follows. Assume, at a point of time, for a person already on the program, there are two options (or states) to choose from for the next period: continue to stay on the program or leave the program for work. Both options are associated with state specific expected utilities or option values. The individuals make a decision by comparing the expected utilities from the two options. If the expected utility associated with continuing to stay on the program were greater than that of leaving, the individual would continue to stay, otherwise the person would leave for work. The expected utility or option value of each choice will be a function of personal characteristics, the program parameters, labour market conditions, etc. All the factors that increase the expected utility of exit (e.g., an increase in the wage rate) and decrease the expected utility of stay (e.g., a decrease in the benefit level) would encourage the recipients to leave and increase the hazard rate from receiving the benefit. This modelling approach can be easily extended to include more than two states. But in this paper, we consider only two states, stay on the program or exit, because the data do not allow more meaningful states to be distinguished[2].

Although the analysis of the duration on DSP can be put in the proceeding framework, we need to assume that exits from DSP are truly based on individual choice. However, in reality this is not always the case for at least two reasons: the first is that the DSP benefit is means-tested, implying that some recipients may be 'forced' out if their incomes or assets are high. The second reason is that some exits may be due to death. Presumably, we can exclude those who leave due to death, but the data do not allow them to be identified. In this paper these complications are set aside and the assumption is that there are only two states for a DSP recipient to choose from, stay on the program or exit.

The starting point of modelling duration is to define the hazard function, which measures the instantaneous tendency of a given event (termination of DSP receipt in the context of this paper) to occur at each point in time. In the paper, a proportional hazard function is used,

$$h(t \mid X(t)) = h_0(t)\exp[X(t)'\beta], \tag{1}$$

where $h(t \mid X(t))$ is the hazard rate at time *t*, $h_0(t)$ is the baseline hazard rate common to all individuals and $X(t)$ is a vector of covariates, some varying with *t*. In our implementation, we have only one time-varying covariate, the unemployment rate. β is a vector of parameters to be estimated. For different values of $X(t)'\beta$ of different recipients, the hazard function is shifted proportionally up or down relative to $h_0(t)$.

To allow for full flexibility of the baseline hazard function, a piece-wise constant baseline hazard is specified. This approach is an extension of Prentice and

[2] Recipients who transferred to the Age Pension from DSP can be identified from the LDS data. But, it is not appropriate to regard the transfer as an exit because the transfer is determined by age. In the estimation, we treat those who transferred to the Age Pension as right-censored observations.

Gloeckler (1978) and is detailed in Meyer (1990) and Lancaster (1990). The time axis is divided into a finite number of intervals and a separate baseline hazard parameter is estimated for each interval;

$$h_0(t) = \begin{cases} \theta_1 & if \quad 0 \le t < c_1 \\ \theta_2 & if \quad c_1 \le t < c_2 \\ \vdots & \vdots \qquad \vdots \\ \theta_M & if \quad c_{M-1} \le t < \infty \end{cases} \tag{2}$$

where θ_k are constants, c_k are defined points in time and $0 < c_1 < c_2 < ... < c_{M-1} < \infty$. A convenient specification is to use $\theta_t = \exp(\gamma(t))$, which means that the hazard function can be written as

$$h(t \mid X(t)) = \exp[\gamma(t) + X(t)'\beta]. \tag{3}$$

This specification for the baseline hazard has an important advantage for it has been shown that misspecification of the baseline hazard is a major source of error in drawing inferences concerning both the presence of duration dependence (Blank, 1989; and Manton, Stallard and Vaupel, 1986) and the impact of covariates (Dolton and van der Klaauw, 1995; and Heckman and Singer, 1985).

The log likelihood function for this specification with a sample of N spells is given by:

$$L = \sum_{i=1}^{N} \{\sigma_i \log[h(t_i \mid X_i(t_i))] - \Lambda(t_i \mid X_i(t_i))\}, \tag{4}$$

where t_i is the observed length of the i^{th} spell, δ_i equals one if the i^{th} spell is completed and zero if right-censored, and

$$\Lambda(t_i \mid X_i(t_i)) = \int_0^{t_i} h(s \mid X_i(s))ds = \sum_{k=0}^{t_i} h(k \mid X_i(k)). \tag{5}$$

As in the general linear model, unobserved heterogeneity is also a concern in duration models. Heckman and Singer (1984a, 1984b) show that the presence of population heterogeneity induces a negative bias in the hazard function, potentially producing estimates of a decreasing hazard when the true underlying hazard is flat or increasing. The heterogeneity may be accounted for by incorporating the unobservable variable, say θ_i for individual *i,* into the hazard function as $h(t, X_i(t), \theta_i)$. The piece-wise proportional hazard model may be extended to allow for the unobserved heterogeneity by assuming that the unobserved variable takes a multiplicative form,

$$h(t \mid X_i(t)) = \theta_i h_0(t) \exp\{X_i(t)'\beta\} . \tag{6}$$

Maximum likelihood estimates of the parameter vector and baseline hazard are then obtained by conditioning on the likelihood function on θ_i and then integrating over the distribution of θ_i . This approach requires specifying an explicit functional form for the distribution of θ. One popular distribution is the gamma, which gives a closed-form expression for the likelihood function (Lancaster, 1990). Alternatively, Heckman and Singer (1984a) suggest using a discrete distribution with a finite numbers of mass-points to approximate the distribution of θ, so that the unobserved heterogeneity takes a non-parametric form. However, when the baseline hazard takes a piece-wise constant form, the choice of heterogeneity distribution may not be important (Meyer, 1990). Nevertheless, estimation of the model with each type of unobserved heterogeneity was attempted but failed to identifying the heterogeneity terms. In the case of unit gamma heterogeneity, the estimate of the variance term always converged to zero. In the case of non-parametric heterogeneity, when two mass-points were attempted, the simplest specification of such a model, the estimated location of the free mass-point always converged to that of the fixed one. Consequently, results by taking into unobserved heterogeneity are not reported in the paper.

