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Te Manatū Whakahiato Ora

Impact of the Job Search Service on client benefit outcomes: Update report: Technical Annex

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Contents

INTRODUCTION

Estimating the impact of the Job Search Service is based on time series models, specifically regression plus ARMA (Autoregressive Moving Average) models. The following section outlines the general modelling approach to estimating the impact of Job Search Service before summarising the analysis for each of the individual models.

The report is divided into the following sections:

- introduction to the modelling approach
- explanatory variables included in the models
- detailed discussion of the modelling approach using Unemployment Benefit grants analysis as an example
- summary of the remaining time series models.

TIME SERIES MODEL DEVELOPMENT

Objective

The aim of a time series model is to be able to explain the change in a series (eg benefit grants) over time. Once we have the best model to explain the series, the next step is to determine whether the introduction of the Job Search Service has any impact on the series.

General approach

One feature of time series data is that there are often repeating patterns as well as correlations between values over time. A common feature of many time series is seasonality; where the series will increase or fall at repeating intervals over time. Further, the information in the preceding periods can help explain what the series will be in following periods.

In addition we can also add information about known events that could alter an outcome over time. For example, we know that overall employment levels are closely related to the number of unemployment benefit grants (Infometrics, 2006). Likewise, recent changes to the administration of the benefit application process (such as the Work for You seminar before applying for Unemployment Benefit) have altered the number of people commencing benefit (CSRE, 2003).

By developing a comprehensive model that can explain the time series we can then test whether the introduction of Job Search Service improves the explanatory power of the model or not. Where the addition of the Job Search Service variable improves the explanatory power of the model, we can then assess the impact of the Job Search Service on the series in question.

Modelling approach

Suppose the dependent variable Y_t (t=1, …n) is a quarterly time series of Unemployment Benefit grants and for which we have several independent X_{st} (t=1, …n) explanatory variables (s = 1 … z). We could consider the linear regression model as follows:

$$Y_t = \beta_0 + \beta_s X_{st} + e_t \qquad (1)$$

The assumptions are:

- the explanatory variables are uncorrelated with the error terms over time

- the residuals (e_t) all have a mean of zero and have a constant variance
- the residuals are not correlated with one another.

In practice, it is often found that these assumptions do not hold, in particular the autocorrelation of residuals in the model. If auto correlation exists then the parameter estimates can be inefficient (ie larger variances). One solution to this problem is to correct for autocorrelation using an ARIMA model framework (see below). The solution involves the following iterative process.

1. Fit regression equation (1) to obtain estimates of the model residuals.
2. Test the residuals for stationarity, if the residuals are not stationary (constant mean and variance) it is not possible to model residuals using ARIMA. If non-stationary then try differencing the dependant and explanatory variables and repeat step 1.
3. If the regression residuals are stationary but are auto correlated (ie not white noise) then identify the best ARIMA model to explain the remaining structure in the regression residuals.
4. Test the regression plus ARIMA models for fit, stationarity and autocorrelation to select the best model.
5. If satisfied with final regression plus ARIMA model, analyse impact of Job Search Service on series.

ARIMA framework

Based on work by George Box and Gwilym Jenkins in the early 1970s the ARIMA model has the following form.

ARIMA models

An autoregressive (p) integrated (d) moving average (q) model for the original series y_t is

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \quad \text{or} \quad y_t = \frac{\theta(B)\varepsilon_t}{\phi(B)(1-B)^d} \qquad (2)$$

where: $\phi(B)$ is the function of the back-shift operator *B* given by

$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$

$\theta(B)$ is the function of the backshift operator given by

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$

$\phi_1, \phi_2 \cdots \phi_p$ are the autoregressive parameters

$\theta_1, \theta_2 \cdots \theta_q$ are the moving average parameters.

We define the operator *B* on the index of any time series y_t such that *B* shifts the series back one period in time; thus, $B^1 y_t \equiv y_{t-1}$. The operator can be repeated, so that in general for any integer d, $B^d y_t \equiv y_{t-d}$. Note that applying $(1-B)$ differences the series (ie $(1-B)^1 = y_t - y_{t-1}$), so $(1-B)^d$ means differencing the series d times.

For economy we use the notation ARIMA(p, d, q) to describe the above model, where

p: number of AR parameters (ie $\phi(B)$)

d: the number of times the series is differenced (ie $(1-B)^d$)

q: number of MA parameters (ie $\theta(B)$)

ARIMA multiplicative models.

In some cases the time series of interest is seasonal. It is possible that simple seasonal differencing will be sufficient to yield a series that is free from seasonality. However, it may be that we need additional seasonal autoregressive or seasonal moving average terms. So an extension of the ARIMA class of models is

$$\phi(B)(1-B)^{d}\Psi(B^{s})(1-B^{s})^{D}y_{t}=\theta(B)\Theta(B^{s})\varepsilon_{t} \qquad (3)$$

where: $\Psi(B^{s})$ is the seasonal function of the back-shift operator *B* given by

$\Psi(B^{s})=1-\Psi_{1}B^{s}-\cdots-\Psi_{P}B^{Ps}$

$\Theta(B^{s})$ is the seasonal function of backshift operator given by

$\Theta(B^{s})=1-\Theta_{1}B^{s}-\cdots-\Theta_{Q}B^{Qs}$

s is the lag at which seasonality occurs (eg s=4 for quarterly series, s=12 for monthly)

$(1-B^{s})^{D}$ takes seasonal differences of the series D times.

This class of models has been widely used to represent seasonal business and economic time series. They are called multiplicative seasonal models and have the following notation ARIMA(p,d,q)(P,D,Q)s.

Assumptions: omitted variable bias

Our analysis rests on several assumptions. The most important is that we have accounted for all variables that should be in the model. Of course, we cannot be sure of this. The danger is that we have missed important variables that are also correlated with variables already included in the model. The effect of such an omitted variable is to bias the estimates of the parameters associated with these variables in the model (ie our parameters estimates of the model variables do not reflect their true influence on benefit trends). The greatest concern will be for the Job Search Service variable in the model. If there is an omitted variable that is correlated with the introduction of the Job Search Service this will bias our estimates over its impact. In other words we will mistakenly attribute the change in trend because of the omitted variable to the introduction of the Job Search Service. We have taken care to reduce this risk by including variables in the model to try and control for all theorised influences on the benefit outcome in question.

Secondary assumptions include:

- the impact of interventions is closely linked to the introduction of the intervention (in other words, there is some predictable association between when an intervention started and subsequent change in the series being analysed)
- the character of the ARIMA model (sometimes called the noise model) is assumed not to change over time.
- there are enough observations in the series before and after the intervention event.

EXPLANATORY VARIABLES

Before outlining the modelling approach in more detail it is useful to introduce the explanatory variables. These are grouped under the following headings.

Demographic trends:

- population aged 15 to 64
- proportion of the population over 55 years
- average age of the population 15 to 64.

Labour market trends:

- total number of people aged 15 to 64 in employment and employment rate
- total number of people in full-time employment and full-time employment rate
- total number of people aged 15 to 64 unemployed and unemployment rate
- reported difficulty in finding unskilled labour by firms
- the proportion of firms reporting labour as the main constraint to growth.

Economic production:

- Gross Domestic Product expenditure and production series.

Seasonal variation:

- dummy variables for each quarter.

MSD interventions:

- alignment of weekly amount paid for Unemployment Benefit and Sickness Benefit in July 1998
- introduction of WRK4U in August 2003
- rollout of the Job Search Service from October 2006
- Sickness and Invalid's Benefit gateways between September 2007 and June 2008.

Working age population

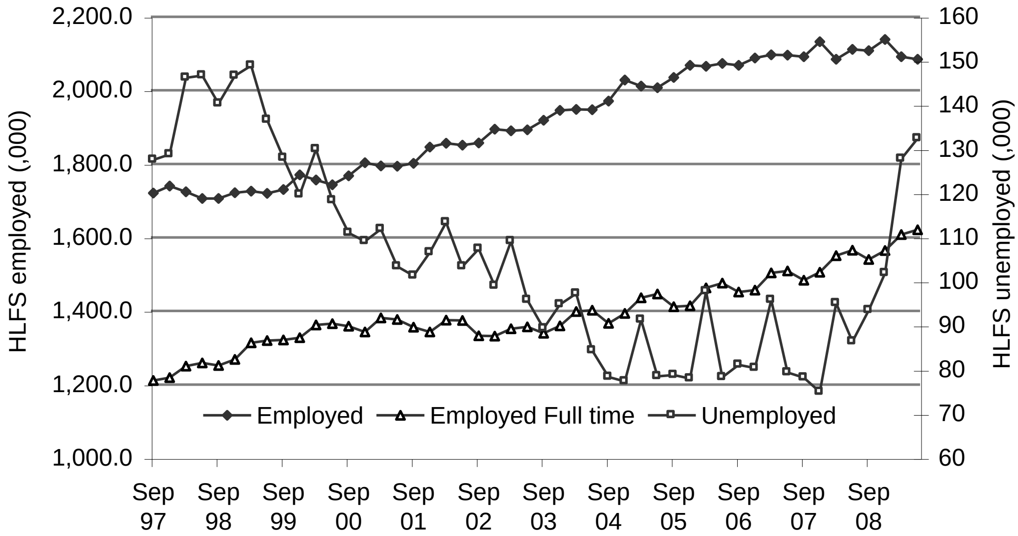
An important underlying trend in the number of people on benefit is the size of the population eligible for working age benefits (ie aged 15-64 years). Further for health-related benefits such as Sickness and Invalid's population aging may also be a contributing factor. These are based on Statistics New Zealand population projections. A small complication in this series is the need to account for change in eligibility for New Zealand Superannuation increasing from 60 to 65. The increase in eligibility age was phased in between 1992 and June 2001 and therefore the eligible population for working age benefits also increased at the same time.

HLFS number of people aged 15 to 64 in employment and unemployed

Previous work on unemployment-related benefit grants found a strong relationship between the number of people commencing benefit and the total number of people in employment (Infometrics, 2006). For this reason we have included HLFS employment and unemployment as potential explanatory variables (Figure 1). Note that HLFS unemployment and the number of people on Unemployment Benefit are not identical concepts. For example, people on the Unemployment Benefit would not meet the HLFS definition of unemployed where:

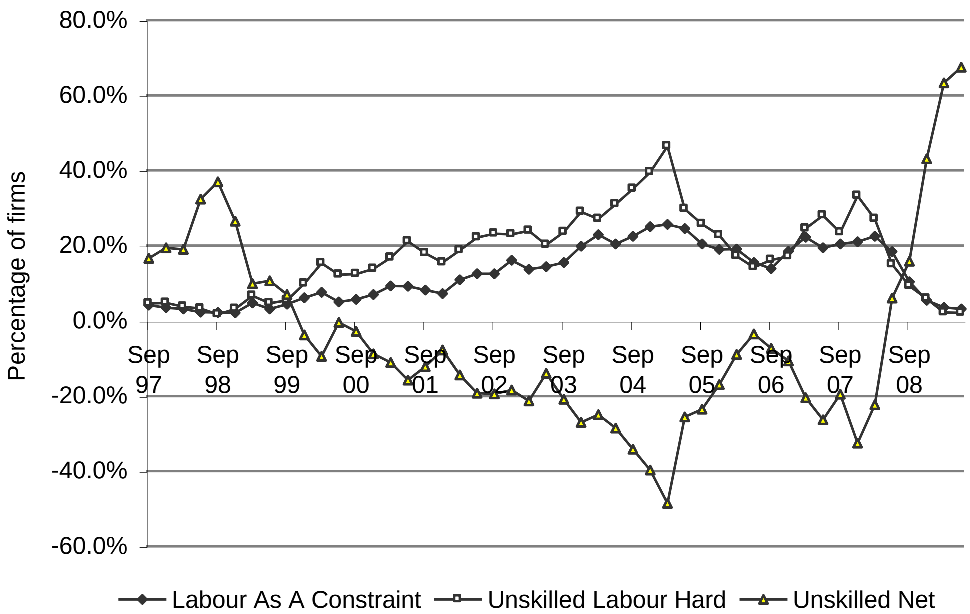
- they have worked for more than one hour in the last week
- they are not actively seeking work (eg do no more than looking at job adverts)
- are expecting to start a job in the next four weeks
- not available for a paid job (eg participating in a training programme).

Figure 1: Estimated number of people employed and unemployed



Source: Statistics New Zealand (Household Labour Force Survey Quarterly series).

Figure 2: Percentage of firms reporting unskilled labour is hard to find and labour as the main constraint on firm growth



Source: NZIER Quarterly Survey of Business Opinion, 2009.

Likewise, not all people defined by the HLFS as unemployed would qualify or choose to be on Unemployment Benefit (eg where a partner is working full time). In addition to total employed and unemployed these were also converted to employment and unemployment rates.

NZIER labour market demand

Alongside the total number of people in employment, we also included variables that directly measure labour market demand by firms. NZIER produces a quarterly series on firms' labour market demand. The three indicators we selected were:

- the percentage of firms reporting that it is harder finding unskilled or semi-skilled staff wanted today than it was three months ago
- the percentage of firms reporting labour as the single biggest factor limiting growth of production/activity
- the net difference between firms reporting skilled and unskilled labour was hard to find today compared to three months ago.

Figure 2 shows the two indicators over the report period. Both track in a similar fashion, with the measure of firms reporting unskilled labour shortages being more volatile than labour as the main constraint indicator.

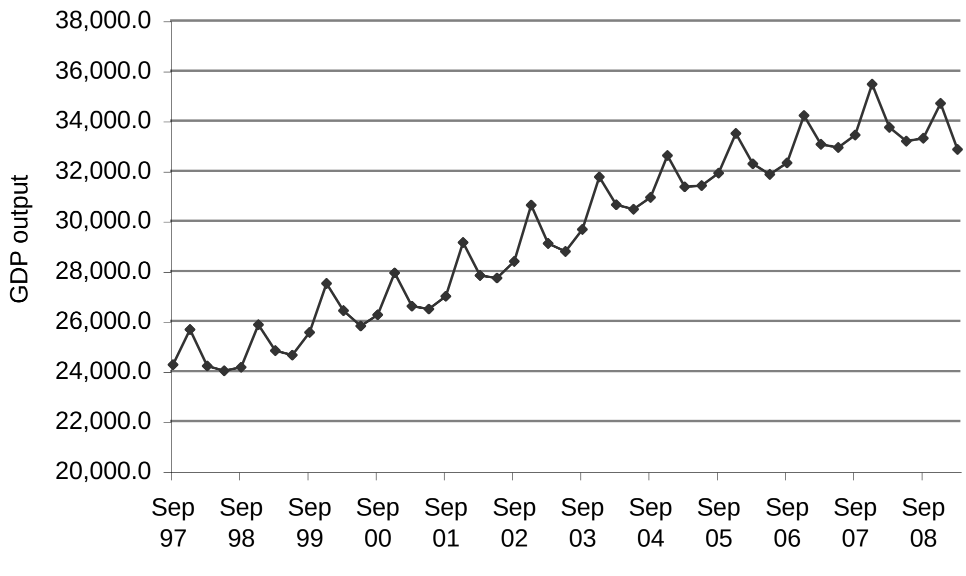
Gross domestic product

In addition to labour market variables we also tested whether GDP series would help explain the trend in benefit grants (Figure 1). One reason for the inclusion of this series is that MSD used GDP Treasury information to forecast the stock of unemployment benefits. However, at a theoretical level, GDP is likely to be an indirect influence on benefit trends and operates through changes in labour market demand.

Alignment of Sickness Benefit and Unemployment Benefit rates

Prior to July 1998 the amount paid for a person on Sickness Benefit was higher than for Unemployment Benefit, but the two rates were aligned from July 1998. The change is included as a dummy variable with a value of 1 from July 1998 onward.

Figure 1: Quarterly trend in Gross Domestic Product



Source: Statistics New Zealand, 2009.

Work for You (WRK4U)

Work for You seminar (WRK4U) was introduced in August 2003 and it is represented as a step function (0 before August 2003 and 1 thereafter). The evaluation of the pilot and the dramatic change in Unemployment Benefit grants after its introduction indicate the initiative was associated with a substantial reduction in the number of people commencing Unemployment Benefit {{50 CSRE 2003}}.

Job Search Service rollout

The graduated rollout of the Job Search Service over eight months from October 2006 through to May 2007 requires an elongated step function from 0 pre-October 2006 to 1 from May 2007. The aim here is to indicate at each quarter of the rollout the proportion of all people applying for Unemployment Benefit affected by the Job Search Service. To achieve this we used information on the number of people granted Unemployment Benefit in the previous year for each of the rollout months (eg October 2005 to May 2006). For each month sites would be divided according to whether the office would be part of Job Search Service in the corresponding month one year later.

Table 1 shows the calculation of the Job Search Service function for each quarter between September 2006 and May 2007 for grants of Unemployment Benefit. In the 2006 September quarter none of the offices will be participating in Job Search Service and therefore the Job Search Service function is zero. By the March 2007 quarter the majority of sites are participating in Job Search Service. In the previous March quarter (2006) there were 11,800 grants in those offices that would be participating in Job Search Service in March 2007 quarter from a total of 15,035 grants. Therefore we calculate the Job Search Service function for the March 2007 quarter to be 0.78 (11,800 divided by 15,035).

Table 1: Calculation of Job Search Service function using Unemployment Benefit (UB) grants (excluding transfers) from September 2005 to September 2006

	UB grants in the same quarter of the previous year		
Quarter	**Non-Job Search Service**	**Job Search Service**	**JSS function**
July-September 2006	16,665	0	0
October-December 2006	9,576	7,416	0.44
January-March 2007	3,235	11,800	0.78
April-June 2007	417	13,852	0.97
July-September 2007	0	17,310	1.00

UB related benefits include: Community Wage Job Seekers-55+, Community Wage Job Seekers-Young, Unemployment Benefit, Unemployment Benefit Hardship.

Transfers are defined when a client starts a benefit within 14 days of cancelling another benefit.

Source: Information Analysis Platform, data extracted 30 September 2009 (research data, not official MSD statistics)

Sickness Benefit / Invalid's Benefit gateways

Sickness and Invalid's Benefit gateways operated between September 2007 and June 2008. The gateway altered how clients entered the benefit system by:

- inviting people applying for, or receiving SB and IB, to engage with Work and Income to plan for a return to work, where appropriate to the client's condition or disability
- using revised medical certificates to improve information gathering from general practitioners (GPs) and other health professionals on:
    - client circumstances (including new medical diagnostic codes)

- expected progress in client's ability to plan for or return to work
- use of existing health- and disability-related information to reduce duplication and smooth the application and confirmation processes for many IB clients
- additional specialist support staff and resources to further assist case managers with decision making and service planning.