At the first glance, the rejection of the model with unobserved heterogeneity is a surprise. Presumably DSP benefits are based on individual health conditions and exit from the program then reflects a recovery from the disability which makes the recipient eligible for the benefit. In addition, Holmes and Lynch (1990) find that health conditions have a significant impact on the hazard rate of male disability benefit recipients in Britain. In effect, omitted variable argument is one of the rationalisations for incorporating unobserved heterogeneity in duration models (Lancaster, 1990). Because the model does not include a health condition variable (since it is not available from the LDS data) and there are some other important variables not available in the data set, we would expect there must be unobserved heterogeneity which at least reflects the health condition of a recipient. That this does not happen implies that the observable variables included in the model can explain the exit behaviour of DSP recipients, or that these variables also reflect the health condition of DSP recipients. The impact of health conditions on the exit behaviour is then absorbed into these included covariates. If this is true, it supports the argument that the disability behaviour is not only determined by medical factors, but individual characteristics (e.g., age) and socio-economic factors (e.g., labour market conditions) may also play important roles (Aarts and de Jone, 1992; and Cai and Gregory, 2004).

The likelihood function in equation (4) uses the standard assumption in duration models that every subject will eventually exit and the probability of survival will become zero as time goes to infinity. In the context of DSP the standard assumption may not be appropriate because it is possible that a proportion of the recipients would never recover and exit[3]. One approach that takes into account the never-exit possibility is the split population survival model proposed by Schmidt and Witte (1989).

To account for the possibility that a proportion of the recipients would never exit, we include in the likelihood function a term representing the probability of eventual leaving and define the hazard function conditional on eventual leaving. The term representing the probability of eventual leaving could be a constant, implying that everyone has the same probability of eventual leaving, or a function of individual characteristics, indicating that the probability of eventual leaving varies across individuals. We take the latter approach because it is more reasonable than the former. Define the probability of eventual leaving as

[3] This assumes that only exits due to recovery from disability are of policy and research interest.

$$P_i = \frac{1}{1+\exp(Z_i^{'}\alpha)}, \tag{7}$$

where Z_i is a vector of individual characteristics and α another vector of parameters to be estimated. The log-likelihood function of the split population model is given by:

$$\begin{aligned} L^{sp} &= \sigma_i\{\log[h(t_i \mid X_i(t_i))] + \log(P_i) - \Lambda(t_i \mid X_i(t_i))\} \\ &\quad +(1-\sigma_i)\times\log\{\exp[-\Lambda(t_i \mid X_i(t_i))]\times P_i + (1-P_i)\}. \end{aligned} \tag{8}$$

Unobserved heterogeneity can also be incorporated into the split population model. We experimented with such models. As in the standard duration models, the unobserved heterogeneity terms could not be identified in the split population model.

The assumption on which the split population model is based is more appealing from policy points of view. However, the observed exits in the LDS data may not only be caused by recovery or means-test[4]. Some observed exits may be due to death. Although death exit is not of policy interest, the possible inclusion of death in the observed exits makes the standard assumption legitimate because eventually everyone would die. If death exits can be distinguished, we can specify a competing risk model, which can incorporate the possibility of never-recovering. However, as mentioned earlier, from the data available we cannot distinguish the exact reason for the observed exits. We therefore estimate both models in the paper, hoping that each model will shed light on the exit behaviour of DSP recipients.

III. The data

As mentioned earlier, the 1 percent sample LDS data set is the data source, from which the DSP sample used for the current analysis is derived. The sample consists of all the fresh DSP spells which started between 3 March 1995 and 30 December 1999 (inclusive). At the time this paper was written, the maximum time window of the LDS data set was from 6 January 1995 to 16 June 2000. The current analysis uses the period that began from 3 March 1995 (inclusive) rather than from 6 January 1995 for two reasons. The first is to identify and exclude the left-censored spells; the second is to identify the sources of new recipients (i.e., transition from unemployment benefits, transition from other income support payments, or entrants from outside the income support system). In our analysis, a spell is defined as a sequence of consecutive fortnights of DSP receipt and an exit is defined as two or more consecutive fortnights not in receipt of DSP benefits. Barrett (2002) uses a similar definition of spells for sole parent pensions. We experimented on different definitions of spells and they produce similar results to those presented in the paper.

The left-censored spells falling into the data period defined above were excluded from the analysis because including the left-censored spells might lead to sample selection bias (Lancaster, 1990). The left-censored spells are a special subset of spells that are typically long as shown by Heckman and Singer (1984) and their inclusion would form a ‘length biased sample’.

Unlike the left-censored spells, the right-censored spells can be easily handled in the likelihood function of duration models and are included in the analysis. However, right-censored spells include two types in our analysis: (a) those spells which were still continuing at the end of the data set (i.e., 16 June 2000); and (b) those spells which ended their DSP spells because of a transfer to the Age Pension. For the latter, had recipients not transferred to the Age Pension, they would have still continued their DSP spells at the time of the transition. They are treated therefore as right-censored at the time of transition.

(i). Descriptive statistics of the sample

Table 1 presents the descriptive statistics of the sample. All variables in Table 1 except for the average duration are included in the model. In total 3936 fresh spells representing 3658 recipients appeared in the defined time window.

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[4] Exits due to means-testing also favour the split population model assumption because there must be a proportion of recipients who will never leave DSP for the reason of mean-tests.

Therefore, in the sample only 7 percent of the spells are repeated spells. Of the whole sample, 805 were completed spells and 3131 right-censored spells. The values of all variables, except for financial variables, are as at the beginning of the spells. The financial variables, especially the amount of earned and unearned income, are included as the average over the DSP receipt spell[5].

The average entry age of the whole sample was 46 years. Recipients with completed spells have a younger entry age on average than right-censored individuals, but the difference is not statistically significant. Males made up of a higher proportion of the sample than females. Among recipients with completed spells the proportion of males was somehow higher than that among the right-censored recipients.

Less than half of the recipients were married. This proportion is similar among both groups of recipients. About 70 percent of the recipients were Australian born. Among recipients with completed spells a slightly higher proportion than in the sample as a whole were born in Australia. The proportion of the sample having children was 14 percent. Among recipients with completed spells, this proportion was slightly higher (19 percent) than among recipients with right-censored spells (13 percent).

Homeowners consist of the largest proportion of the sample, which is followed by the proportion of recipients who rented from private markets. Compared with those recipients whose spells are completed, a slightly higher proportion of the right-censored recipients were homeowners, while a slightly lower proportion of right-censored recipients were renting from private markets. The housing tenure information is missing for 8 percent of the spells.

For the financial variables, about 12 percent of the sample had earned income. For those who had earned income, the average amount was $143 per fortnight. Recipients with completed spells had a higher proportion (18 percent) having earned income and their earned income almost doubled that of right-censored

[5] The reason for using the average over a DSP receipt spell rather than the value at entry or as a time-varying variable is that for DSP recipients the records of earned and unearned income show

recipients. The proportion having unearned income was 37 percent and among those who had unearned income the average amount was just under $100 per fortnight.

Table 1: Summary statistics of the sample

	All spells		Completed spells		Right-censored [a]	
	Mean	St.De.	Mean	St.De.	Mean	St.De.
Demographic characteristics						
entry age	46.27	13.24	44.11	12.66	46.82	13.33
sex (male=1)	0.6336	0.4819	0.6733	0.4693	0.6234	0.4846
marital status (single=1)	0.5379	0.4986	0.5391	0.4988	0.5375	0.4987
country of birth (foreign=1)	0.3006	0.4586	0.2584	0.4380	0.3114	0.4631
proportion having children	0.143	0.350	0.185	0.388	0.132	0.338
# of children if having children	1.916	1.098	1.926	0.994	1.913	1.134
Homeownership and rental type						
home owner	0.3570	0.4792	0.3242	0.4684	0.3654	0.4816
purchasing home	0.0246	0.1551	0.0261	0.1595	0.0243	0.1539
other home owners	0.0582	0.2341	0.0534	0.2250	0.0594	0.2364
private rent	0.2429	0.4289	0.2944	0.4561	0.2296	0.4207
government rent	0.0831	0.2760	0.0696	0.2546	0.0866	0.2812
other rent	0.0864	0.2810	0.0919	0.2891	0.0850	0.2789
no rent paid	0.0643	0.2453	0.0584	0.2346	0.0658	0.2480
missing	0.0836	0.2768	0.0820	0.2745	0.0840	0.2774
Financial variables						
earned income>0	0.1222	0.3276	0.1764	0.3814	0.1083	0.3108
average amt if earned income>0	143.04	174.37	213.99	224.55	113.32	138.35
unearned income>0	0.3714	0.4833	0.3031	0.4599	0.3890	0.4876
average amt if unearned income>0	98.32	152.86	113.54	175.98	95.27	147.69
equivalised maximum payment (OECD scale)	241.70	91.19	240.73	94.18	241.95	90.42
Recipients origination						
from outside of income support system	0.3821	0.4860	0.4696	0.4994	0.3596	0.4800
from unemployment benefits	0.3976	0.4894	0.2957	0.4563	0.4238	0.4942
from other payments	0.2203	0.4145	0.2348	0.4241	0.2165	0.4120
State of residence						
NSW&ACT	0.3404	0.4739	0.3354	0.4721	0.3417	0.4743
NT	0.0074	0.0855	0.0124	0.1108	0.0061	0.0777
QLD	0.1977	0.3983	0.2087	0.4066	0.1948	0.3961
SA	0.0927	0.2901	0.0919	0.2891	0.0929	0.2904
TAS	0.0328	0.1781	0.0286	0.1667	0.0339	0.1809
VIC	0.2424	0.4286	0.2261	0.4186	0.2466	0.4311
WA	0.0866	0.2813	0.0969	0.2960	0.0840	0.2774

irregularity because earned and unearned income may not be reported and recorded fortnightly.

Table 1: Continued

	All spells		Completed spells		Right-censored [a]	
Variables	Mean	st.de.	Mean	st.de.	Mean	st.de.
Entry cohort						
enter in 95	0.1959	0.3969	0.2261	0.4183	0.1881	0.3908
enter in 96	0.1875	0.3904	0.2224	0.4161	0.1785	0.3830
enter in 97	0.1885	0.3912	0.1863	0.3896	0.1891	0.3916
enter in 98	0.2088	0.4065	0.2385	0.4264	0.2012	0.4010
enter in 99	0.2193	0.4138	0.1267	0.3329	0.2431	0.4290
Whether being a repeated spell						
repeated spell (=1)	0.0711	0.2571	0.1230	0.3286	0.0578	0.2334
unemployment rate (%)						
average duration (fortnights)	62.47	39.60	32.15	30.66	70.27	37.86
Number of obs (spells)	3936		805		3131	

Note: a, Right-censored spells include those who transferred to the Age Pension.

The impact of program payments on DSP participation is of great policy interest. But it is not easy to identify it because, although information on benefits received is available in the data set, benefits received are affected by recipients' labour market behaviour and are thus endogenous. One other option is to use the maximum potential payment. But, DSP benefits are paid in flat rates and indexed twice a year in line with changes in CPI. So, the variation of maximum potential payment must be very small if there is any. To get around of this problem, we use the standardised maximum potential payment, recognising that family needs vary with family size. This is also the strategy taken by Barrett (2002). In Table 1, the reported maximum potential payment is standardised using OECD equivalence scale. Other equivalence scales were attempted; the estimation results were virtually the same.