The main effect of the change was to substantially increase the number of clients coming onto Invalid's Benefit. Because of this unexpected increase the gateway system was changed by June 2007 and benefit inflow patterns returned to their historical trend.

REGRESSION WITH ARIMA MODEL DEVELOPMENT

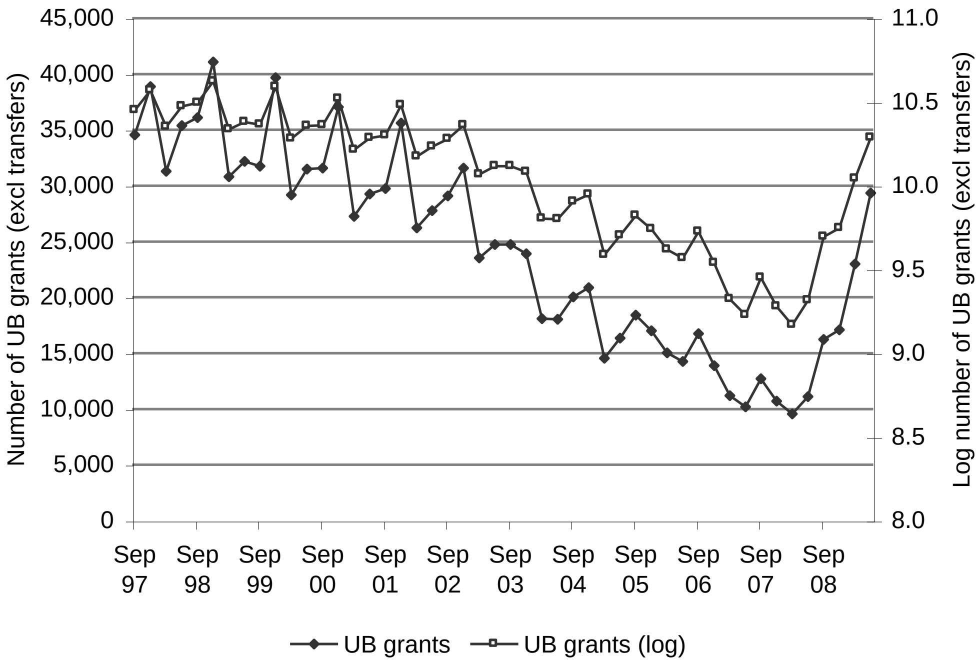
The following section provides a general outline of the modelling approach used to estimate the impact of Job Search Service on each of the outcomes included in the analysis.

A worked example

Below is a detailed description of our modelling strategy. To aid with the discussion we use the Unemployment Benefit grants time series as an example. The development of each model involved the following iterative process:

1. exploratory data analysis
2. regression model selection (regression)
3. testing for model stationarity and white noise
4. develop the ARMA part of the regression model
5. testing robustness of full model (regression plus ARMA)
6. analysis of Job Search Service impact.

Figure 2: Quarterly grants of Unemployment Benefit (excluding transfers)



1, Exploratory data analysis

The first step is to closely examine the time series in question, in this instance the number of grants for Unemployment Benefit (see Figure 2). Unemployment Benefit includes: Community Wage Job Seekers-55+, Community Wage Job Seekers-Young, Unemployment Benefit, Unemployment Benefit Hardship, and excludes Training and Student Hardship benefits. The basis for excluding the latter two benefits is that these reflect instances where people are either temporarily unemployed but with the intent of returning to study, or they are engaged in training programmes and not participating in the Job Search Service programme. We also exclude any transfers between main benefits, that is any grant of unemployment-related benefit where there has been a cancellation of a main benefit within the last two weeks. We decided to exclude transfers as we are looking at the effect of Job Search Service on people commencing benefit, before looking at how long they remain on benefit after grant.

Properties of the Unemployment Benefit grant series

The Unemployment Benefit grant series is non-stationary with a deterministic trend as well as a seasonal component. Further, it appears the seasonality has changed over the period,

Figure 3: Quarterly grants of Unemployment Benefit (UB) differenced lag 1

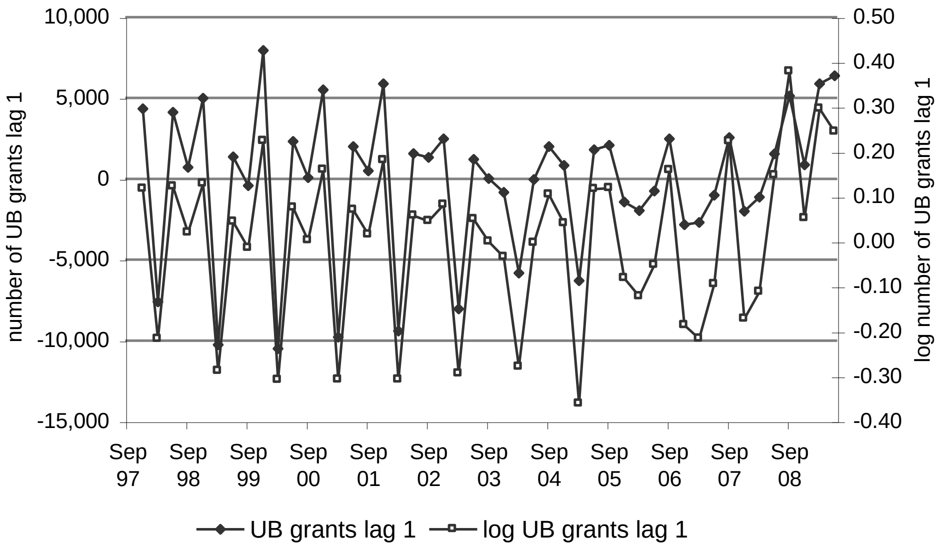
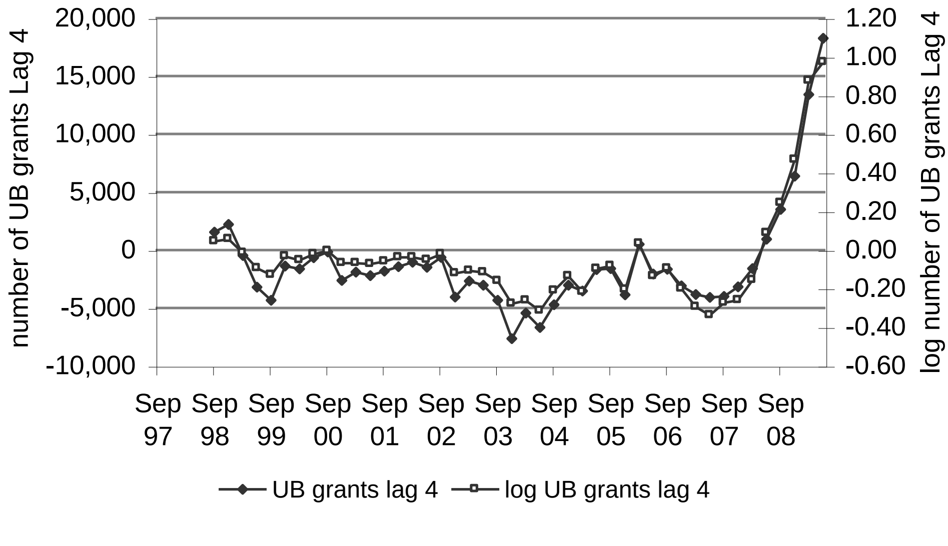


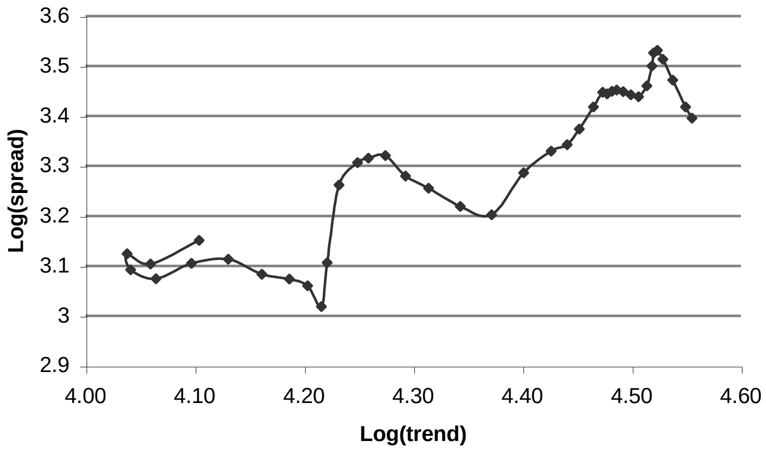
Figure 4: Quarterly grants of Unemployment Benefit (UB) differenced lag 4



showing a regular pattern in the first four years. However, from 2003 onwards the seasonal pattern is less pronounced (untransformed series from March 2003 onward in the first chart in Figure 3) and appears to be related to the sharp fall in Unemployment Benefit grants over this period. Figure 4 shows the series differenced by lag 4 to remove the seasonal pattern and show the underlying trend. What is evident is that there has been a fall in the number of Unemployment Benefit grants since June 1998, averaging at around 2,000 each quarter. This pattern is marked by two periods when the rate of decline increased. The first increase occurred over the December 2003 to June 2004 period where year-on-year Unemployment Benefit grants fell by an average of 6,123 per quarter. The second increase occurred between December 2006 and December 2007. Most recently there has been a dramatic reversal in the trend, with a sharp increase in the number of grants from September 2007 onward.

To check whether transformation of the series is necessary we plot log(spread) to log(level) and fit a robust linear model with a slope b. Based on Tukey (1977) the slope of b provides a guide to the best transformation as follows:

Figure 5: Log(spread) log(level) plot of quarterly grants of Unemployment Benefit (excluding transfers)



log(spread) = 1.48 + 0.87 log(trend)

- if b>1 $y \to y^{1-b}$
- if b<1 $y \to -y^{1-b}$
- if b = 1 log(y).

The results are shown in Figure 5, with b close to 1 for a log transformation to be warranted. However, testing the weak stationarity of series indicates there is no gain in logging the series (SBC score for untransformed was 896.8, while for logged the score was 904.4).

2, Regression model selection

It is common to have several competing models for a given series and we need a method for selecting the best of these models. A plausible criterion for choosing the best model might appear to be choosing the one that gives the smallest sum of squared errors or the largest value for the maximum likelihood. However, this approach does not work where models contain different numbers of parameters, since model fit can be improved by simply adding more parameters. Therefore we need to adjust for the additional of parameters when comparing models. For ARIMA models, the maximum likelihood value is penalised for each addition term in the model. We used Schwarz's Bayesian information criterion (SBC) as the penalised likelihood procedure.

$$SBC = -2\ln(L) + \ln(N)\, k \qquad (4)$$

Where: L is the value of the likelihood function evaluated.

N is the number of observations

k is the number of parameters.

The preference for SBC over AIC is that SBC imposes a higher penalty for including additional parameters and is therefore more likely to produce a more parsimonious model.

Example: Unemployment Benefit grants regression model

Trends in the number of people being granted Unemployment Benefit are influenced by several factors. We already can see that there is a strong seasonal component in the series (Figure 3). While Figure 4 also shows there is a trend in Unemployment Benefit grants over time.

The labour market: the number of people needing unemployment benefits is to a large extent determined by labour market growth, and by extension the overall growth of the economy. In periods of high economic growth we expect to see fewer people needing income support since increasing labour demand reduces the time needed to find work. We identified four measures of labour market demand:

- total number of people employed
- total number of people unemployed
- proportion of firms reporting it is hard to find unskilled labour
- proportion of firms reporting labour is the main constraint on their growth.

Benefit eligibility and administration rules: any changes to eligibility rules for main benefits will also influence the number of benefit grants. Unemployment Benefit grants are not only influenced by changes to the Unemployment Benefit, but also by changes in other main benefits that may alter the benefits people apply for. Over the report period, we have identified the following change is potentially having an influence:

- alignment of Sickness Benefit rate to the Unemployment Benefit rate in July 1998.

Administration of benefits and employment assistance: how benefits are administered can also have some influence on the number of people commencing benefit. In addition, Work and Income provides employment assistance to people prior to being granted benefit and this would also influence the number of people commencing benefit. We have included the following operational changes in our analysis:

- introduction of the Work for You (WRK4U) seminar
- introduction of the Job Search Service.

We have selected initiatives that represent substantial departures from previous practice as these are most likely to alter the trend in grants of Unemployment Benefit. In practice Work and Income is continually changing its operation and procedures. But because these are often marginal changes to existing practice it is unlikely that they would alter the trend in Unemployment Benefit grants in any detectable way.

How these factors influence the grants of Unemployment Benefit

Within the New Zealand context, labour market conditions will determine the overall trend in the number of people commencing unemployment benefit. In periods of economic growth there will be a downward trend in grants, whilst in periods of contraction there should be an upward trend. Therefore, we would expect to see a long-term relationship between labour market growth and grants of unemployment-related benefits.

On the other hand, changes in the administration of benefits is unlikely to influence the long-term trend in Unemployment Benefit grants, but instead change the level of Unemployment Benefit grants relative to labour market demand. For example, a benefit administration change may reduce the ratio between benefit grants and the number of people in employment from 15 per 10,000 to 10 per 10,000. Further, it is also possible that changes in the administration of benefits may interact with labour market trends. For example, a policy may have a relatively larger impact on Unemployment Benefit grants during periods of increased labour market demand.

An important question when examining initiatives that are expected to produce ‘level shifts’ in Unemployment Benefit grants, is what form this level shift will take. An obvious example is a short duration factor such as an advertising campaign. In these instances we would expect to see a temporary level shift. More complex initiatives are those which may have both short- and long-term level shifts. One example of this was the introduction of work testing for people aged 55 to 59 years old on Unemployment Benefit. The immediate effect was for a large proportion of the group to move to Sickness Benefit, after this initial ‘shock’ the rate of transfers from Unemployment to Sickness Benefit returned to previous levels.

In our analysis we are assuming that effects of changes in the administration of benefits remain largely constant. The only complicating factor is where initiatives are rolled out over several months and we need to account for the proportion of clients in each quarter affected by the initiative, as was the case with Job Search Service (see page 11 for more detail).

Variable selection

The variable selection process was done in four stages:

1. labour market variables
2. MSD interventions
3. seasonal variables
4. repeat steps 1 to 3 until no changes are made to the selected variables.

Table 2 provides the correlation matrix of the continuous variables included in the regression modelling, whilst Table 3 and Table 4 summarise model fit and parameters estimates for the various regression models. Note that for economy we have not shown all variables or model tested.

Table 2: Correlation matrix for log Unemployment Benefit (UB) grants and independent variables

	UB grants	Unemployed	Employed	Labour as a Constraint	Unskilled Hard	GDP production
UB grants	1.00	0.78	-0.89	-0.80	-0.59	-0.85
Unemployed	0.78	1.00	-0.76	-0.86	-0.77	-0.78
Employed	-0.89	-0.76	1.00	0.68	0.46	0.98
Labour as a Constraint	-0.80	-0.86	0.68	1.00	0.90	0.71
Unskilled Hard	-0.59	-0.77	0.46	0.90	1.00	0.51
GDP production	-0.85	-0.78	0.98	0.71	0.51	1.00

Labour market variables

The first set of models looked at just the labour market variables. The correlation in Table 2 shows that HLFS employment has the strongest correlation to Unemployment Benefit grants, followed by GDP. However, neither of these variables account for the sharp up-turn in Unemployment Benefit grants in 2009.

Comparing the alternative labour market models (Trend in Table 3 and Table 4) we can see from the SBC scores that HLFS employment achieves the lowest score (model 2), the second best model includes GDP production (model 1). However, in combination with other explanatory variables it is HLFS unemployment that is best able to explain the overall trend, in particular the very large increase in Unemployment Benefit grant from December 2008 onward. To confirm this is the case we developed the best possible modelling using HLFS employment as the trend variable (model 23). Here none of the MSD interventions are significant and the model only includes a dummy for the December quarter. Despite being more parsimonious, this model has a poorer fit to the series than the final set of variables selected (model 24). On this basis we use HLFS unemployment as the trend variable to test the MSD and seasonal variables.

Table 3: Regression model summary fit statistics for grants of Unemployment Benefit

Model	Model variables	Log(L)	SBC	Parameters	Obs
1	Trend: GDP production	-514.4	1036.7	2	52
2	Trend: Employed	-506.2	1020.4	2	52
3	Trend: Unemployed	-522.5	1052.9	2	52
4	Trend: LabourAsAConstraint	-519.0	1045.9	2	52
5	MSD: NI Trend JSS	-511.2	1030.3	2	52
6	MSD: Trend WRK4U	-504.8	1021.4	3	52
7	MSD: NI Trend SBUBRateAlign	-522.6	1053.2	2	52
8	MSD: Trend JSS WRK4U	-501.4	1018.7	4	52
9	MSD: JSS*Trend JSS WRK4U Trend	-497.8	1015.3	5	52
10	Seasonal: MarchQtr NI MSD Trend	-485.5	990.7	5	52
11	Seasonal: JuneQtr MSD Trend	-497.3	1018.3	6	52
12	Seasonal: SepQtr MSD Trend	-496.9	1017.5	6	52
13	Seasonal: DecQtr MSD Trend	-484.2	992.1	6	52
14	Seasonal: MarchQtr DecQtr NI MSD Trend	-474.8	973.4	6	52
15	Seasonal: MarchQtr JuneQtr NI MSD Trend	-478.4	980.5	6	52
16	Seasonal: MarchQtr DecQtr JuneQtr NI MSD Trend	-472.6	972.9	7	52
17	Interactions: WRK4U*DecQtr NI	-466.5	960.6	7	52
18	Interactions: WRK4U*SepQtr NI	-470.0	967.6	7	52
19	Interactions: WRK4U*DecQtr WRK4U*SepQtr NI	-484.7	997.1	7	52
20	MSD: Wrk4U*Trend Trend Seasonal	-460.7	953.0	8	52
21	Trend: Unemployed Working Age Seasonal MSD	-448.4	932.3	9	52
22	Trend: Unemployed% Seasonal MSD	-452.9	937.5	8	52
23	Trend: Employed DecQtr no MSD	-497.6	1007.1	3	52
24	Final Regression Variables	-448.4	932.3	9	52

NI: no intercept term

MSD interventions

Of the four MSD interventions, JSS and WRK4U are both significant and reduce the SBC score of the model (models 5, 6), whilst SBUBRateAlign is not (model 7). Further JSS and WRK4U are both significant when combined in a single model (8). Accordingly we include WRK4U and JSS for the next stage. We then tested the interaction between JSS and the trend variable (model 9) and find the interaction improves model fit and the interaction has the expected effect of decreasing the impact of JSS as unemployment increases. There was no evidence of an interaction between WRK4U and the trend variable (model 20).

Table 4: Parameter estimates for alternative regression model specifications

				Labour market and demographic variables					MSD interventions		Seasonal dummies			
Model	**Intercept (MU)**	**GDPprod**	**Unemployed**	**UnemployedPer**	**Employed**	**LabourAsA Constraint**	**WorkingAge**	**SBUBRateAlign**	**WRK4U**	**JSS**	**MarchQtr**	**JuneQtr**	**SepQtr**	**DecQtr**
1	*** 87,284	*** -2												
2	*** 124,532				*** -52									
3	*** -8,958		*** 319											
4	*** 36,461					*** -95,878								
5			*** 253							*** -9,583				
6	*** 15,469		*** 137						*** -11,281					
7			*** 266					*** -3,755						
8	*** 12,425		*** 163						** -8,543	*** -4,506				
9	*** 19,903		*** 100						*** -10,752	*** -22,985				
10			*** 278						*** -4,067	*** -13,651	*** -6,968			
11	*** 20,604		*** 97						*** -10,906	*** -23,512		*** -1,120		
12	*** 18,653		*** 108						*** -10,487	*** -23,111			*** 1,477	
13	*** 16,777		*** 116						*** -10,329	*** -24,373				*** 5,174
14			*** 267						*** -4,570	*** -15,478	*** -5,625			*** 3,898
15			*** 287						*** -3,795	*** -14,559	*** -8,210	*** -3,306		
16			*** 275						*** -4,307	*** -15,561	* -6,610	*** -1,811		*** 3,012
17			*** 262						*** -3,310	*** -14,329	*** -5,577			*** 6,356
18			*** 264						*** -5,587	*** -17,414	*** -4,885			*** 4,691
19			*** 277						*** -4,884	*** -14,957	*** -6,553			
20			*** 200				*** 3.00			*** -25,530	*** -4,909			*** 6,213
21	*** 68,421		*** 111				*** -20.04		*** -4,731	*** -25,697	*** -4,396			*** 5,734
22	*** 13,166			*** 289,552					*** -6,341	*** -25,253	*** -4,608			*** 6,137
23	*** 124,708				*** -53									*** 5,024
24	*** 68,421		*** 111				*** -20.04		*** -4,731	*** -25,697	*** -4,396			*** 5,734

*: significant at 90%, **: significant at 95%, *** significant at 99%
Not all models tested are shown in the table.

Table 4 continued

	Interaction Terms				
Model	**WRK4U DecQtr**	**WRK4U SepQtr**	**WRK4U unemployed**	**JSS unemployed**	**JSS UnemployedPer**
0					
1					
2					
3					
4					
5					
6					
7					
8				*** 199	
9				*** 81	
10				*** 206	
11				*** 200	
12				*** 214	
13				*** 103	
14				*** 92	
15				*** 104	
16	*** -5,475			*** 90	
17		*** 3,624		*** 125	
18	1,241	*** 1,818		*** 96	
19	*** -5,365		*** -75	*** 219	
20	*** -4,720			*** 248	
21	*** -4,902				*** 497,290
22					
23	*** -4,720			*** 248	

*: significant at 90%, **: significant at 95%, *** significant at 99%
Not all models tested are shown in the table

Seasonal dummies

The next stage of the regression was to include dummies variables to control for seasonal variation in the trend. Including each separately indicates December and March quarters are significant and produce lower SBC scores (models 10 and 13). We then combined these dummies into a single model (14) and found March and December quarters were significant. From the EDA stage we noted the seasonal pattern changes with the introduction of WRK4U. We tested the interaction terms of WRK4U and December and September quarters (models 17 and 18). While individually the interactions were significant neither were significant within the single model (model 19). On this basis we selected the interaction with December Quarter as this produced a lower SBC score.

Re-check labour market variables

We re-checked the labour market variables with the seasonal and MSD variables (models 21-22). Here we found no improvement in model fit of any of the alternative trend variables tested. However, including trend variables with HLFS unemployed did identify an improvement in model fit with the inclusion of Working Age population. The likely reason is that the number of people coming onto benefit is partly a function of the total eligible population. Of interest is that HLFS unemployment expressed as a percentage of working age did not result in a better model fit (model 21).

The final model selected for the next stage of the analysis is summarised below.

Table 5: Regression model of Unemployment Benefit grants

	Model
Observations	52
Log(l)	-448.4
AIC	914.7
SBC	932.3
Parameters	9
Estimate	
MU	*** 68,421.1
Unemployed	*** 111.4
WorkingAge	*** -20.0
MarchQtr	*** -4,396.4
DecQtr	*** 5,734.0
WRK4U	*** -4,731.1
WRK4U_DecQtr	*** -4,719.8
JSS	*** -25,697.5
JSS_unemployed	*** 247.6

*: significant at 90%, **: significant at 95%, *** significant at 99%

3. Testing for model stationarity

Once we have specified a regression model, the next step is to test the residuals for stationarity. If the resulting residuals are stationary, then we can use ARMA to model the regression error term to correct for auto-correlation (Robert & Monnie, 2000).

Example testing the stationarity of the Unemployment Benefit regression model residuals

For the Unemployment Benefit grant regression model the resulting residuals need to be stationary. Figure 6 plots the residuals for the regression model in Table 5 above, whilst

Figure 6: Plot of Unemployment Benefit grants regression model residuals

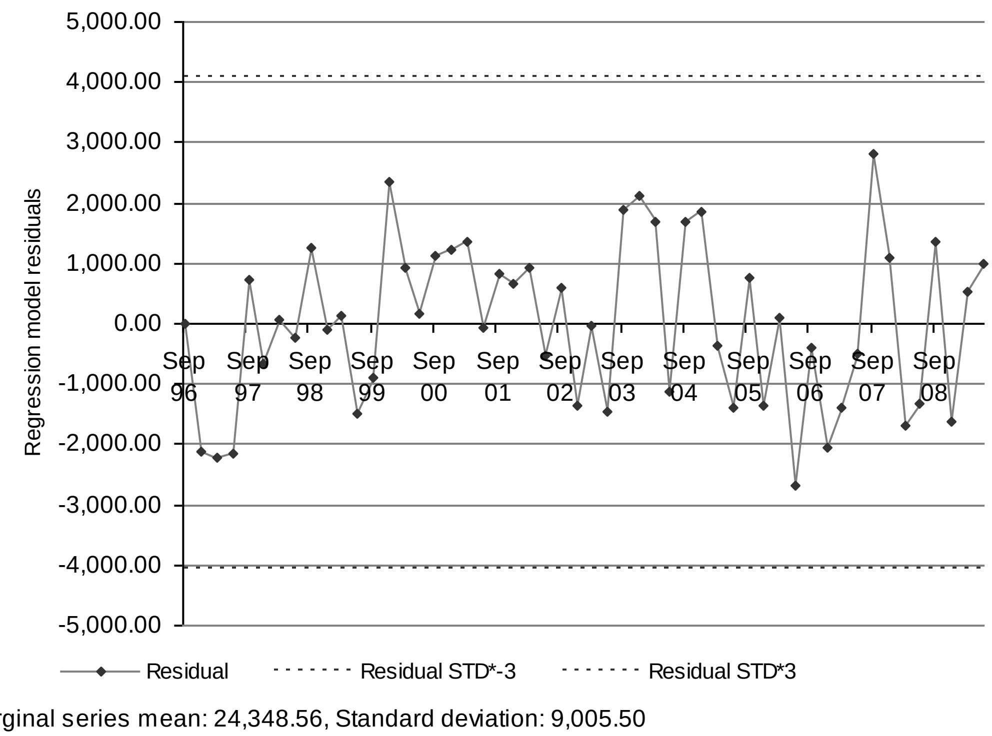


Figure 7: ACF and PACF Unemployment Benefit grants regression model residuals

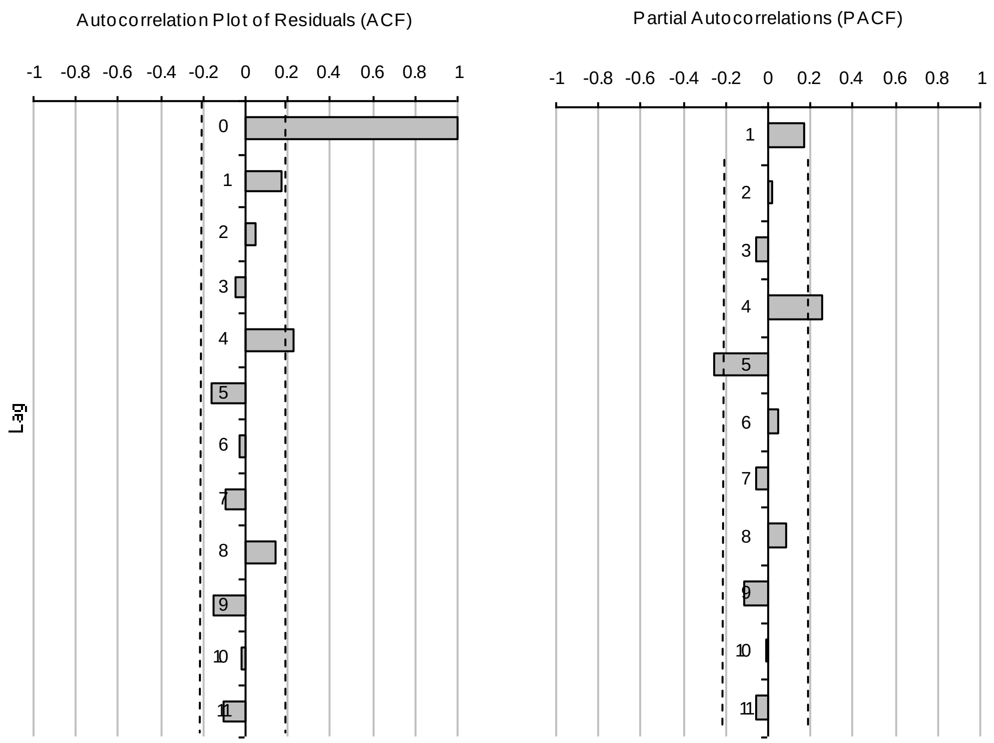


Figure 7 shows the Autocorrelation and Partial Autocorrelations of the regression residuals. It is apparent from the plots that:

- the mean and variation of the residuals are constant around zero
- the autocorrelation plots decrease rapidly from lag one (ie the series is stationary)
- there is considerable level of information remaining in the residuals (ie the residuals are auto correlated at lags 1, 4 and 5 and likely to bias the parameter estimates shown in Table 5).

4, Selection of ARIMA models

Being satisfied the regression residuals are stationary, the next stage of the analysis is to model the non-random component of the residuals. We achieve this through the ARMA model. Selection of the most appropriate combination of AutoRegressive (p) and Moving Average orders (q) is based on examination of the autocorrelations and partial autocorrelations of the regression residuals.

For pure autoregressive model of order p, all partial autocorrelations of order higher than p is (are) zero. The autocorrelations of pure autoregressive model do not abruptly cut off, but rather decay toward zero.

For a pure moving average model of order q, all autocorrelation of order high than q is zero. The partial autocorrelations of pure moving average process do not abruptly cut off, but decay toward zero.

For an AR(p) MA(q) model, with values for both p and q greater than zero, neither the autocorrelations nor the partial autocorrelations exhibit abrupt cut off. But decrease exponentially or have a sinusoidal change. However, the possible combinations of p and q are not large. Experience suggests that very often a good model fit can be achieved with small values for p or q or both (eg 0, 1, 2).

If the ACF and PACF have regular lags that are large and significantly different from zero will indicate the presence of seasonality in the time series. Such information provides information on the types of ARIMA models to test. For example, if there are no significant ACF after lag q, a MA(q) model may be appropriate. If there are no significant PACF after lag p, an AR(p) model may be appropriate. If there is no clear pattern of MA or AR, a mixed model may be necessary.

Example: Selection of ARIMA for Unemployment Benefit grants regression model residuals

Examining the PACF and ACF plots suggests there is autocorrelation at lags 1, 4 and 5 (see Figure 7). To select the best model we examined both the overall SBC score as well as test for white noise (eg the resulting residuals are randomly distributed over time). Table 6 shows the SBC and white noise test over 24 lags for the selected ARIMA models. Of those tested the ARIMA$(0,0,1)_1(0,0,1)_4$ has the lowest SBC values and high p values for the white noise test. Table 7 shows the estimates for each of the parameters in the alternative Regression plus ARIMA models. White noise test is an approximate statistical test of the hypothesis that none of the autocorrelations of the series up to a given lag are significantly different from 0. If this is true for all lags, then there is no information remaining in the model residuals. The hypothesis being tested is that the residuals are correlated; therefore if the white noise test has high p-values this means you cannot reject the hypothesis that the residuals are uncorrelated.

Table 6: Model fit for competing ARMA models

Model	Model parameters	SBC	White noise test (p values) 6	12	18	24
ARIMA(0,0,0)(1,0,0)4	10	931.0	0.279	0.631	0.641	0.592
ARIMA(1,0,0)	10	934.2	0.196	0.237	0.055	0.078
ARIMA(0,0,1)(1,0,0)4	11	928.8	0.957	0.970	0.915	0.904

Not all models tested are shown in the table.

Figure 8: Simulation of ARIMA(1,0,0)(1,0,0)$_4$ on quarterly Unemployment Benefit grant series

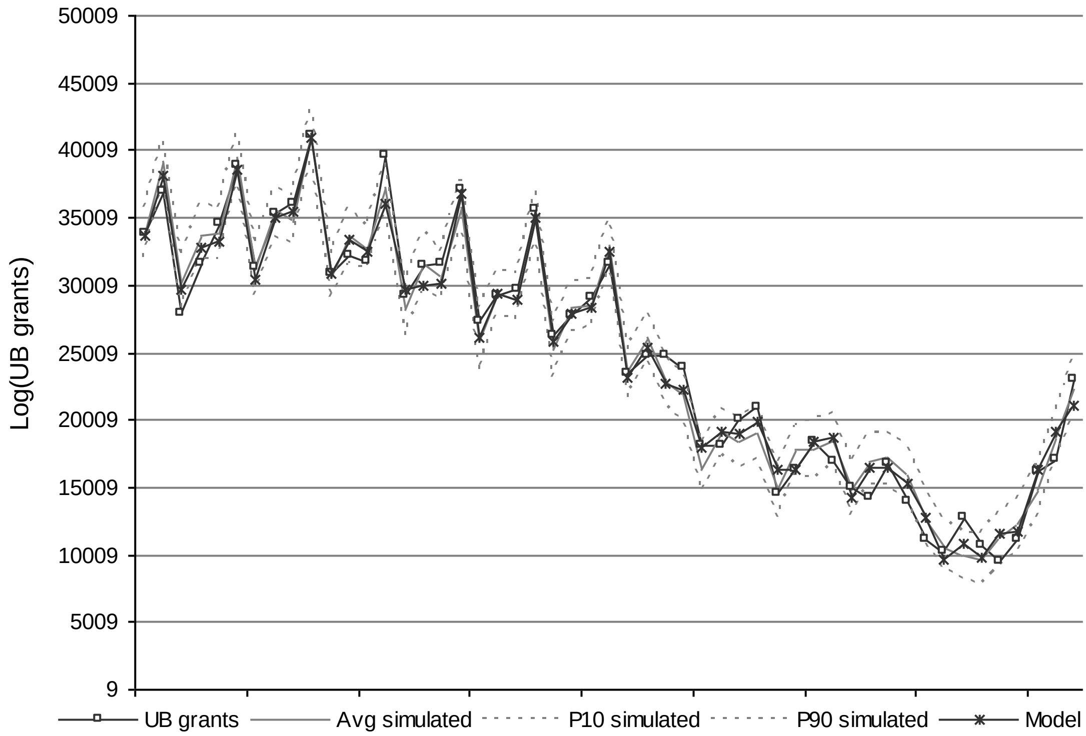


Table 7: Variable parameters of competing ARMA models

									Regression variables			Autoregressive and moving average parameters
Model	**MU**	**Unemployed**	**Working Age**	**MarchQtr**	**DecQtr**	**WRK4U**	**WRK4U_ DecQtr**	**JSS**	**JSS_ unemployed**	**MA(1)**	**AR(1)**	**AR(4)**
ARIMA(0,0,0)(1,0,0)4	*** 73,356	*** 124	*** -23	*** -4,684	*** 5,151	*** -3,481	*** -4,108	*** -23,690	*** 236			*** 0.49
ARIMA(1,0,0)	*** 70,020	*** 114	*** -21	*** -4,263	*** 5,644	*** -4,343	*** -4,902	*** -25,240	*** 243		0.22	
ARIMA(0,0,1)(1,0,0)4	*** 71,715	*** 127	*** -22	*** -4,175	*** 4,990	** -3,194	*** -4,826	*** -22,968	*** 227	*** -0.42		*** 0.48

*: significant at 90%, **: significant at 95%, *** significant at 99%

Not all models tested are shown in the table.

Sensitivity testing of ARIMA model

There is a risk in selecting alternative ARMA models of over-fitting the data, since it is possible that the ARMA model selected happens to fit the particular series. To test whether the selected ARMA model is the best model we test it against a simulated ARMA process. If the selected ARMA model is robust, then we should see the simulated ARMA processes follow the series data fairly well (eg the simulations are not consistently higher or lower than the series or that the simulations fail to capture important features of the series). We ran 100 simulations and calculated the mean as well as 90 and 10 percentiles (Avg simulated, P10 simulated and P90 simulated in Figure 8); these are shown in Figure 8. In general the simulated models show a very similar pattern to the actual model (model in Figure 8).

4, Specification of full model

Final regression and ARIMA models

Regression model:

$$y_t = \beta_0 + \beta_s X_{s,t} + e_t \tag{5}$$

Where: β_0 intercept

β_s parameter estimates for the explanatory variables (s = 1 … 7) included in the model

e_t residuals (stationary, but auto correlated).

The ARIMA model:

$$(1 - \Psi B^4)e_t = \theta B^1 \varepsilon_t \tag{6}$$

where: e_t are the residuals of the regression model

B is back-shift operator

Ψ is the autoregressive parameter at backshift operator 4

θ is the moving average parameter at backshift operator 1

ε_t is white noise (ie $\varepsilon_t = N(0, \sigma^2)$).