For the whole sample, about 40 percent had transferred from unemployment benefit programs and another 22 percent from other income support payment programs. Among recipients with completed spells, the proportion from unemployment benefit programs was smaller than that of right-censored recipients.

Table 1 also presents the distribution of recipients by state and entry year. The state variables are included to control for any state fixed effect. The entry cohort variables are to control for cohort specific effect over the five entry years.

As mentioned earlier, only 7 percent of the sample are identified as repeated spells over the data window, but this proportion is much higher among recipients with completed spells than among those with right-censored spells. It is unlikely that recipients with repeated spells would behave in the same way in the first spell as in the second and subsequent spells. To account for this difference we included a repeated spell indicator in the model.

On average, the whole sample spent 62 fortnights (2.4 years) on the program, but the duration of the right-censored spells more than doubles that of the completed spells.

To examine the impact of local labour market conditions on the hazard rate of DSP recipients, we added the unemployment rate to the LDS data. To maximise the variation of this variable we added the unemployment rate to each fortnight record differentiated by state, gender, year and quarter. Hence the unemployment rate is a time-varying variable.

(ii). Empirical survival and hazard functions

To further describe the duration distribution of the sample, we plot the empirical survival and hazard functions of these spells. The survival function shows the proportion of spells that are at least x fortnights long, while the empirical hazard function at fortnight x is computed as the ratio of the number of spells which exit in the time interval $[x, x+1)$ to the number of spells which survive to time t.

Figure 1a plots the empirical survival function for the whole sample. From the figure, after a half year (13 fortnights) 92 percent of the spells are still continuing, after one year 88 percent, after the two years 83 percent and after five years 71 percent.

Figure 1a: Empirical survival function, the whole sample

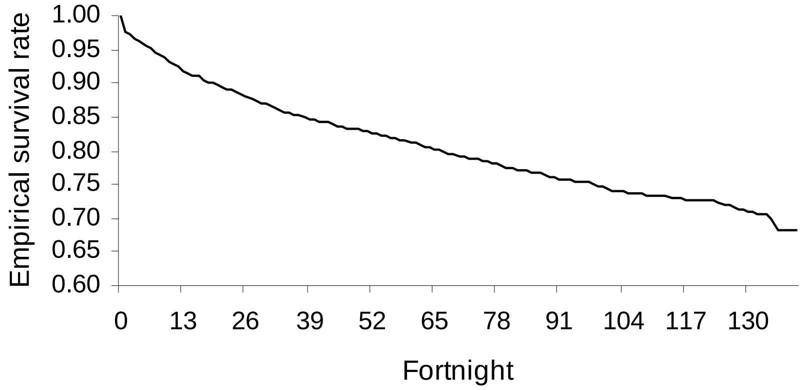
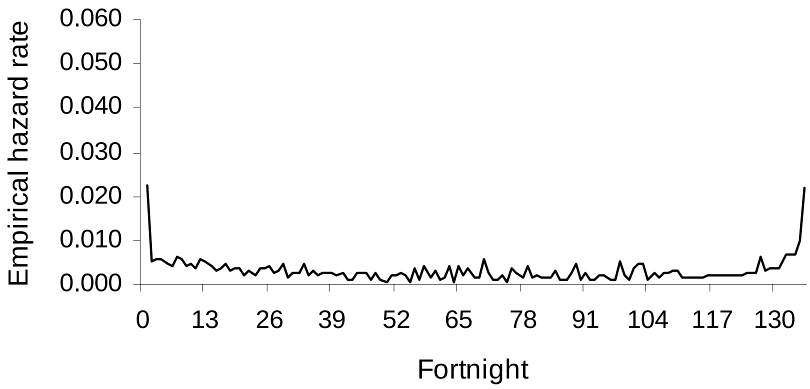


Figure 1b plots the empirical hazard function for the whole sample. For duration less than two years (52 fortnights), the empirical hazard rate appears to decline with duration. But at about two-year point the hazard rate starts to increase. This may be because there is a review on recipients' eligibility after two years of DSP receipt. This review may move out those who are no longer eligible. Also the variation of the hazard rate after two years duration increases dramatically. The hazard rate for very long durations behaves erratically because only a few spells have such a long duration in the sample.

Figure 1b: Empirical hazard function, the whole sample



The spell sample can be stratified according to one set of characteristics at a time, to obtain a better sense of the relationship between each characteristic and spell duration. The empirical survival and hazard functions for selected characteristics are plotted in the following series of figures.

Figures 2a and 2b plot the empirical survival and hazard functions by gender. It appears that the survival rate for males is lower than that for females except for durations less than 7 fortnights, implying females may overall stay longer than males. The male empirical hazard function is much like the hazard function of the whole sample (males are more than 60 percent in the sample). It also appears that the main difference of the hazard rate between males and females takes place at durations of less than one year and after two and a half years.

Figure 2a: Empirical survival function by gender

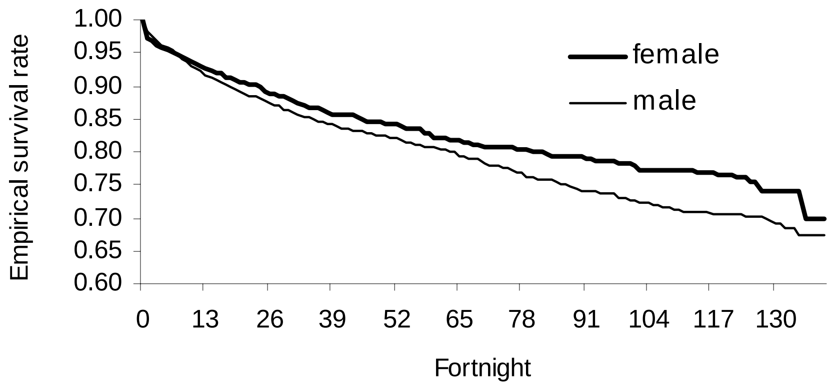
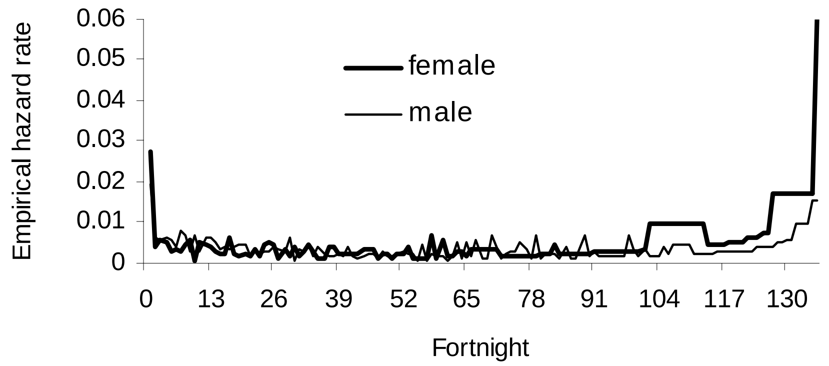