Now we re-estimate simultaneously all parameters to get joint equation (7) by using maximum likelihood estimates

$$Y_t = \hat{\beta}_0 + \hat{\beta}_s X_{s,t} + \frac{\theta B^1 \hat{\varepsilon}_t}{(1 - \hat{\Psi} B^4)} \tag{7}$$

which can be re-written as:

$$Y_t = \hat{\beta}_0 + \hat{\beta}_s X_{s,t} + \hat{\Psi}_4 (Y_{t-4} - \hat{\beta}_0 - \hat{\beta}_s X_{s,t-4}) - \hat{\theta}_1 \hat{\varepsilon}_{t-1} + \hat{\varepsilon}_t \tag{8}$$

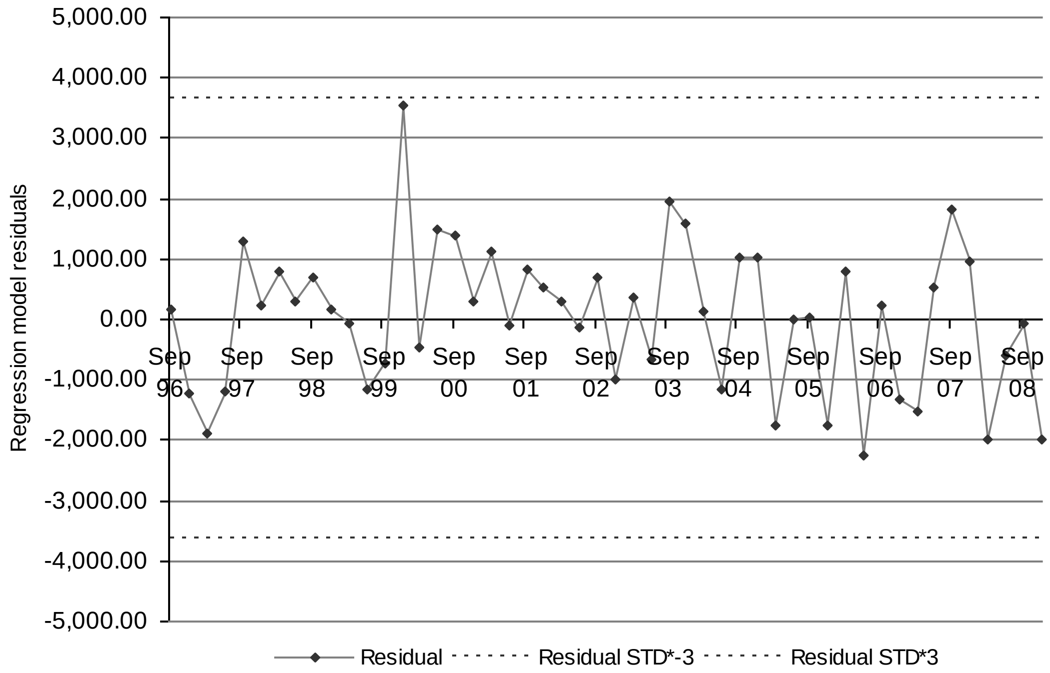
Table **8** summarises the model statistics and the beta estimates (ie $\hat{\beta}_{0,} \hat{\beta}_s, \hat{\Psi}_4, \hat{\theta}_1$) for each of the parameters in the full model. Figure 9 provides the model residuals with Figure 10 showing the autocorrelation plots. The autocorrelation plots are satisfactory.

Table 8: Model of Unemployment Benefit grants model fit

	Model
Observations	52
Log(l)	-442.7
AIC	907.4
SBC	928.8
Parameters	11
Estimate	
MU	*** 71,715.49
Unemployed	*** 127.17
WorkingAge	*** -22.29
MA(1)	*** -0.42
AR(4)	*** 0.48
DecQtr	*** 4,989.87
MarchQtr	*** -4,174.96
WRK4U	** -3,194.03
WRK4U_DecQtr	*** -4,825.65
JSS	*** -22,968.31
JSS_unemployed	*** 226.8

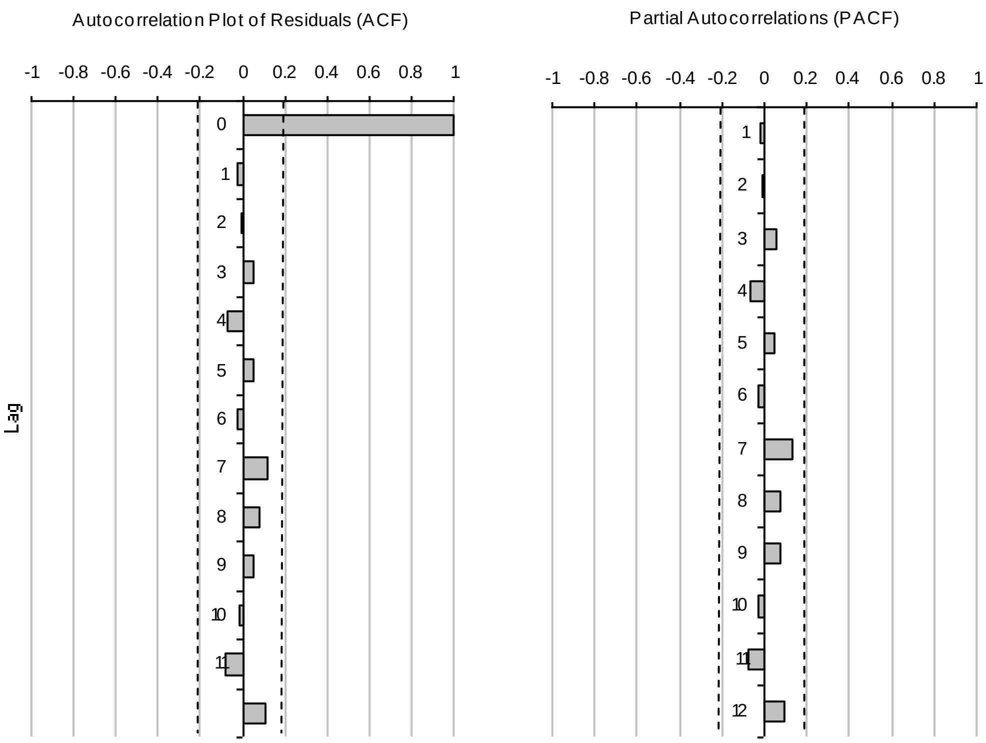
*: significant at 90%, **: significant at 95%, *** significant at 99%

Figure 9: Plot of Unemployment Benefit grants regression plus ARMA model residuals



Orginal series mean: 24,348.56, Standard deviation: 9,005.50

Figure 10: ACF and PACF Unemployment Benefit grants regression plus ARMA model residuals



5, Analysis of the Job Search Service impact

Having arrived at the full model to describe the Unemployment Benefit grant series; the discussion turns to interpretation of the model results.

Calculating the impact of Job Search Service on Unemployment Benefit grants

Because the final model contains an auto-correlation term it is not easy to interpret the parameter estimates in

Table **8**. To assist with communicating the findings we have simulated the difference Job Search Service makes to the number of Unemployment Benefit grants. In other words we use the model parameters to estimate what would be the number of Unemployment Benefit grants if Job Search Service had not existed.

The observed number of Unemployment Benefit grants can be written as

$$Y_t = \hat{\beta}_0 + \hat{\beta}_s X_{s,t} + \hat{\beta}_{JSS} X_{JSS,t} + \frac{\hat{\theta} B^1 \hat{\varepsilon}_t}{(1-\hat{\Psi} B^4)} \qquad (9)$$

Where: Y_t is the observed number of Unemployment Benefit grants

$X_{JSS,t}$ is the Job Search Service variable (leaving aside the interaction with unemployment for clarity)

$X_{s,t}$ are the other variables included in the model

$\hat{\beta}_0, \hat{\beta}_s, \hat{\beta}_{JSS}, \hat{\Psi}_4, \hat{\theta}_1$ are the estimated parameters

$\hat{\varepsilon}_t$ are the residuals.

Our counterfactual model for the number of Unemployment Benefit grants would be:

$$Y_t' = \hat{\beta}_0 + \hat{\beta}_s X_{s,t} + \hat{\beta}_{JSS} X'_{JSS,t} + \frac{\hat{\theta} B^1 \hat{\varepsilon}_t}{(1-\hat{\Psi} B^4)} \qquad (10)$$

Where: Y_t' is the counterfactual number of Unemployment Benefit grants if Job Search Service had not existed

X'_{JSSt} is the counterfactual Job Search Service variable ($X'_{JSSt} = 0$ for all t).

$\hat{\beta}_0 + \hat{\beta}_s X_{st}$ are the values and estimated beta parameters for all other explanatory variables in the model; the values of the other explanatory variables remain unchanged in the counterfactual scenario

$\hat{\Psi}_4, \hat{\theta}_1$ is estimated autoregressive and moving average parameters

$\hat{\varepsilon}_t = Y_t - \hat{Y}_t$, assume the residuals are the same in the counterfactual scenario.

We assume the other explanatory variables ($X_{s,t}$), the estimated parameters ($\hat{\beta}_0, \hat{\beta}_s, \hat{\beta}_{JSS}, \hat{\Psi}_4, \hat{\theta}_1$) and the residuals ($\hat{\varepsilon}_t$) are the same in equations 10 and 11.

Then our estimate of the impact of the Job Search Service on the number of Unemployment Benefit grants is the difference between the observed log Unemployment Benefit grants and the counterfactual estimate.

$$I_{JSSt} = Y_t - Y_t' \qquad (11)$$

It can be shown that

$$Y_t' = Y_t - \hat{\beta}_{JSS} X_{JSS,t} \tag{12}$$

and therefore

$$I_{JSS,t} = \hat{\beta}_{JSS} X_{JSS,t} \tag{13}$$

Impact of Job Search Service over time

Because there is an interaction between JSS and labour market conditions the impact of JSS changes over time in line with the increase or decrease in HLFS unemployment. Table 9 shows the estimate impact of JSS over each quarter after its introduction. What the table shows is the impact of Job Search Service increases over to 2007 to reach 36 percent by December 2007. As the economic recession starts to increase unemployment throughout 2008 and 2009 the impact of JSS steadily decreases to become significantly positive by March 2009. In other words, it appears Job Search Service under high unemployment conditions increases Unemployment Benefit grants (somewhat implausible for a work first programme). However, we need to interpret this impact of Job Search Service in combination with Work for You.

Table 9: Estimated impact of Job Search Service over successive quarters

Quarter	Observed grants	Counterfactual number of grants (without Job Search Service)	Impact of Job Search Service
December 2006	13,900	15,500	-1,600
March 2007	11,200	12,100	-900
June 2007	10,200	14,900	-4,800
September 2007	12,700	18,000	-5,200
December 2007	10,700	16,700	-6,000
March 2008	9,600	11,000	-1,400
June 2008	11,100	14,500	-3,400
September 2008	16,200	18,000	-1,800
December 2008	17,100	16,900	100
March 2009	23,000	17,000	6,000
June 2009	29,400	22,300	7,100
Total	79,400	102,700	-11,700

Job Search Service plus Work for You

Job Search Service and Work for You are intimately linked interventions. Both interventions have a strong influence on the number of people coming onto Unemployment Benefit. Further, Job Search Service incorporated Work for You as part of the Unemployment Benefit application process. Therefore, the distinction between Work for You and Job Search Service in our time series model is somewhat misleading. It would be preferable to have a single parameter with three values to represent:

1. No Work for You (pre-August 2003)
2. Work for You (August 2003 to September 2006)
3. Work for You plus Job Search Service (September 2006 onward)

The problem is that we do not have any prior value that we can place on what the difference is between Work for You and Work for You plus Job Search Service in influencing benefit receipt. For this reason we included each intervention as a separate parameter. The problem this poses is that any interaction between labour market conditions and Work for You plus Job Search Service is entirely attributed to the Job Search Service parameter.

Table 10 shows the combined impact of Work for You and Job Search Service together. The reduction in the overall impact of Work for You plus Job Search Service is still large after December 2008. However, the overall impact remains non-significant. In other words, the model suggests that in periods of rising unemployment the impact of work-first strategies incorporated in Work for You and Job Search Service diminishes.

Table 10: Combined impact of Work for You and Job Search Service on Unemployment Benefit grants

Quarter	Observed grants	Counterfactual number of grants	Impact	Confidence interval
December 2006	13,900	23,500	-9,600	3,800
March 2007	11,200	15,300	-4,100	4,600
June 2007	10,200	18,100	-8,000	5,100
September 2007	12,700	21,100	-8,400	5,200
December 2007	10,700	24,700	-14,000	5,600
March 2008	9,600	14,200	-4,600	5,300
June 2008	11,100	17,700	-6,600	5,200
September 2008	16,200	21,200	-5,000	5,300
December 2008	17,100	25,000	-7,900	5,800
March 2009	23,000	20,100	2,800	6,900
June 2009	29,400	25,500	3,900	7,200
Total	165,100	134,600	-55,300	34,800

UB related benefits include: Community Wage Job Seekers-55+, Community Wage Job Seekers-Young, Unemployment Benefit, Unemployment Benefit Hardship.

Transfers are defined when a client starts a benefit within 14 days of cancelling another benefit.

Values may not add to totals due to rounding.

Source: Information Analysis Platform, (research data, not official MSD statistics)

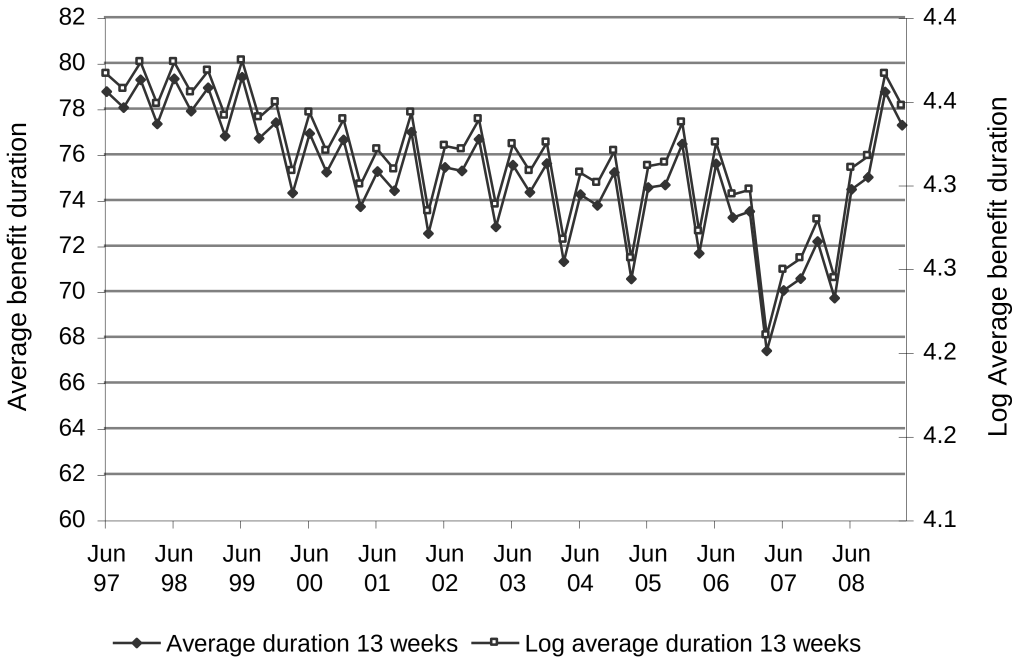
DURATION ON BENEFIT IN FIRST 13 WEEKS AFTER GRANT OF UNEMPLOYMENT RELATED BENEFIT

The next outcome is the average number of days that people are on main benefit in the first 13 weeks after being granted an unemployment-related benefit (excluding transfers).

1, Exploratory data analysis

Figure 11 shows the quarterly trend in the average time that people remain on main benefits in the first 13 weeks after being granted an unemployment-related benefit (excluding transfers). The selection of 13 weeks coincides with the end of the Job Search Service programme. Because the measure includes time on any benefit, the purpose of the measure is to determine whether the Job Search Service programme alters the overall time people remain on benefit rather than looking at just the time they are on Unemployment Benefit. Later analysis will examine the impact of Job Search Service on transfers from Unemployment Benefit to other benefits.

Figure 11: Quarterly series of average time on main benefits in the first 13 weeks after being granted an unemployment-related benefit (excluding transfers)



Properties of the series

The average duration on benefit 13 weeks after Unemployment Benefit grant series is non-stationary with a weak trend as well as a strong seasonal component. Further, it appears the amplitude of the seasonal pattern has increased over the period, especially from December 2001 (Figure 12). Logging the series does not help in reducing the change in variance over this period (Figure 11). Figure 13 shows the series differenced by lag 4 to remove the seasonal pattern and show the underlying trend. After an initial rise in December 1997 and subsequent fall to December 2000, the series remains stable until December 2004 where it starts to rise before trending down sharply from December 2006 to September 2007. This downward trend coincides with the introduction of the Job Search Service in September 2006. From June 2007 the economic downturn has seen a sharp increase in the average time that clients remain on benefit after grant and now dominates the overall trend in the series.

Figure 12: Quarterly average benefit duration 13 weeks after Unemployment Benefit grant differenced lag 1

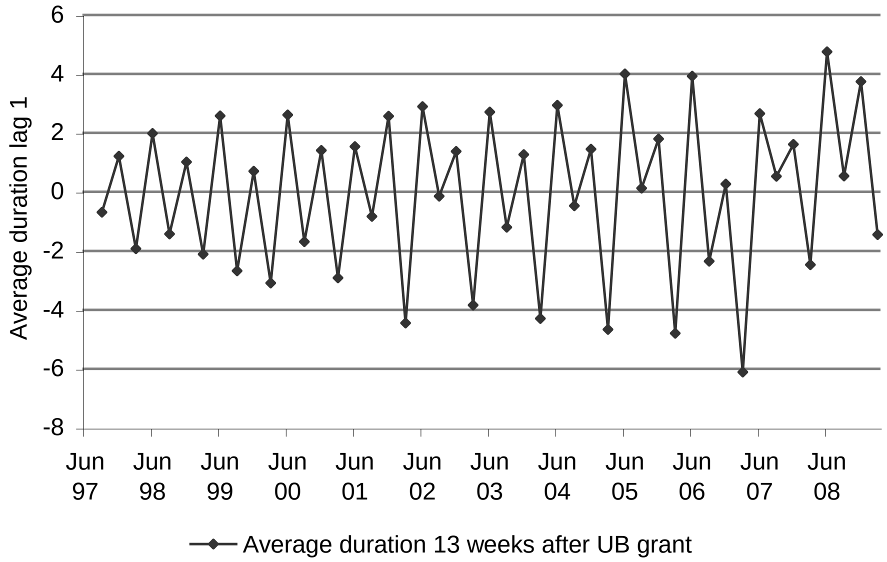
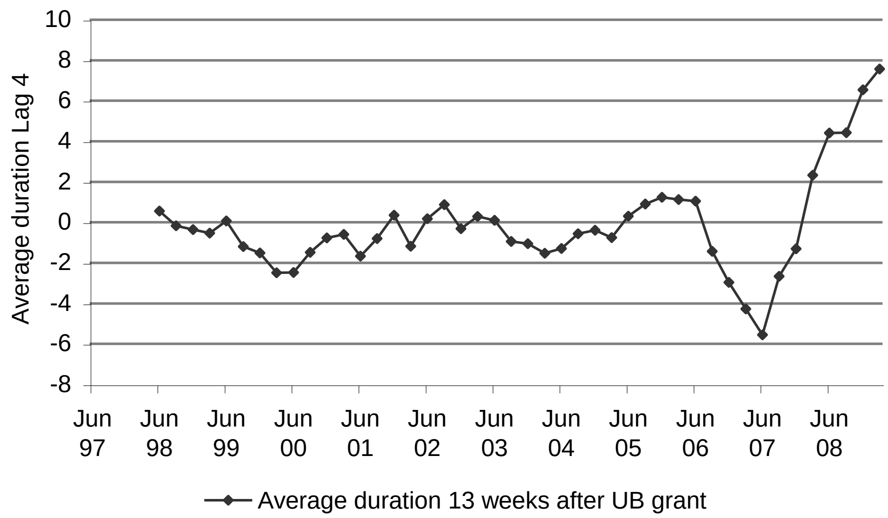


Figure 13: Quarterly average benefit duration 13 weeks after Unemployment Benefit grant differenced lag 4



2, Regression model selection

Trends in the average duration on benefit after 13 weeks after unemployment-related benefit grant are likely to be influenced by several factors. We already can see that there is a strong seasonal component in the series (Figure 12). Figure 13 also shows there is a weak trend over time that we believe is determined by:

The labour market: how fast someone moves off Unemployment Benefit is likely to be influenced by available job opportunities. In periods of high economic growth we expect to see people move off benefit into work at a faster rate since there are increasing numbers of job opportunities. However, countervailing effect is that fewer people would need to come onto Unemployment Benefit and therefore those that do come onto benefit are on average less employable. Currently we have identified four measures of labour market demand:

- total number of people employed
- total number of people unemployed
- proportion of firms reporting it is hard to find unskilled labour
- proportion of firms reporting labour is the main constraint on their growth.

Benefit eligibility and administration rules: any changes to eligibility rules for main benefits will also influence how long people remain on benefit. These not only include changes to rules around Unemployment Benefit, but also rules for other main benefits that may alter the behaviour of people on Unemployment Benefit. Over the report period, we have identified the following change is potentially having an influence:

- alignment of Sickness benefit rate to the Unemployment benefit rate in July 1998.

Administration of benefits and employment assistance: how benefits are administered can also have some influence on the time people are on benefit. In addition, Work and Income provides employment assistance to people on benefit and this would also influence the number of people commencing benefit. We have included the following operational changes in our analysis:

- introduction of the WRK4U seminar
- introduction of the Job Search Service.

We have selected initiatives that represent substantial departures from previous practice as these are most likely to alter the trend in the time people are on Unemployment Benefit. In practice Work and Income is continually changing its operation and procedures. But because these are often marginal changes to existing practice it is unlikely that they would alter the trend in any detectable way.

Trend variables expressed as moving averages

All trend variables have been transformed into forward moving two-quarter averages. The reason for this transformation is to ensure the trend covers the period that clients are on benefit. In the case of the 13-week period, the moving average covers the two quarters from the quarter of grant. Therefore the value of the trend variable represents the average for the two quarters after clients are granted a unemployment-related benefit.

We compared the performance of the moving average and untransformed trend variables and found the moving average transformation provided a better fit for the series. This indicates that it is the conditions over the period on benefit, rather than in the quarter of grant, that explain the trend in average time on benefit.

Variable selection

Table 11 provides the correlation matrix of the continuous variables included in the regression modelling, whilst Table 12 and Table 13 summarise model fit and parameters estimates for the various regression models.

Table 11: Correlation matrix for average duration on benefit within 13 weeks of grant of unemployment-related benefit and continuous independent variables

	Benefit duration 13 wks	Employed	Unemployment rate	Labour as a Constraint	Unskilled Hard	GDP expenditure
Benefit duration 13 wks	1.00	-0.62	0.72	-0.74	-0.67	-0.63
Employed	-0.62	1.00	-0.89	0.72	0.50	0.98
Unemployment rate	0.72	-0.89	1.00	-0.89	-0.76	-0.89
Labour as a Constraint	-0.74	0.72	-0.89	1.00	0.92	0.75
Unskilled Hard	-0.67	0.50	-0.76	0.92	1.00	0.55
GDP expenditure	-0.63	0.98	-0.89	0.75	0.55	1.00

Labour market variables

The first set of models looked at just the labour market variables. Looking at the correlation in Table 11 it is NZIER Labour as the main constraint followed by HLFS Unemployed rate that has the strongest correlation to average benefit duration within 13 weeks. The correlations are reflected in the trend models (1 to 4) in Table 12. The following models begin with Unemployment as the trend variable.

Table 12: Regression model summary fit statistics for average duration on benefit within 13 weeks of grant of unemployment-related benefit

Model	Model variables	Log(L)	SBC	Parameters	Obs
1	Trend: Employed%	-103.7	215.2	2	48
2	Trend: Unemployed	-98.5	204.8	2	48
3	Trend: LabourAsAConstraint	-97.5	202.8	2	48
4	Trend: UnskilledHard	-102.1	212.0	2	48
5	MSD: JSS Trend	-96.4	204.4	3	48
6	Seasonal: MarchQtr Trend MSD	-75.9	167.2	4	48
7	Seasonal: JuneQtr Trend MSD	-94.0	203.5	4	48
8	Seasonal: DecQtr Trend MSD	-92.4	200.3	4	48
9	Seasonal: DecQtr MarchQtr Trend MSD	-74.8	169.0	5	48
10	Seasonal: JuneQtr MarchQtr Trend MSD	-75.6	170.6	5	48
11	Seasonal: SepQtr MarchQtr Trend MSD	-73.5	166.3	5	48
12	MSD: JSS*Trend Trend MSD Seasonal	-54.2	131.6	6	48
13	Trend: Unemployed UnskilledNet Seasonal MSD	-49.6	126.3	7	48
14	MSD: WRK4U MSD Trend Seasonal	-49.4	129.7	8	48
15	MSD: WRK4U_SepQtr MSD Trend Seasonal	-47.1	125.1	8	48
16	Seasonal: MarchQtr DecQtr MSD Trend	-53.0	133.1	7	48
17	Seasonal: MarchQtr SepQtr DecQtr MSD Trend	-48.7	128.4	8	48
18	Final Regression Variables	-47.1	125.1	8	48

Not all models tested are shown in the table.

MSD interventions

Of the four MSD interventions, Job Search Service is the only variable to be significant and reduce the SBC score of the model (model 5).

Seasonal dummies

The next stage of the regression was to include dummies variables to control for seasonal variation in the trend. Including each separately indicates June, December and March quarters are significant and produce lower SBC scores, with March providing the largest improvement in SBC score (models 8 and 10). We then tested the remaining seasonal dummies, the inclusion of September quarter improved model fit (11).

Interaction terms

We tested the interaction between JSS and the trend variable (model 12) and found the impact of JSS on benefit duration decreased with increased unemployment.

Retesting trend variables

Because of the similarity of SBC scores between the trend variables we retested the model with each of the trend variables (model 13). In combination, Unemployed and NZIER Unskilled Labour Hard to Find Net improved model fit. Because of the change in the trend variable we re-tested the MSD and seasonal variables.

Retesting MSD and seasonal variables

The inclusion of NZIER Unskilled Labour Hard to Find did not change the significance of the MSD interventions (models not shown), or the reaming two seasonal variables (16-17). However, including the interaction between WRK4U and September Quarter (model 15) did result in improved model fit. This result may indicate WRK4U produced a small increase in the time spent on benefit after grant, but the increase is only detectable for the September quarter.

Table 13: Parameter estimates for alternative regression model specifications

Model	Intercept (MU)	Labour market variables					Seasonal dummies				MSD interventions		Interaction terms	
		UnemployedMA	LabourAsAConstraintMA	UnskilledNetMA	UnskilledHardMA	EmployedPerMA	MarchQtr	JuneQtr	SepQtr	DecQtr	WRK4U	JSS	WRK4U_SepQtr	JSS_unemployedMA
1	*** 135.8					*** -83.9								
2	*** 65.2	*** 0.09												
3	*** 78.5		*** -27.5											
4	*** 78.2				*** -17.8									
5	*** 66.2	*** 0.09										** -1.50		
6	*** 66.1	*** 0.09					*** -3.18					** -1.16		
7	*** 65.6	*** 0.09						** 1.29				* -1.40		
8	*** 66.1	*** 0.08								*** 1.63		** -1.56		
9	*** 66.0	*** 0.09					*** -2.97			0.60		** -1.21		
10	*** 65.9	*** 0.10					*** -3.09	0.29				** -1.15		
11	*** 66.5	*** 0.09					*** -3.47		** -0.89			** -1.20		
12	*** 68.2	*** 0.08					*** -3.75		*** -0.85			*** -13.44		*** 0.13
13	*** 71.3	*** 0.05		*** 3.43			*** -3.55		*** -1.00			*** -10.28		*** 0.08
14	*** 70.5	*** 0.06		** 3.21			*** -3.57		*** -0.98		0.26	*** -10.22		*** 0.08
15	*** 70.4	*** 0.06		** 2.98			*** -3.58		*** -1.44			*** -10.72	** 1.02	*** 0.09
16	*** 71.2	*** 0.05		*** 4.03			*** -2.89			** 0.81		*** -9.46		*** 0.07
17	*** 71.7	*** 0.05		*** 3.99			*** -3.31		*** -0.84	0.39		*** -9.62		*** 0.08
18	*** 70.4	*** 0.06		** 2.98			*** -3.58		*** -1.44			*** -10.72	** 1.02	*** 0.09

Not all models tested are shown in the table.

*: significant at 90%, **: significant at 95%, *** significant at 99%

Table 14: Average duration on benefit within 13 weeks of grant of unemployment-related benefit

	Model
Observations	48
Log(l)	-47.1
AIC	110.1
SBC	125.1
Parameters	8
Estimate	
Intercept	*** 70.4
UnemployedMA	*** 0.1
UnskilledNetMA	** 3.0
MarchQtr	*** -3.6
SepQtr	*** -1.4
JSS	*** -10.7
WRK4U_SepQtr	** 1.0
JSS_unemployedMA	*** 0.1

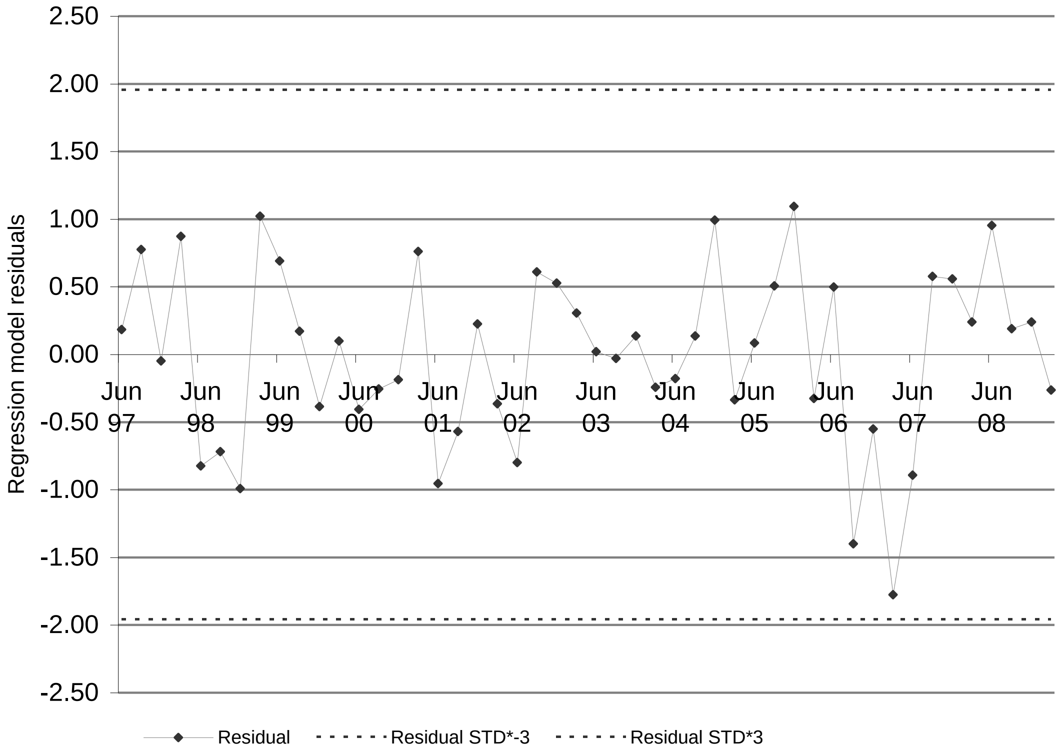
*: significant at 90%, **: significant at 95%, *** significant at 99%

3, Testing for model stationarity

Having selected the final regression variables, the next step is to check whether the resulting residuals are stationary. Figure 14 plots the residuals for the regression model in Table 14 above, whilst Figure 15 shows the Autocorrelation and Partial Autocorrelations of the regression residuals. It is apparent from the plots that:

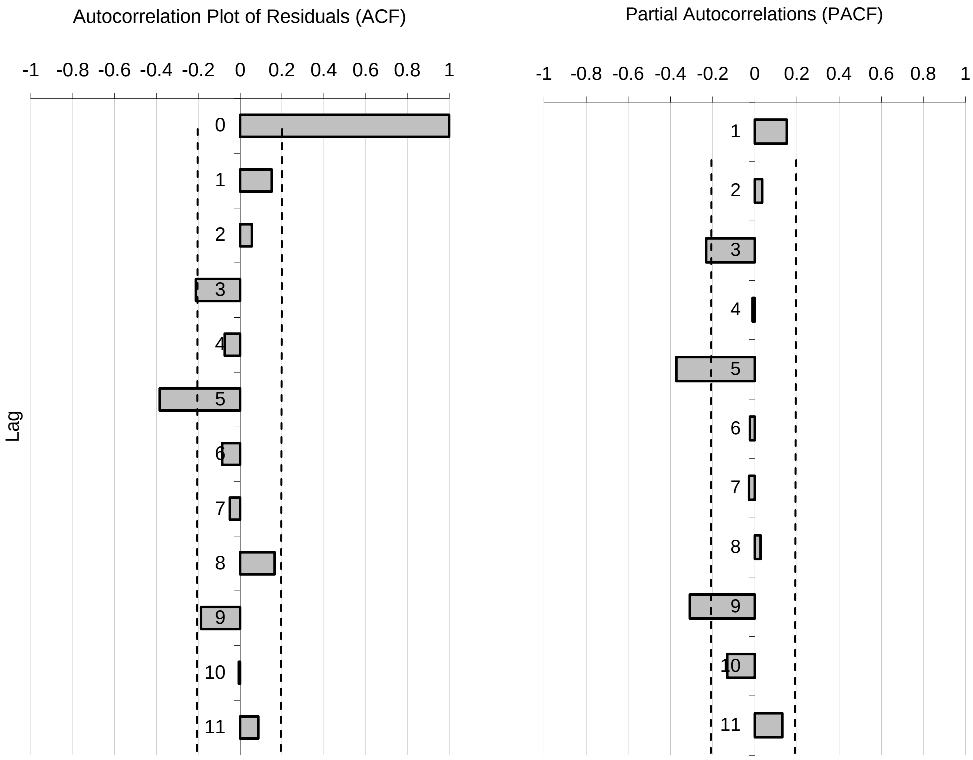
- the mean and variation are constant around zero
- the autocorrelation plots do not show the presence of autocorrelation
- there is little information remaining in the residuals other than weak autocorrelations at lag 1 and 5 (Figure 15).

Figure 14: Plot of average benefit duration within 13 weeks of Unemployment Benefit grant regression model residuals



Orginal series mean: 75.02, Standard deviation: 2.77

Figure 15: ACF and PACF Unemployment Benefit grants regression model residuals



4, Selection of ARIMA models

Table 15 and Table 16 summarise the testing of alternative ARIMA models. Inclusion of an AR5 or MA3 terms produces the best model fit and dropping insignificant explanatory variables. The final model is ARIMA(0,0,0)$(0,0,1)_5$.

Table 15: Model fit for competing ARIMA models

Model	Model parameters	SBC	White noise test (p values) 6	12	18	24
ARIMA(0,0,0)(0,0,1)3	9	124.5	0.111	0.327	0.329	0.232
ARIMA(0,0,0)(0,0,1)5	9	119.5	0.492	0.586	0.747	0.603
ARIMA(0,0,0)(1,0,0)3	9	125.2	0.049	0.186	0.237	0.177
ARIMA(0,0,0)(1,0,0)5	9	119.1	0.299	0.509	0.602	0.479
ARIMA(0,0,1)3(1,0,0)5	10	119.0	0.593	0.828	0.758	0.510

Not all models tested are shown in the table.