Figure 2b: Empirical hazard function by gender



Figures 3a and 3b plot the empirical functions by whether or not individuals have earned income. The survival rate of recipients who have earned income is slightly higher than that of those who have no earned incomes for durations of less than

24 fortnights, but thereafter the survival rate becomes lower and the difference becomes larger with duration. From the empirical hazard function, the hazard rate of those who have earned income appears higher than those who have no earned income after 24 fortnights.

Figure 3a: Empirical survival function by whether having earned income

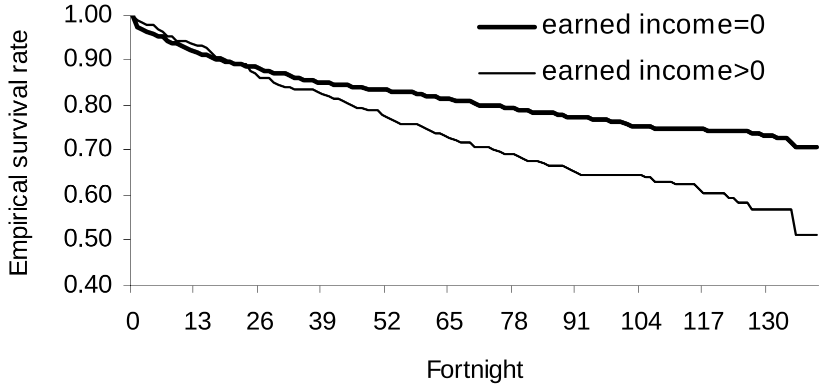
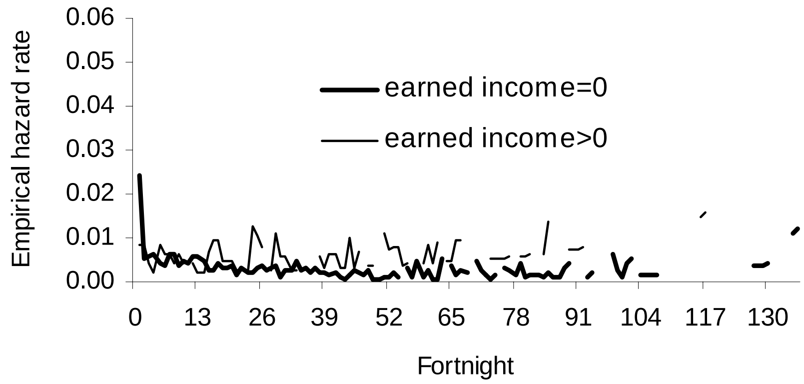


Figure 3b: Empirical hazard function by whether having earned income



Figures 4a and 4b plot the empirical functions by recipient source. The survival rate of recipients who transferred from unemployment benefits is higher than those who entered DSP from outside the income support system. Similarly, the hazard rate of those who transfer from unemployment benefits is lower than those who came from outside the income support system.

Figure 4a: Empirical survival function by recipient source

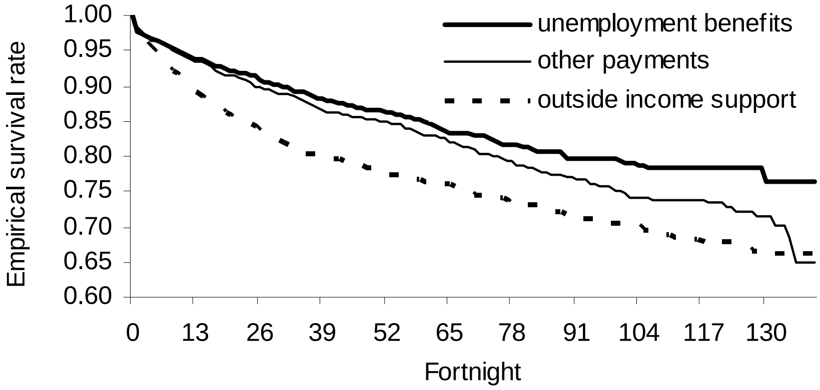
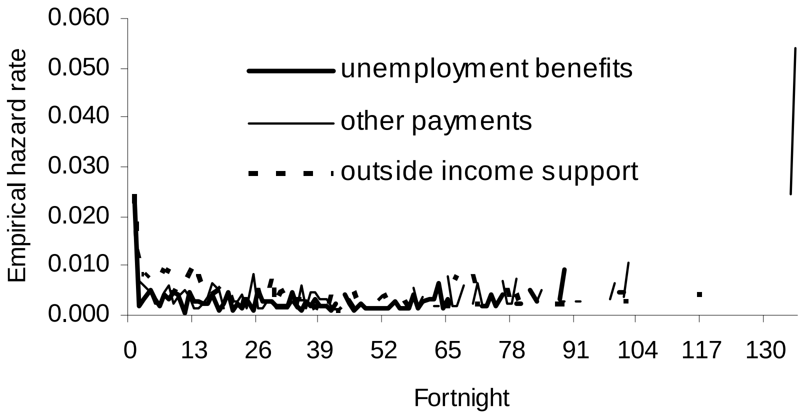


Figure 4a: Empirical hazard function by recipient source



IV. Estimation results

Tables 2 and 3 present the estimates of the covariates for the standard model and the split population model, respectively. The estimates of the baseline hazard are reported in the Appendix.