Table 16: Variable parameters of competing ARIMA models

	Regression Variables								Autoregressive and moving average parameters		
Model	**Intercept (MU)**	**UnemployedMA**	**UnskilledNetMA**	**MarchQtr**	**SepQtr**	**WRK4U_S**	**JSS**	**JSS_unemployedMA**	**MA(3)**	**AR(3)**	**MA(5)**
ARIMA(0,0,0)(0,0,1)3	*** 70.1	*** 0.06	** 2.77	*** -3.61	*** -1.60	*** 1.44	*** -11.8	*** 0.10	** 0.37		
ARIMA(0,0,0)(0,0,1)5	*** 70.2	*** 0.06	** 2.85	*** -3.52	*** -1.52	** 1.25	*** -11.0	*** 0.09			*** 0.45
ARIMA(0,0,0)(1,0,0)3	*** 69.8	*** 0.07	** 2.60	*** -3.62	*** -1.69	*** 1.66	*** -12.0	*** 0.10		* -0.36	
ARIMA(0,0,0)(1,0,0)5	*** 69.6	*** 0.07	** 2.36	*** -3.50	*** -1.53	*** 1.48	*** -12.0	*** 0.10			
ARIMA(0,0,1)3(1,0,0)5	*** 69.7	*** 0.07	** 2.46	*** -3.50	*** -1.62	*** 1.70	*** -12.6	*** 0.11	* 0.31		

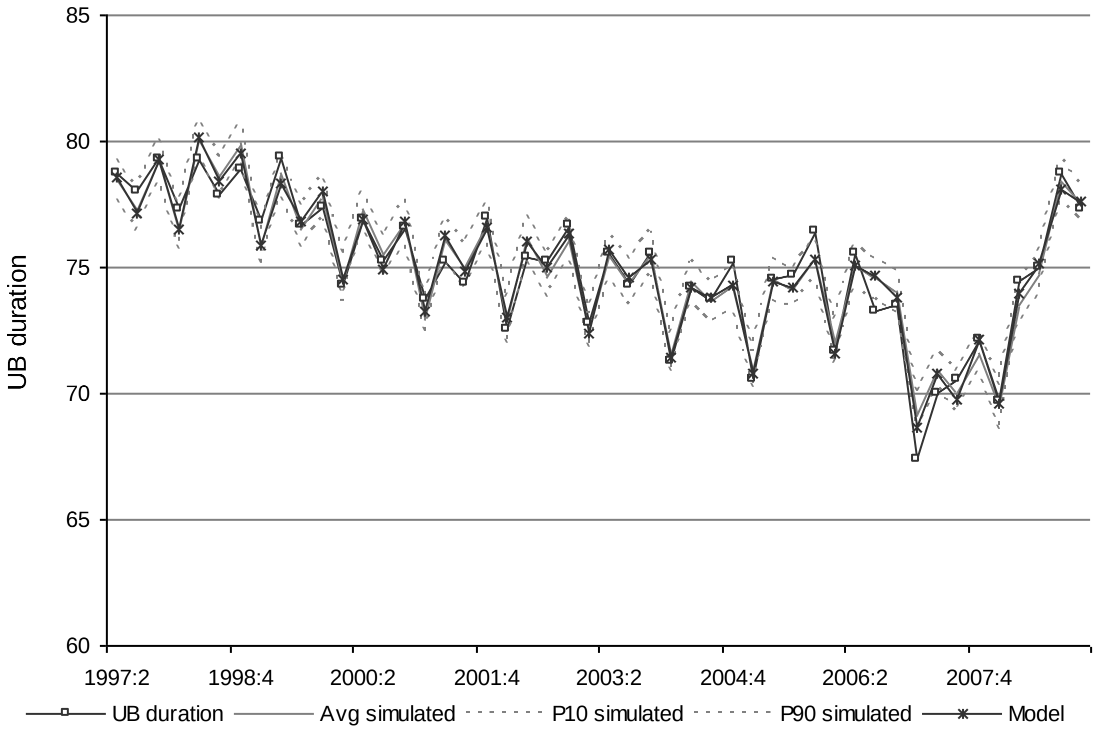
*: significant at 90%, **: significant at 95%, *** significant at 99%

Not all models tested are shown in the table.

Simulation of ARIMA process

There is a risk in selecting alternative ARIMA models of over-fitting the data, since it is possible that the ARIMA model selected happens to fit the particular series. To test whether the selected ARIMA model is the best model we test it against a simulated ARIMA process. If the selected ARIMA model is robust, then we should see the simulated ARIMA processes fit the series data fairly well (eg the simulations are not consistently higher or lower than the series or that the simulations fail to capture important features of the series). We ran 100 simulations and calculated the mean as well as 90 and 10 percentiles (Avg simulated, P10 simulated and P90 simulated in Figure 16); these are shown in Figure 16. In general the simulated models show a similar pattern to the actual model (model in Figure 16).

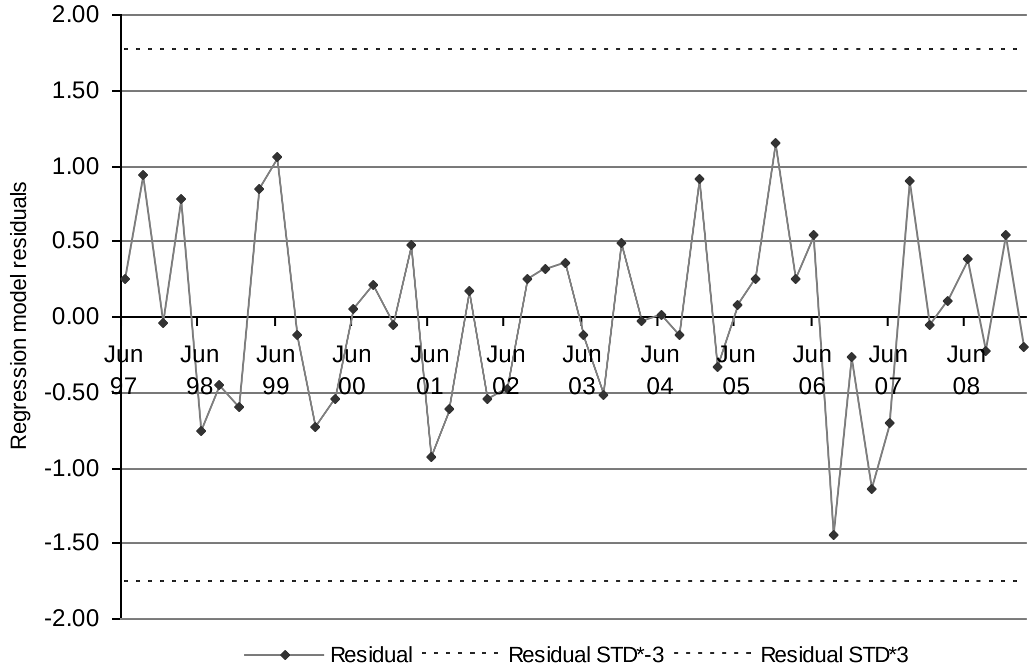
Figure 16: Simulation testing regression model of average benefit duration at 13 weeks



4, Specification of full model

Table 17 summarises the model statistics and the beta estimates for each of the parameters in the full model. Figure 17 provides the model residuals with Figure 18 showing the autocorrelation plots. The autocorrelation plots are satisfactory.

Figure 17: Plot of average time on main benefit within 13 weeks of Unemployment Benefit grant regression plus ARIMA model residuals



Orginal series mean: 75.02, Standard deviation: 2.77

Figure 18: ACF and PACF average time on main benefit within 13 weeks of Unemployment Benefit grant regression plus ARIMA model residuals

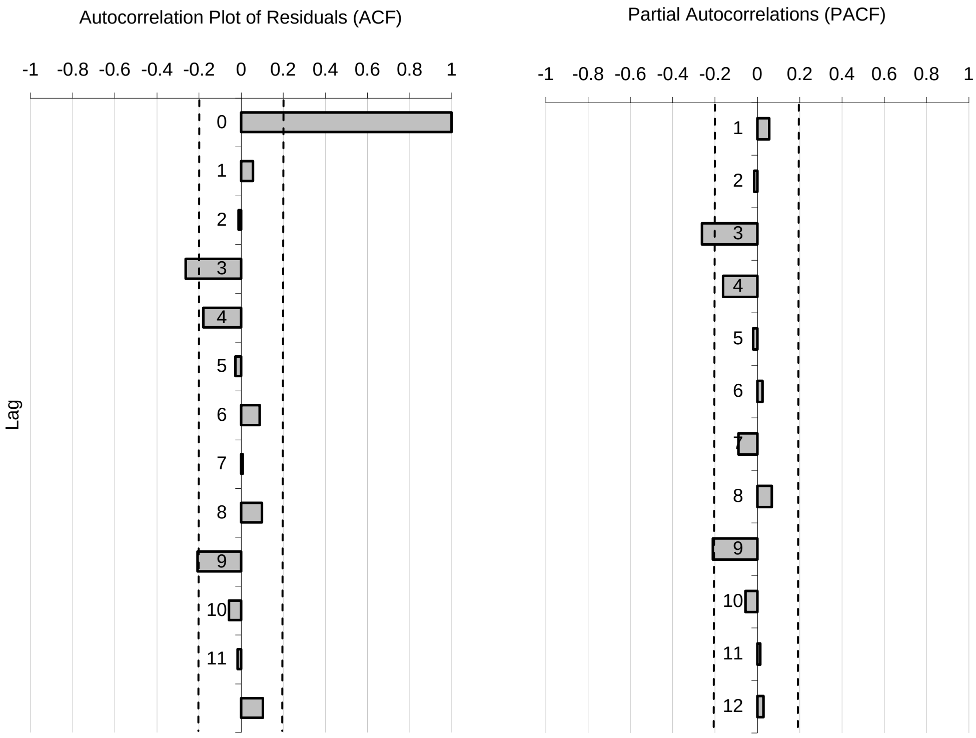


Table 17: Model of average time on main benefit within 13 weeks of Unemployment Benefit grant model fit

	Model
Observations	48
Log(l)	-42.1
AIC	102.2
SBC	119.1
Parameters	9
Estimate	
Intercept	*** 69.63
AR(5)	*** -0.49
UnskilledNetMA	** 2.36
UnemployedMA	*** 0.07
MarchQtr	*** -3.50
SepQtr	*** -1.53
JSS	*** -11.96
WRK4U_SepQtr	*** 1.48
JSS_unemployedMA	*** 0.10

*: significant at 90%, **: significant at 95%, *** significant at 99%

5, Analysis of the Job Search Service impact

Having arrived at the full model to describe the average benefit duration 13 weeks after Unemployment Benefit grant series; the discussion turns to interpretation of the model results (Table 18).

Table 18: Estimated impact of Job Search Service over time

Quarter	Observed duration	Counterfactual duration (without Job Search Service)	Impact of Job Search Service	
			Days	% of counterfactual
Dec 06	73.5	73.5	-1.26	-1.7%
Mar 07	67.4	69.7	-2.31	-3.3%
Jun 07	70.0	73.8	-3.73	-5.1%
Sep 07	70.6	74.6	-4.07	-5.5%
Dec 07	72.2	75.4	-3.20	-4.3%
Mar 08	69.7	72.3	-2.62	-3.6%
Jun 08	74.5	77.2	-2.70	-3.5%
Sep 08	75.0	76.9	-1.90	-2.5%
Dec 08	78.7	78.9	-0.14	-0.2%
Mar 09	77.3	75.8	1.43	1.9%
Weighted average	73.6	75.2	-2.05	-2.7%

UB related benefits include: Community Wage Job Seekers-55+, Community Wage Job Seekers-Young, Unemployment Benefit, Unemployment Benefit Hardship.

Transfers are defined when a client starts a benefit within 14 days of cancelling another benefit.

Values may not add to totals due to rounding.

Source: Information Analysis Platform, (research data, not official MSD statistics)

Impact of Job Search Service over time

Because the model includes an interaction term between JSS and HLFS number of unemployed, the impact of Job Search Service changes with each quarter. After reaching its largest impact in September 2007, Job Search Service impact on the average time Unemployment Benefit clients are on benefit in the first 13 weeks has fallen with each successive quarter. By March 2009 the impact is positive, in other words under JSS and conditions of high unemployment people remain longer on benefit had JSS not been introduced.

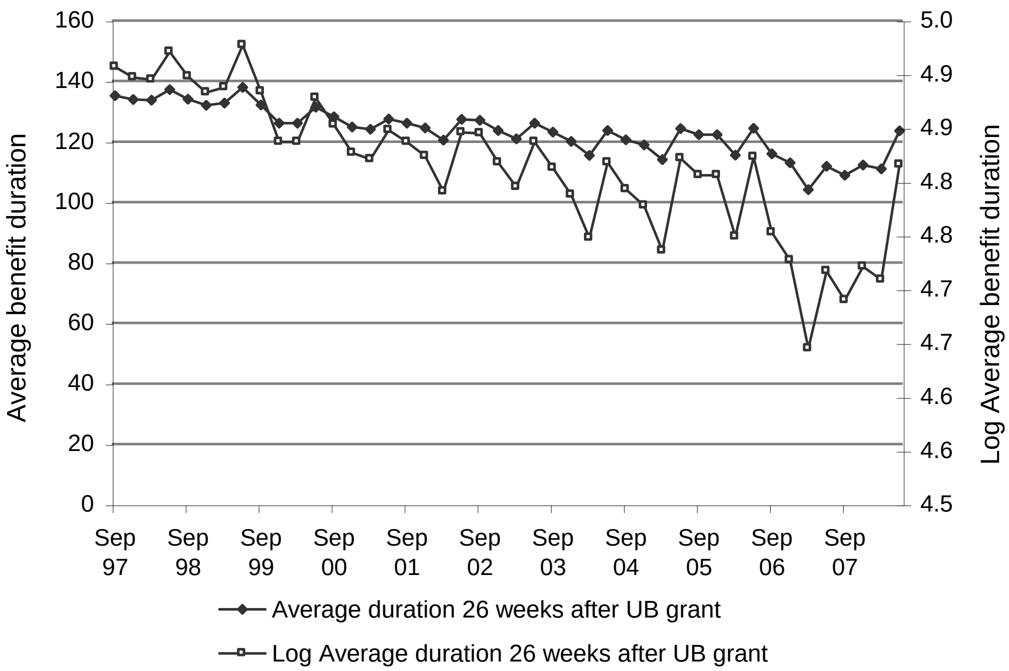
DURATION ON BENEFIT IN FIRST 26 WEEKS AFTER GRANT OF UNEMPLOYMENT RELATED BENEFIT

The next outcome is the average number of days that people are on main benefit in the first 26 weeks after being granted an unemployment-related benefit (excluding transfers).

1, Exploratory data analysis

Figure 19 shows the quarterly trend in the average time that people remain on main benefits in the first 26 weeks after being granted an unemployment-related benefit (excluding transfers).

Figure 19: Quarterly series of average time on main benefits in the first 26 weeks after being granted an unemployment-related benefit (excluding transfers)



Properties of the series

The average duration on benefit 26 weeks after Unemployment Benefit grant series is non-stationary with a weak trend as well as a strong seasonal component. Further, it appears the amplitude of the seasonal pattern has increased over the period, especially from March 2004 (Figure 20). Logging the series does not help in reducing the change in variance over this period (Figure 19). Figure 21 shows the series differenced by lag 4 to remove the seasonal pattern and show the underlying trend. After an initial rise in December 1997 and subsequent fall to December 2000, the series remains stable until December 2004 where it starts to rise before trending down sharply from December 2006 to September 2007, coinciding with the introduction of the Job Search Service in September 2006. From September 2007 onwards we see a sharp rise in average duration that corresponds to the economic downturn starting in 2008.

Figure 20: Quarterly average benefit duration 26 weeks after Unemployment Benefit grant differenced lag 1

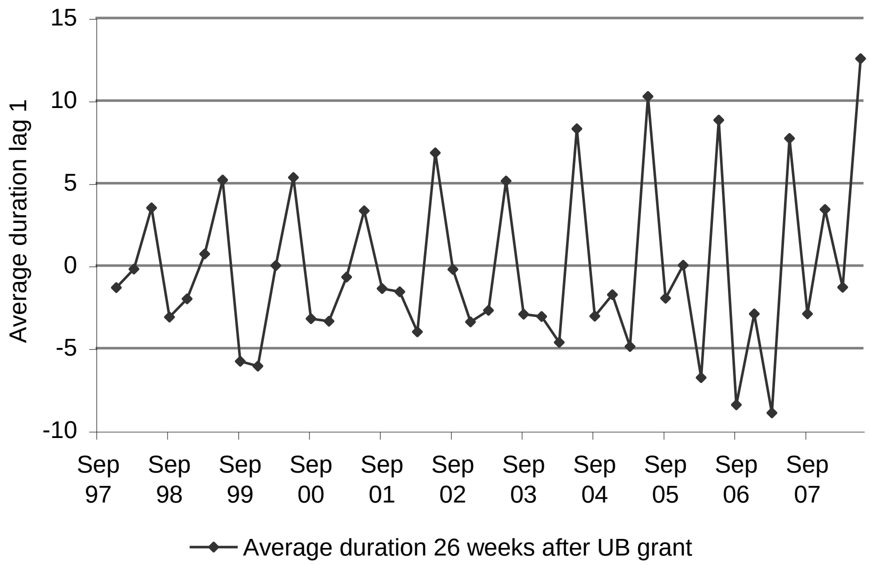
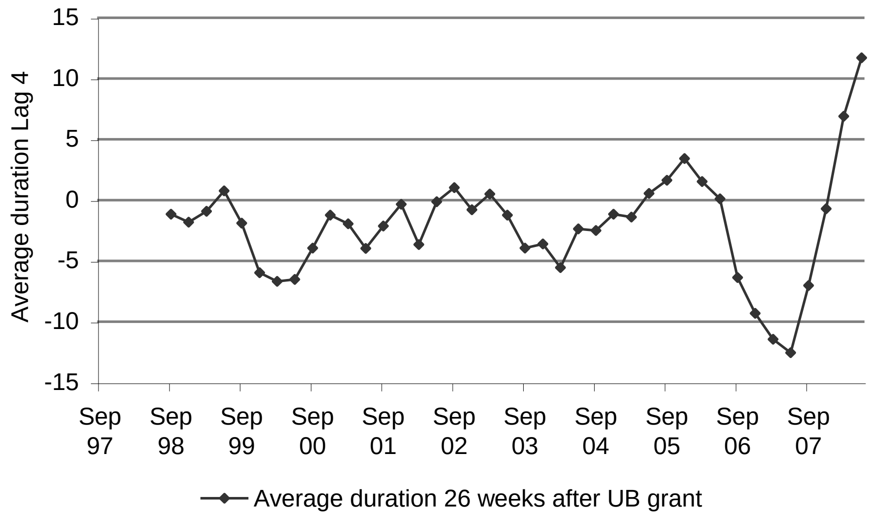


Figure 21: Quarterly average benefit duration 26 weeks after Unemployment Benefit grant differenced lag 4



2, Regression model selection

For discussion of the explanatory variables in the model see section on average duration on benefit after 13 weeks (page 32). Also, the trend variables have been converted into a forward three-quarter moving average with the following weightings 0.5, 1, 0.5. Table 19 provides the correlation matrix of the continuous variables included in the regression modelling, whilst Table 12 and Table 13 summarise model fit and parameters estimates for the various regression models.

Table 19: Correlation matrix for average duration on benefit within 26 weeks of grant of unemployment-related benefit and continuous independent variables

	Benefit duration 26 wks	Employed	Unemployment rate	Labour as a Constraint	Unskilled Hard	GDP expenditure
Benefit duration 26 wks	1.00	-0.79	0.83	-0.81	-0.70	-0.80
Employed	-0.79	1.00	-0.91	0.76	0.54	0.99
Unemployment rate	0.83	-0.91	1.00	-0.90	-0.79	-0.92
Labour as a Constraint	-0.81	0.76	-0.90	1.00	0.92	0.79
Unskilled Hard	-0.70	0.54	-0.79	0.92	1.00	0.60
GDP expenditure	-0.80	0.99	-0.92	0.79	0.60	1.00

Labour market variables

The first set of models looked at just the labour market variables. Looking at the correlation in Table 19 the HLFS Unemployment rate has the strongest correlation to average benefit duration within 26 weeks. Comparing the alternative labour market models (Trend) we find HLFS Unemployment rate provides the best fit (model 2).

MSD interventions

Of the three MSD interventions, only Job Search Service is significant (model 5).

Seasonal dummies

The next stage of the regression was to include dummies variables to control for seasonal variation in the trend. Including each separately indicates March and June quarters are significant and produce lower SBC scores (models 6 and 7). We then combine these dummies into a single model (model 8) where both variables are significant and decrease the SBC score.

Interaction terms

The interaction between JSS and HLFS unemployed was significant (model 12).

Retesting trend variables

No alternative trend variables improved model fit (models not shown).

Seasonal dummies

When we tested the other two quarters not already in the model we found that the September quarter was now also significant (model 11).

Table 20: Regression model summary fit statistics for average duration on benefit within 26 weeks of grant of unemployment-related benefit

Model	Model variables	Log(L)	SBC	Parameters	Observations
1	Trend: Employed	-143.9	295.5	2	48
2	Trend: Unemployed%	-139.0	285.8	2	48
3	Trend: LabourAsAConstraint	-141.4	290.6	2	48
4	Trend: UnskilledNet	-155.8	319.4	2	48
5	MSD: JSS Trend	-135.8	283.1	3	48
6	Seasonal: MarchQtr Trend MSD	-126.2	267.9	4	48
7	Seasonal: JuneQtr Trend MSD	-126.0	267.5	4	48
8	Seasonal: JuneQtr MarchQtr Trend MSD	-119.3	258.0	5	48
9	Seasonal: JuneQtr SepQtr Trend MSD	-121.8	262.9	5	48
10	Seasonal: JuneQtr MarchQtr SepQtr Trend MSD	-118.3	259.8	6	48
11	MSD: JSS*trend SepQtr Seasonal Trend MSD	-94.9	216.9	7	48
12	MSD: JSS*trend Trend Seasonal MSD	-99.9	223.0	6	48
13	Final Regression Variables	-94.9	216.9	7	48

Not all models tested are shown in the table.

Table 21: Parameter estimates for alternative regression model specifications

Model	Intercept (MU)	Labour market variables				Seasonal dummies			MSD interventions	Interactions
		EmployedMA	**UnemployedPerMA**	**LabourAsAConstraintMA**	**UnskilledNetMA**	**MarchQtr**	**JuneQtr**	**SepQtr**	**JSS**	**JSS_ UnemployedPerMA**
1	*** 204	*** -0.04								
2	*** 99		*** 480							
3	*** 135			*** -87						
4	*** 125				*** 22					
5	*** 102		*** 434						** -4.62	
6	*** 103		*** 438			*** -5.42			*** -4.79	
7	*** 100		*** 446				*** 5.47		*** -4.39	
8	*** 101		*** 446			*** -4.05	*** 4.12		*** -4.57	
9	*** 98		*** 451				*** 6.58	*** 3.30	*** -4.27	
10	*** 100		*** 449			** -3.20	*** 4.97	1.69	*** -4.47	
11	*** 102		*** 412			** -2.10	*** 6.16	*** 2.39	*** -45.94	*** 968
12	*** 103		*** 410			*** -3.33	*** 4.92		*** -44.37	*** 928
13	*** 102		*** 412			** -2.10	*** 6.16	*** 2.39	*** -45.94	*** 968

*: significant at 90%, **: significant at 95%, *** significant at 99%

Not all models tested are shown in the table.

3, Selection of ARIMA models

Table 22 and Table 23 summarise the testing of alternative ARIMA models. ACF PACF plots indicate autocorrelation. Of the ARIMA models tested, ARIMA$(0,0,1)_3(1,0,0)_5$ was most successful in generating a random residual series.

Table 22: Model fit for competing ARIMA models

Model	Model Parameters	SBC	White noise test (p values)			
			6	12	18	24
ARIMA(0,0,0)(0,0,1)3	8	208.1	0.084	0.347	0.174	0.201
ARIMA(0,0,1)3(1,0,0)5	9	202.8	0.342	0.792	0.453	0.329
ARIMA(0,0,0)(1,0,0)5	8	211.9	0.001	0.009	0.033	0.005

Not all models tested are shown in the table.

Table 23: Variable parameters of competing ARIMA models

Model	Intercept (MU)	Regression variables						Autoregressive and moving average parameters	
		UnemployedPerMA	MarchQtr	JuneQtr	SepQtr	JSS	JSS_UnemployedPerMA	MA(3)	AR(5)
ARIMA(0,0,0)(0,0,1)3	*** 101.7	*** 409.8	** -2.2	*** 6.3	*** 2.4	*** -47.3	*** 996.3	*** 0.54	
ARIMA(0,0,1)3(1,0,0)5	*** 101.9	*** 407.2	** -2.3	*** 6.2	* 2.2	*** -46.1	*** 964.0	*** 0.51	*** -0.44
ARIMA(0,0,0)(1,0,0)5	*** 101.8	*** 409.6	** -2.2	*** 6.1	** 2.2	*** -45.4	*** 951.4		*** -0.43

*: significant at 90%, **: significant at 95%, *** significant at 99%

Not all models tested are shown in the table.

4, Specification of full model

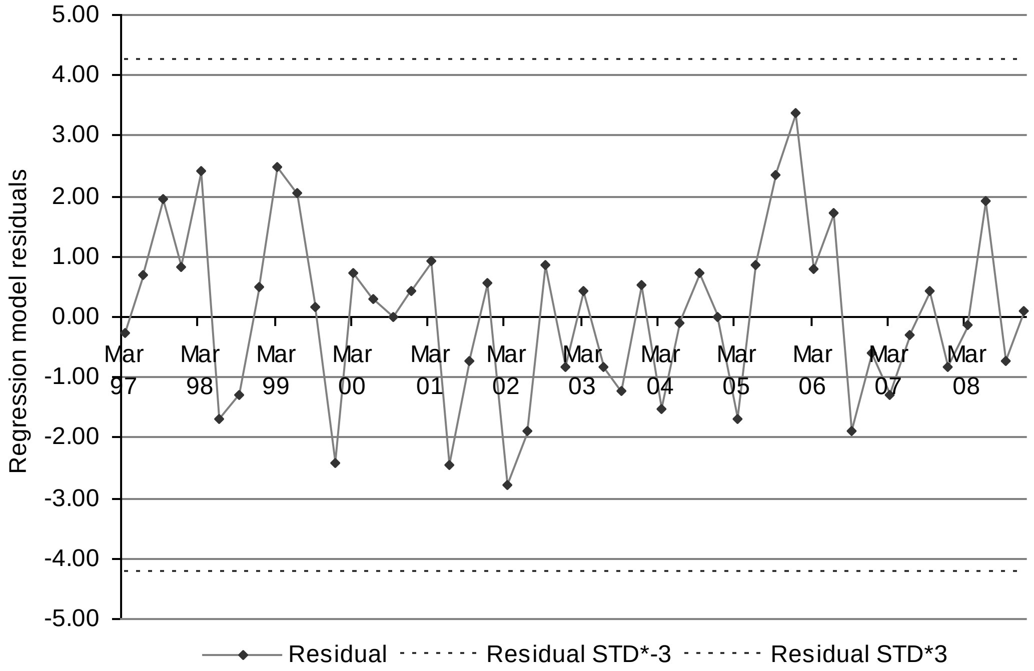
Table 24 summarises the model statistics and the beta estimates for each of the parameters in the full model. Figure 22 provides the model residuals with Figure 23 showing the autocorrelation plots. The autocorrelation plots are satisfactory.

Table 24: Model of average time on main benefit within 26 weeks of Unemployment Benefit grant model fit

	Model
Observations	48
Log(l)	-84.2
AIC	186.3
SBC	203.2
Parameters	9
Estimate	
Intercept	*** 101.63
MA(3)	*** 0.50
AR(5)	*** -0.43
UnemployedPerMA	*** 411.12
MarchQtr	* -2.18
JuneQtr	*** 6.24
SepQtr	** 2.31
JSS	*** -45.89
JSS_UnemployedPerMA	*** 959.90

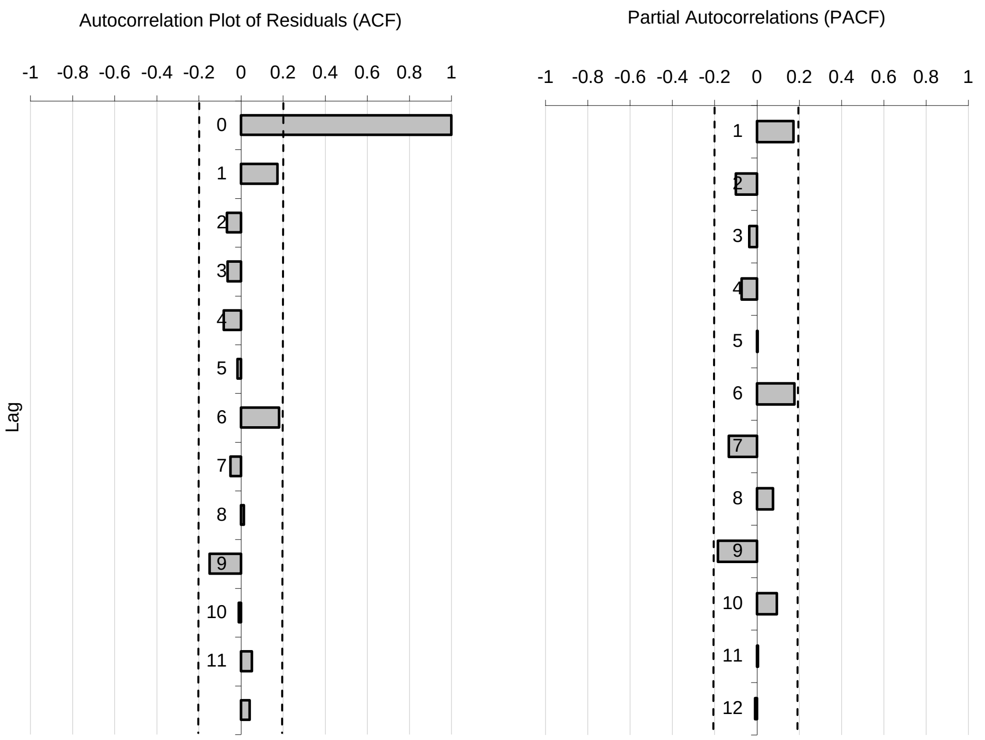
*: significant at 90%, **: significant at 95%, *** significant at 99%

Figure 22: Plot of average time on main benefit within 26 weeks of Unemployment Benefit grant regression plus ARIMA model residuals



Orginal series mean: 124.09, Standard deviation: 7.91

Figure 23: ACF and PACF average time on main benefit within 26 weeks of Unemployment Benefit grant regression plus ARIMA model residuals



5, Analysis of the Job Search Service impact

Having arrived at the full model to describe the average benefit duration 26 weeks after Unemployment Benefit grant series; the discussion turns to interpretation of the model results.

Changing impact of Job Search Service

With each new quarter in the series the impact of Job Search Service is decreasing.

Table 25: impact of Job Search Service over successive quarters

Quarter	Observed duration	Counterfactual duration (without Job Search Service)	Impact of Job Search Service	
			Days	% of counterfactual
Dec 06	113.6	116.2	-3.2	-2.7%
Mar 07	105.4	111.4	-7.3	-6.5%
Jun 07	112.1	123.1	-11.3	-9.2%
Sep 07	108.4	119.3	-10.5	-8.8%
Dec 07	113.1	119.7	-7.4	-6.2%
Mar 08	111.0	117.2	-6.4	-5.4%
Jun 08	121.6	128.7	-5.2	-4.0%
Sep 08	123.7	123.0	-0.1	0.0%
Dec 08	131.3	124.3	7.0	5.6%
Average (weighted)	116.7	120.6	-3.8	-3.2%

UB related benefits include: Community Wage Job Seekers-55+, Community Wage Job Seekers-Young, Unemployment Benefit, Unemployment Benefit Hardship.

Transfers are defined when a client starts a benefit within 14 days of cancelling another benefit.

Source: Information Analysis Platform, (research data, not official MSD statistics)

DURATION ON BENEFIT IN FIRST 52 WEEKS AFTER GRANT OF UNEMPLOYMENT RELATED BENEFIT

The analysis over 52 weeks is broadly similar to the 26-week period and for economy details on model development are not shown in the report.

4, Specification of full model

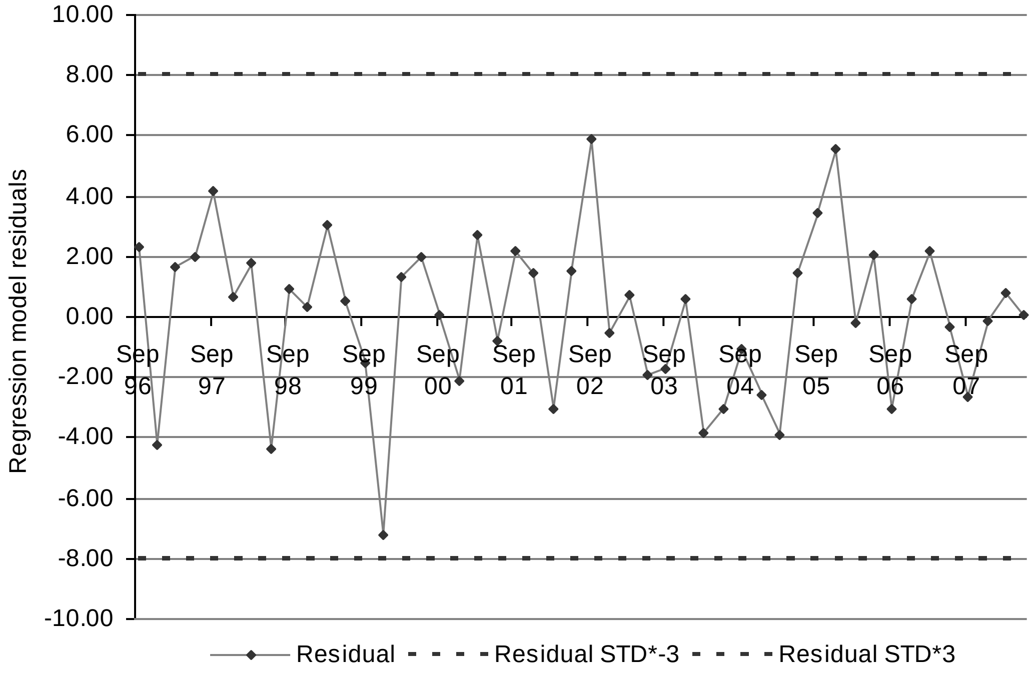
Table 24 summarises the model statistics and the beta estimates for each of the parameters in the full model. Figure 22 provides the model residuals with Figure 23 showing the autocorrelation plots. The autocorrelation plots are satisfactory however we do see autocorrelation at lag 7.

Table 26: Model of average time on main benefit within 52 weeks of Unemployment Benefit grant model fit

	Model
Observations	44
Log(l)	-111.4
AIC	234.9
SBC	245.6
Parameters	6
Estimate	
Intercept	*** 142.02
MA(4)	** 0.37
MA(3)	*** 0.70
AR(5)	*** -0.65
UnemployedPerMA	*** 1,017.56
JuneQtr	*** 11.10
JSS	*** -124.25
JSS_UnemployedPerMA	*** 2,790.97

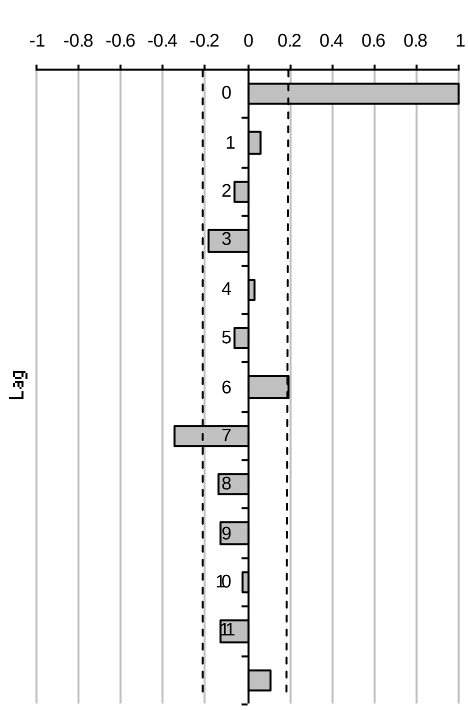
*: significant at 90%, **: significant at 95%, *** significant at 99%

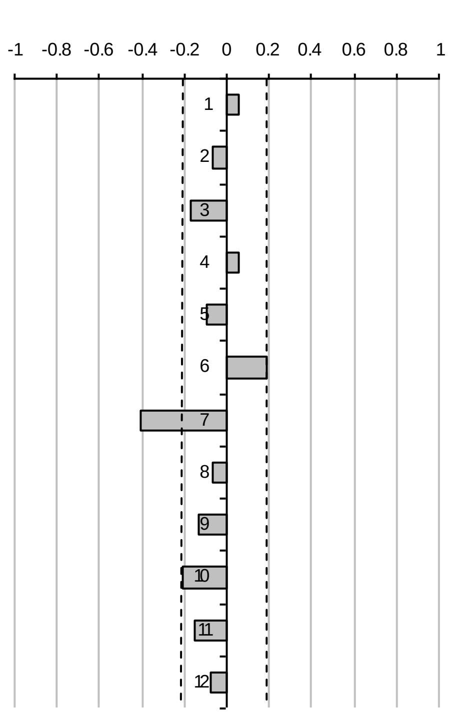
Figure 24: Plot of average time on main benefit within 52 weeks of Unemployment Benefit grant regression plus ARIMA model residuals



Orginal series mean: 196.04, Standard deviation: 16.91

Figure 25: ACF and PACF average time on main benefit within 52 weeks of Unemployment Benefit grant regression plus ARIMA model residuals





5, Analysis of the Job Search Service impact

Having arrived at the full model to describe the average benefit duration 52 weeks after Unemployment Benefit grant series; the discussion turns to interpretation of the model results.

Changing impact of Job Search Service

With each new quarter in the series the impact of Job Search Service is decreasing.

Table 27: Impact of Job Search Service over successive quarters

Quarter	Observed duration (days)	Counterfactual duration (without Job Search Service)	Impact of Job Search Service	
			Days	% of counterfactual
Dec 06	168.3	175.0	-6.8	-3.9%
Mar 07	157.3	176.6	-16.2	-9.2%
Jun 07	171.2	193.0	-21.2	-11.0%
Sep 07	166.9	182.2	-17.0	-9.3%
Dec 07	177.2	188.9	-11.5	-6.1%
Mar 08	180.9	189.9	-6.7	-3.5%
Jun 08	205.1	202.7	2.7	1.3%
Average (weighted)	174.8	186.2	-11.5	-6.2%

UB related benefits include: Community Wage Job Seekers-55+, Community Wage Job Seekers-Young, Unemployment Benefit, Unemployment Benefit Hardship.