(i). Estimation of the standard model

Due to the non-linear nature of the model, the interpretation of the coefficient estimate is not straightforward. But the sign of the coefficient gives the impact direction of the covariate on the hazard rate. That is, a positive coefficient means that an increase in the covariate is associated with an increase in the hazard rate. However, for convenience of interpretation the last column in Table 2 also reports the hazard ratio estimates of the covariates. For categorical (or dummy) variables, the hazard ratio estimate for a category (e.g., being single) shows the ratio of the hazard rate of a recipient belonging to that category (e.g., being single) to the hazard rate of a recipient who belongs to the omitted category in the model specification (e.g., being married). For a continuous variable, the hazard ratio estimate shows the ratio of the hazard rate of a recipient with one more unit of that variable to the hazard rate of a recipient without the one more unit.

Entry age enters the model as a deviation from 16, the minimum eligible age for DSP, and in units of 10 years. The results show that the impact of entry age on the hazard rate is of an inverse U shape. The hazard rate increases with entry age up to the age of 34 years. After that, the hazard rate decreases with entry age. That recipients with young and old entry age have a lower hazard rate may be due to different reasons. For those who enter DSP at a young age, their disabilities might have presented for a long time (say, from birth) and recovery may be difficult. Therefore, they have a lower hazard rate. On the other hand, for the recipients who enter at old ages, their pre-benefit work experience might make them prefer to work if they could recover. But because of their old age the probability of getting a job might be lower, and the older the age the lower the probability. Thus for the old recipients the hazard rate decreases with entry age.

The hazard rate between males and females is significantly different. Other things being equal, males have a hazard rate which is 26 percent higher than their female counterparts. If exiting DSP is not dominated by death, this difference may reflect difference in labour market opportunities between males and females. It is also possible that the difference in socially expected roles between males and females may also have a greater stigma impact on male DSP recipients than on female recipients.

Among the homeownership and rental type variables, only the government rent variable is significant with a negative sign, indicating that, compared with those rented from private markets, recipients living in accommodations rented from the government have a hazard rate which is 30 percent lower.

Table 5.2: Estimation results for the standard model

Covariates	Coef.	Std.err.	Hazard Ratio
Demographic characteristics			
entry age (minus 16)	0.3092*	0.1596	1.3623
entry age squared	-0.0868***	0.0295	0.9169
sex (male=1)	0.2305***	0.085	1.2592
marital status (single=1)	-0.6814*	0.3616	0.5059
country of birth (foreign=1)	-0.1634*	0.0851	0.8493
having children	0.1341	0.1968	1.1435
# of children if having children	0.0511	0.0894	1.0524
Homeownership and rent type			
home owner	-0.0046	0.1053	0.9954
purchasing home	-0.1395	0.24	0.8698
other home owners	-0.0665	0.1713	0.9357
government rent	-0.3758**	0.155	0.6867
other rent	-0.1692	0.1434	0.8443
no rent paid	-0.2399	0.1768	0.7867
information missing	-0.0718	0.1455	0.9307
Financial variables			
earned income>0	-0.139	0.1249	0.8702
average amt ($100) if earned income>0	0.2544***	0.0292	1.2897
unearned income>0	-0.3880***	0.0976	0.6784
average amt ($100) if unearned income>0	0.0426	0.036	1.0435
equivalised maximum payment (OECD scale)	0.3234*	0.1852	1.3818
Recipients source			
from outside of income support system	0.6180***	0.0994	1.8552
from other payments	0.3401***	0.1092	1.4051
State living in			
NT	0.5550*	0.3352	1.7419
QLD	-0.0754	0.1361	0.9274
SA	0.0322	0.1802	1.0327
TAS	-0.4438	0.3017	0.6416
VIC	-0.1005	0.1107	0.9044
WA	0.1796	0.1287	1.1967
Entry cohort			
enter in 96	0.2247**	0.1127	1.2519
enter in 97	0.3392***	0.1294	1.4038
enter in 98	0.7218***	0.1488	2.0581
enter in 99	0.3742**	0.1866	1.4538
Whether being a repeated spell			
repeated spell (=1)	0.4796***	0.1239	1.6154
unemployment rate (%)	0.0181	0.0607	1.0183
Log-likelihood	-5165.92		

Note: *** Significant at 1 percent; ** 5 percent; * 10 percent.

The financial variables are interesting. Having earned income seems to reduce the hazard rate, but the estimate is not statistically significant. The amount of earned income, however, does have a significant impact. The variables measuring the amount of earned and unearned income enter the model in units of $100. The magnitude of the hazard ratio estimate implies that an increase in earned income by $100 per fortnight will raise the hazard rate by 29 percent[6]. Having earned income shows that the person has some ability to work, but having earned income, of itself, may not make a significant difference in terms of the probability of leaving the program, since DSP recipients are allowed to have earned income (though up to a specified level[7]). In addition, recipients may tend to combine earned income and DSP benefits, implying a negative impact of having earned income. However, if the earned income is very high, the person may have an incentive to leave DSP for work because the opportunity cost of staying on DSP is high now. In addition, the benefit will be cancelled if a recipient's earned income is too high because DSP benefits are subject to means-test.

Having unearned income reduces the hazard rate, compared with having no unearned income, by 32 percent. One explanation may be that having unearned income may reduce the incentive of a recipient to leave the program for work, and they prefer to combine the disability benefit with other unearned income than leave DSP for work. The amount of unearned income has no significant impact, although it has the right sign, this may be because the amount of unearned income is relative small on average.

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[6] As the variable, the amount of earned income, is the individual average over the DSP receipt period, its coefficient is identified by the variation of this variable across individuals. It is likely, however, that the earned income of each individual may vary with the duration on DSP. Individual earned income may increase with duration if the individual recovers from disability gradually. It may also decrease with duration if individual disability becomes worse or receipt of benefit makes the individual prefer to work less.

[7] Income subject to an income test in Australia is the combination of earned and unearned income. For example, in June 2002, for a single DSP recipient, income up to $112 per fortnight has no impact on DSP payment. Income over this threshold will reduce DSP payment. DSP payment will be totally withdrawn if income is equal or greater than $1181 per fortnight for a single person. These thresholds vary with number of children and marital status.

The standardised maximum potential benefit variable has a positive sign. This is contradictory to expectation, but it is only weakly significant. Different equivalence scales are attempted. They produce similar results on this variable.

For the recipient source variables, the omitted category is the recipients who transferred from unemployment benefits. The estimates imply that the hazard rate of those who entered DSP from outside the income support system is 86 percent higher than those who transferred from unemployment benefits. The hazard rate of those who transferred from other income support payments is 41 percent higher than those who transferred from unemployment benefits. Recipients who transferred from unemployment benefits have the lowest hazard rate.

The cohort variables provide some information on whether recipients entering DSP at different years are statistically different in terms of leaving the program. All cohort hazard rates are compared with the 1995 cohort. It appears that recipients entering in the later years have a higher hazard rate than those entered in 1995. It is not clear why this happens.

Those repeated spells have a higher hazard rate than those first spells. This is a surprising result because duration dependence predicts that this variable should have a negative sign. The significant and positive coefficient on this variable indicates that those recipients who had multiple spells might be cycling on and off the program.

As mentioned earlier, the unemployment rate is included as a time varying variable. The estimate of the unemployment rate variable has an unexpected sign, but it is insignificant. This suggests that labour market conditions may not have much effect on DSP outflows. This is in contrast to the finding in DSP inflows, where a significant effect of labour market conditions represented by the unemployment rate is found (Cai and Gregory, 2004). This may imply that when individuals make a decision on whether to participate in the DSP program, they take into account labour market conditions and their prospects of employment. But, once on the program, labour market conditions are not important in their decision on whether to stay in the program or leave it.

(ii).Estimation of the split population model

The split population model is based on the assumption that some recipients may not eventually exit from the program. There are two objectives in estimating this model as an alternative to the standard one. The first is to examine how the estimation results for the hazard function change when the standard assumption on duration models is relaxed. The second is to see whether there are some individual characteristics that are associated with the probability of eventual leaving.

The variables included in the probability function of eventual leaving and their estimates are presented in the last two columns in Table 3. The definition of the probability function in equation (7) implies that variables with a negative sign increase the probability of eventual leaving, vice versa.

The estimates for the hazard function in the split population model are presented in the first two columns in Table 3. By taking into account the probability of eventual leaving, the hazard function is a conditional one – it is the hazard function of those who will eventually leave DSP.

From the last two column, some variables, such as entry age (and its square), gender, country of birth, government rent, no rent paid, having earned income, recipients from unemployment benefits, recipients from other income support payments and repeated spells, have significant impacts on the probability of eventual leaving.

An increase in entry age increases the probability of eventual leaving up to the age of 40 years. After that a further increase in entry age reduces the probability of eventual leaving. Being a male recipient, having earned income, recipients from unemployment benefits or other income support payments, and repeated spells are associated with a higher probability of eventual leaving. Being born overseas, living in accommodations rented from the government or no rent paid is associated with a lower probability of eventual leaving.

Table 3: Estimation results for the split population model

Covariates	Conditional hazard function		Probability of eventual leaving	
	Coef.	**Std.err.**	**Coef.**	**Std.err.**
Demographic characteristics				
entry age (minus 16)	0.0574	0.255	-0.5704***	0.2212
entry age squared	-0.0403	0.0492	0.1191***	0.0448
sex (male=1)	-0.1083	0.1315	-0.4288***	0.1363
marital status (single=1)	-0.592	0.4913	-0.026	0.1623
country of birth (foreign=1)	0.2954**	0.1476	0.3684***	0.1422
having children	-0.4224	0.2971	-0.4416	0.3508
# of children if having children	0.1215	0.1233	0.0674	0.1492
Homeownership and rent type				
home owner	0.2824*	0.1715	0.213	0.1866
purchasing home	-0.1728	0.4956	-0.0873	0.5509
other home owners	0.4949*	0.281	0.2918	0.2904
government rent	0.5053***	0.2183	0.8227***	0.246
other rent	-0.1313	0.2248	0.2336	0.2511
no rent paid	0.197	0.2932	0.5543**	0.2786
information missing	0.2431	0.2509	0.2383	0.257
Financial variables				
earned income>0	-1.8013***	0.2141	-2.1272***	0.4264
average amt ($100) if earned income>0	0.3949***	0.0523		
unearned income>0	-0.4243***	0.1637	0.2193	0.1615
average amt ($100) if unearned income>0	0.0602	0.0528		
equivalised maximum payment (OECD scale)	0.2637	0.246		
Recipients source				
from outside of income support system	0.5547***	0.1749	-0.4472***	0.1721
from other payments	-0.1861	0.2041	-0.6095***	0.2096
State living in				
NT	0.7729*	0.4129		
QLD	0.094	0.1648		
SA	-0.0077	0.2291		
TAS	-0.5255	0.3778		
VIC	0.0377	0.1408		
WA	0.222	0.1754		
Entry cohort				
enter in 96	0.2403	0.147		
enter in 97	0.5046***	0.1682		
enter in 98	1.0626***	0.1863		
enter in 99	0.4727**	0.2219		
Whether being a repeated spell				
repeated spell (=1)	-0.0049	0.1975	-0.7180***	0.2333
unemployment rate (%)	0.0253	0.0691		
constant			1.6946***	0.3664
Log-likelihood	-5129.4			

Note: *** Significant at 1 percent; ** 5 percent; * 10 percent.

Comparing the estimates for the conditional hazard function in Table 3 with those for the unconditional one in Table 2, it appears that some significant variables in the unconditional hazard function become insignificant when the probability of eventual leaving is controlled for, such as entry age, gender, recipients from other income support payments and repeated spells. This may suggest that the significance of these variables in impacting on the unconditional hazard function might actually result from their significant impacts on the probability of eventual leaving. Hence, once the probability of eventual leaving is controlled for, these variables become insignificant in the hazard function.

Some variables are significant with the same sign in both hazard function, such as the amount of earned income, having unearned income, recipients from unemployment benefits. Controlling for the probability of eventual leaving does not change the impact direction and significance of these variables in the hazard function.

Other changes in the estimates for the hazard functions are: The estimate of the country of birth variable changes from being negative and weakly significant in the unconditional hazard function to being positive and significant in the conditional one. The estimate for the government rent variable changes from being negative and significant to being positive and significant. The variable, having earned income, becomes significant in the conditional hazard function.

V. Conclusion and discussion

This paper has applied the duration model to the FaCS LDS data to identify factors that determine the duration on the DSP program. We estimated two models based on two competing assumptions on the probability of eventual leaving. Although the split population model is preferred from policy point of view, the missing information on the reasons for exits in the LDS data makes it also reasonable to use the standard duration model.

The estimation results from both models show that there is a link between some recipient characteristics and their durations on the DSP program. Very young and very old recipients tend to leave the program slower or to have a lower probability of eventual leaving. Males are more likely to leave faster or to have a higher probability of eventual leaving. Recipients who transfer from unemployment benefits tend to leave the slowest or to have the lowest probability of eventual leaving, while recipients who come from outside the income support system have the fastest hazard rate or the highest probability of eventual leaving. Repeated spells tend to leave faster or to have a higher probability of eventual leaving. Therefore, in both model, these variables appear to impact on the duration in the same direction.

It is also found that the amount of earned income increases the hazard rate no matter whether the probability of eventual leaving is controlled for. Recipients having non-earned income have a lower hazard rate from both models.

An important policy implication of the finding that recipients with different characteristics have different potential to leave is that any policy or program aimed at facilitating outflows of DSP recipients should focus on those who are most likely to leave and treat recipients differently.

Although the unemployment rate variable produces an insignificant impact, this may nevertheless have important implications. Using aggregate data, a number of studies find that worsening labour market conditions during a recession raise inflows of disability benefit recipients (Cai and Gregory, 2004; Rupp and Stapleton, 1995; and Lando, Coate and Kraus, 1979). However, it is also found that an economic recovery does not increase the outflows rate (Rupp and Stapleton, 1995). Therefore, while worsening labour market conditions push the disabled people into the disability benefit program, a recovery or a boom of an economy would not draw the recipients out of the program. Because once in, DSP recipients tend to stay on the program for a long time, this suggests that we need to search for better programmatic responses to the variation of labour market conditions.

It is also worth some comments on the finding that the recipients who transfer from unemployment benefits have the potential to stay on the program the longest. Given the fact that those who transferred from unemployment benefits did not directly enter DSP, it is highly likely that these persons’ disabilities were not as severe (or obvious) as those who entered DSP directly (i.e. from outside the income support system). However, once having entered, the previously unemployed leave more slowly than the direct entrants. The lower hazard rate might imply that the experience of unemployment could have reduced their incentive to give up DSP for work. Perhaps they have had bad experiences in the labour market and lack confidence about their ability to perform if they leave DSP. If this is the case, it provides supportive evidence for the discouraged worker story. Because this group of recipients makes up a large proportion of DSP inflows (Cai, 2002), the behaviour of this recipient group requires further study.

The overall significance of the model without inclusion of a health condition variable and the rejection of unobserved heterogeneity imply that demographic and economic factors are important in determining disability benefit participation and disability is not only determined by health conditions per se. This does not necessarily mean that some recipients are not really disabled, but may suggest that other factors can signify their disabilities, such as losing a job.

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Appendix: Estimates of the baseline hazard

Duration intervals	**Standard model**		**Split population model**	
	Coef.[a]	St. Err.	Coef.[a]	St. Err.
d1-2	-5.8694	0.6001	-4.3353	0.7437
d3-4	-6.5481	0.596	-4.9298	0.7396
d5-8	-6.6233	0.5866	-4.9583	0.7315
d9-12	-6.7393	0.5854	-5.0012	0.7321
d13-16	-6.6917	0.5846	-4.8723	0.7308
d17-20	-6.8896	0.5891	-5.0098	0.7354
d21-24	-7.1987	0.582	-5.265	0.7232
d25-28	-6.9247	0.5775	-4.9408	0.7324
d29-32	-7.0493	0.5828	-5.0003	0.7269
d33-36	-7.0117	0.5766	-4.8774	0.7356
d37-40	-7.2879	0.5825	-5.076	0.7412
d41-44	-7.676	0.5952	-5.4231	0.74
d45-52	-7.4696	0.5642	-5.173	0.7275
d53-58	-7.4166	0.5698	-5.0804	0.7253
d59-64	-7.0556	0.5547	-4.6799	0.7255
d65-70	-7.291	0.5786	-4.8601	0.7414
d71-76	-7.1707	0.5648	-4.6483	0.7203
d77-82	-7.0364	0.5494	-4.4722	0.7323
d83-88	-7.466	0.5854	-4.8053	0.7508
d89-94	-7.234	0.5645	-4.5371	0.7331
d95-103	-7.1755	0.538	-4.381	0.7334
d104+	-7.4164	0.5014	-4.4061	0.7301

a, All coefficients are significant at 1 percent.