Transfers are defined when a client starts a benefit within 14 days of cancelling another benefit.

Source: Information Analysis Platform, (research data, not official MSD statistics)

SICKNESS BENEFIT GRANTS (EXCLUDING TRANSFERS)

The next outcome is the average number of sickness-related benefit grants (excluding transfers).

1, Exploratory data analysis

Figure 26 shows the quarterly trend in the number of sickness-related benefit grants.

Properties of the series

The sickness-related benefit grants (excluding transfers) series is non-stationary with an upward trend as well as a strong seasonal component. Further, it appears the amplitude of the seasonal pattern has increased over the period, especially from March 2004 (Figure 27). Logging the series does help in reducing the change in variance over this period (Figure 27). Figure 28 shows the series differenced by lag 4 to remove the seasonal pattern and show the underlying trend. After an initial fall to September 1999 the series remains stable until December 2004 where it starts show increased volatility. From December 2007 we see the largest annual increase. This corresponds to the economic downturn starting in 2008. Testing logged and untransformed series indicated a more stationary series could be achieved using a logged series.

Figure 26: Quarterly series of sickness-related benefit grants (excluding transfers)

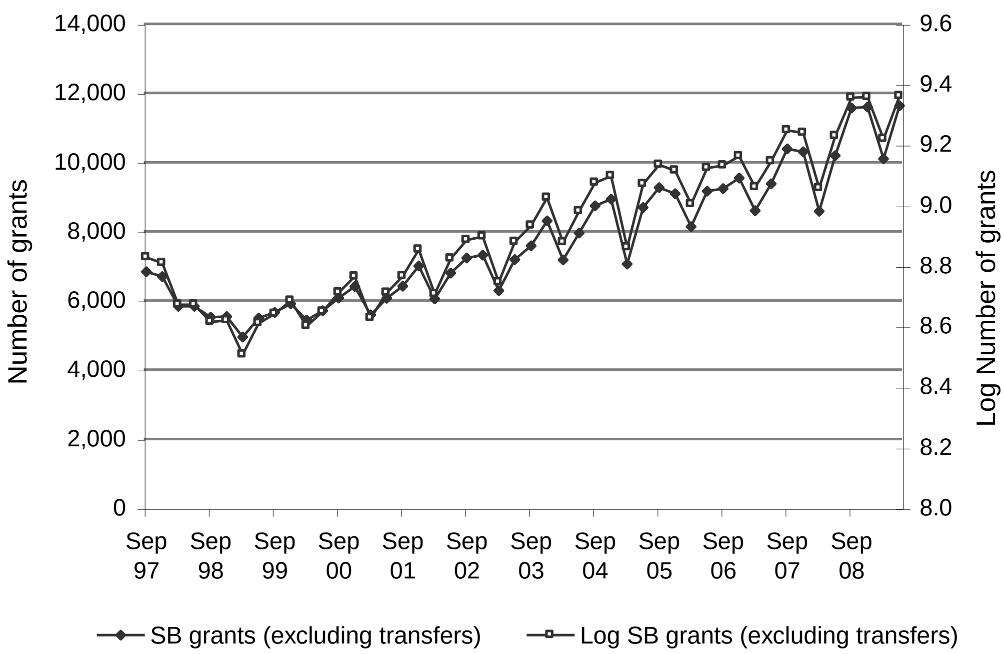


Figure 27: Quarterly sickness-related benefit grants (excluding transfers) differenced lag 1

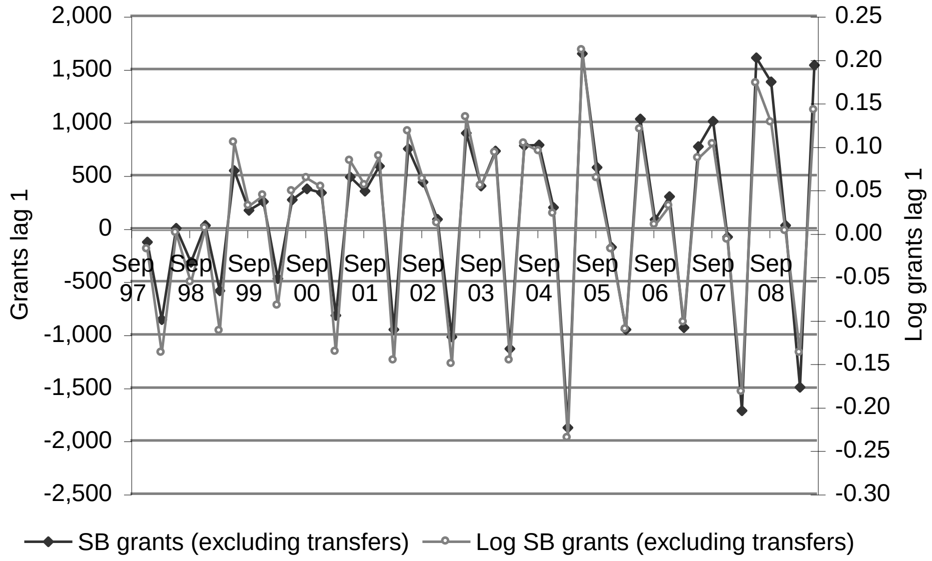
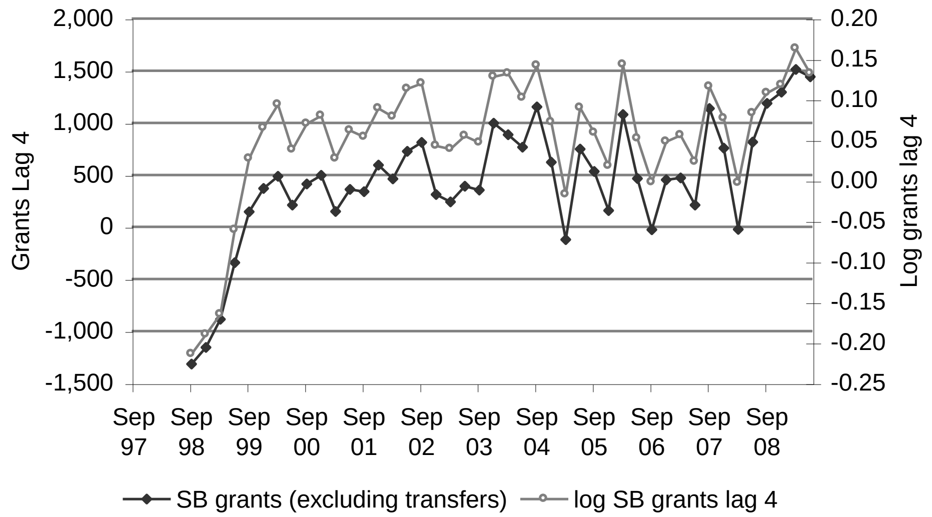


Figure 28: Quarterly sickness-related benefit grants (excluding transfers) differenced lag 4



2, Regression model selection

For discussion of the explanatory variables in the model see section on average duration on benefit after 13 weeks (page 32). In addition to these variables we also developed additional variables to represent the overall population (15 to 64 years) as well as variables to represent the aging of the population over the analysis period. Our model is based on selection of variables to represent the five potential influences on the number of SB grants.

Population growth: the overall growth in SB grants is simply due to increased eligible population. The increased eligible population is a combination of population growth and raising the eligibility for NZ superannuation from 60 to 65.

Population aging: as the population ages we would anticipate more people will experience ill-health or disabilities that would make them eligible for Sickness Benefit.

Economic cycle: economic downturn increases both the number of people coming onto unemployment-related benefits, but may also be associated with increases in the number of Sickness Benefit grants.

MSD interventions: there are several potential MSD interventions that could alter the number of people coming onto SB. The four included in the analysis are:

- alignment of SB and UB rates
- Work for You
- Job Search Service
- SBIB Working New Zealand changes.

Seasonality: from Figure 27 it is clear that Sickness Benefit grants has a strong seasonal pattern.

Table 28 provides the correlation matrix of the continuous variables included in the regression modelling, whilst Table 29 and Table 30 summarise model fit and parameters estimates for the various regression models.

Table 28: Correlation matrix for log quarterly sickness-related benefit grants and selected continuous independent variables

	SB grants	WorkingAge	AvgAge	Prop55Plus	employedPer	unemployedPer	UnskilledNet
SB grants	1.00	0.92	0.84	0.90	0.88	-0.79	-0.08
WorkingAge	0.92	1.00	0.95	0.99	0.92	-0.83	-0.22
AvgAge	0.84	0.95	1.00	0.98	0.90	-0.83	-0.31
Prop55Plus	0.90	0.99	0.98	1.00	0.92	-0.85	-0.29
EmployedPer	0.88	0.92	0.90	0.92	1.00	-0.92	-0.40
UnemployedPer	-0.79	-0.83	-0.83	-0.85	-0.92	1.00	0.61
UnskilledNet	-0.08	-0.22	-0.31	-0.29	-0.40	0.61	1.00

Working age population

Of all the variables, working age population has the highest correlation with Sickness Benefit grants. All the models are tested with Work Age population as the main explanatory variable for the overall trend in SB grants.

Population aging

Both population aging variables show strong correlation with both SB grants and population growth. Because of the close correlation with working age population they do not provide any further explanatory power and therefore do not improve model fit (results not shown).

Labour market variables

Like population aging several of the labour market variables show stronger correlation with the trend in working age population than with Sickness Benefit grants and for this reason provide little further information for the model. NZIER Unskilled Net and Labour as a Constraint showed weaker correlation with working age population, and combined with working age population provided the best indicator of economic trend in the regression models (model 2). The trend variables for the next stage were: working age and NZIER Unskilled Net.

MSD interventions

Of the four MSD interventions, only alignment of SB UB benefit rates is significant (model 3). At this stage NZIER Unskilled Net become insignificant in the model and was omitted for the next stage of analysis.

Seasonal dummies

Including each separately showed March, September and December quarters are significant and produce lower SBC scores (models 8 to 10). When we then combine these dummies into a single model (model 11), March and December are significant.

Retesting trend, MSD and seasonal variables

Once the MSD and seasonal variables are included we find the NZIER Labour as a Constraint is significant (model 12). Based on working age and NZIER Labour as a Constraint we also re-tested MSD and seasonal variables. Inclusion of NZIER Labour as a Constraint changed the seasonal variables to March and June quarters (model 13), but none of the MSD variables come into the model (results not shown). Once March and June quarters were included in the model, NZIER Labour as a Constraint variable is significant and stable.

Table 29: Regression model summary fit statistics for log quarterly Sickness related benefit grants

Model	Model variables	Log(L)	SBC	Parameters	Observations
1	Trend: WorkingAge	-422.3	852.5	2	52
2	Trend: WorkingAge UnskilledNet	-416.8	845.4	3	52
3	MSD: SBUBRateAlign Trend	-407.1	830.0	4	52
4	MSD: WRK4U Trend	-413.8	843.4	4	52
5	MSD: JSS Trend	-415.2	846.2	4	52
6	MSD: SBUBRateAlign JSS WorkingAge	-408.0	831.8	4	52
7	MSD: SBUBRateAlign WRK4U JSS WorkingAge	-407.7	835.1	5	52
8	Seasonal: MarchQtr Trend MSD	-385.6	791.0	5	52
9	Seasonal: SepQtr Trend MSD	-403.7	827.2	5	52
10	Seasonal: DecQtr Trend MSD	-403.0	825.8	5	52
11	Seasonal: MarchQtr SepQtr DecQtr Trend MSD	-378.5	784.7	7	52
12	Trend: WorkingAge LabourAsAConstraint SBUBRateAlign Seasonal	-375.7	779.0	7	52
13	Seasonal: MarchQtr JuneQtr Trend MSD	-375.8	775.2	6	52
14	Final Regression Variables	-375.8	775.2	6	52

Not all models tested are shown in the table.

Table 30: Parameter estimates for alternative regression model specifications

		Labour market variables			Seasonal dummies				MSD interventions		
Model	**Intercept (MU)**	**WorkingAge**	**LabourAsACon straint**	**UnskilledNet**	**MarchQtr**	**JuneQtr**	**SepQtr**	**DecQtr**	**SBUBRateAlig n**	**JSS**	**WRK4U**
1	*** -21,455	*** 11									
2	*** -24,168	*** 12		*** 1,520							
3	*** -27,599	*** 14		** 989					*** -1,459		
4	*** -15,482	*** 8		*** 1,660							** 1,165
5	*** -19,871	*** 10		** 1,048						* 753	
6	*** -22,525	*** 12							*** -1,470	** 729	
7	*** -18,698	*** 10							*** -1,327	** 835	379
8	*** -22,658	*** 12			*** -1,085				*** -1,508	*** 723	
9	*** -23,036	*** 12					*** 555		*** -1,507	** 733	
10	*** -22,844	*** 12						*** 594	*** -1,486	** 727	
11	*** -23,318	*** 12			*** -764		*** 469	*** 497	*** -1,542	*** 727	
12	*** -30,389	*** 15	*** -4,076		*** -701		*** 487	*** 535	*** -1,686		
13	*** -29,882	*** 15	*** -4,068		*** -1,212	*** -511			*** -1,687		
14	*** -29,882	*** 15	*** -4,068		*** -1,212	*** -511			*** -1,687		

*: significant at 90%, **: significant at 95%, *** significant at 99%

Not all models tested are shown in the table.

3, Selection of ARIMA models

Table 31 and Table 32 summarises the testing of alternative ARIMA models. ACF PACF plots indicate autocorrelation. Of the ARIMA models tested, ARIMA(0,0,1)(1,0,0)$_7$ was most successful in generating a random residual series.

Table 31: Model fit for competing ARIMA models

Model	Model parameters	SBC	White noise test (p values) 6	12	18	24
ARIMA(0,0,0)(0,0,1)7	7	774.1	0.210	0.101	0.197	0.112
ARIMA(0,0,1)	7	775.5	0.585	0.290	0.470	0.311
ARIMA(0,0,0)(1,0,0)7	7	774.1	0.578	0.302	0.411	0.310
ARIMA(1,0,0)(0,0,1)7	8	775.1	0.515	0.558	0.663	0.579

Not all models tested are shown in the table.

Table 32: Variable parameters of competing ARIMA models

		Regression Variables					Autoregressive and moving average parameters		
Model	Intercept (MU)	LabourAsAConstraint	WorkingAge	MarchQtr	JuneQtr	SBUBRateAlign	MA(1)	MA(7)	AR(7)
ARIMA(0,0,0)(0,0,1)7	*** -30,045.0	*** -4,280.3	*** 15.24	*** -1,217.48	*** -522.36	** -1,664.15		*** 0.33	
ARIMA(0,0,1)	*** -29,624.0	*** -3,992.1	*** 15.07	*** -1,226.36	** -497.91	*** -1,635.61	*** -0.31		
ARIMA(0,0,0)(1,0,0)7	*** -30,030.4	*** -4,286.2	*** 15.23	*** -1,204.92	*** -533.79	*** -1,654.88			*** -0.34
ARIMA(1,0,0)(0,0,1)7	*** -29,959.9	*** -4,262.6	*** 15.20	*** -1,229.11	** -523.12	*** -1,620.42	* -0.32		*** -0.32

*: significant at 90%, **: significant at 95%, *** significant at 99%

Not all models tested are shown in the table.

4, Specification of full model

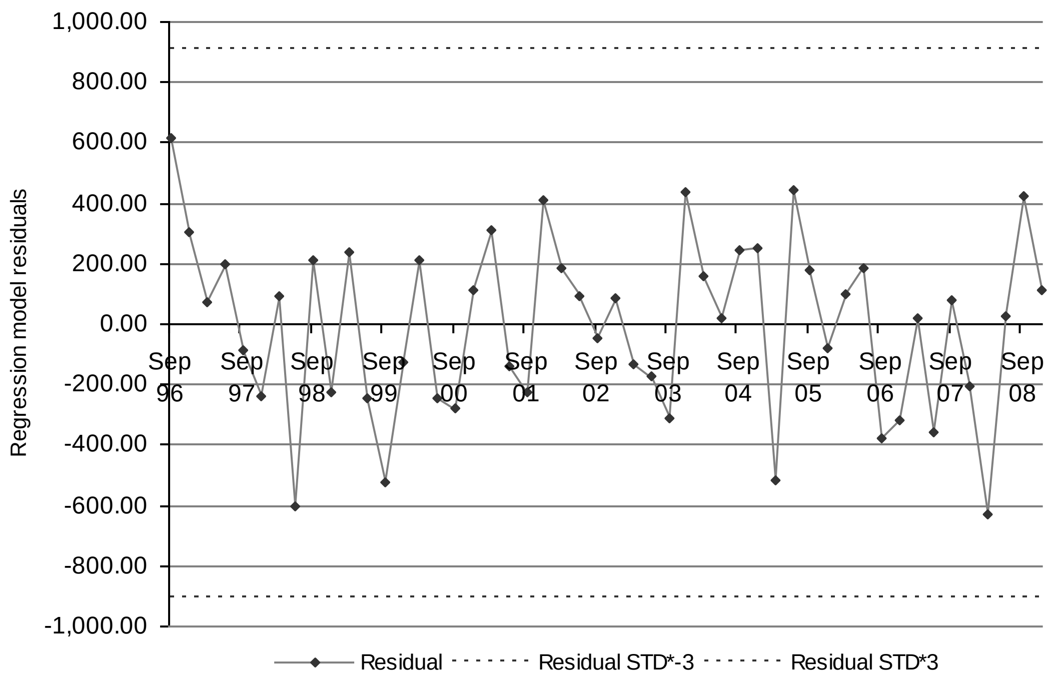
Table 33 summarises the model statistics and the beta estimates for each of the parameters in the full model with Job Search Service. Including Job Search Service does alter the ARMA terms slightly and diminishes overall model fit. Figure 29 provides the model residuals with Figure 30 showing the autocorrelation plots. The autocorrelation plots are satisfactory.

Table 33: Model of log quarterly sickness-related benefit grants model fit

	Model
Observations	52
Log(l)	-370.1
AIC	758.2
SBC	775.8
Parameters	9
Estimate	
Intercept	*** -26,031.66
MA(1)	** -0.34
AR(7)	* -0.33
WorkingAge	*** 13.55
MarchQtr	*** -1,245.44
JuneQtr	*** -522.17
LabourAsAConstraint	* -2,592.38
SBUBRateAlign	*** -1,490.08
JSS	496.05

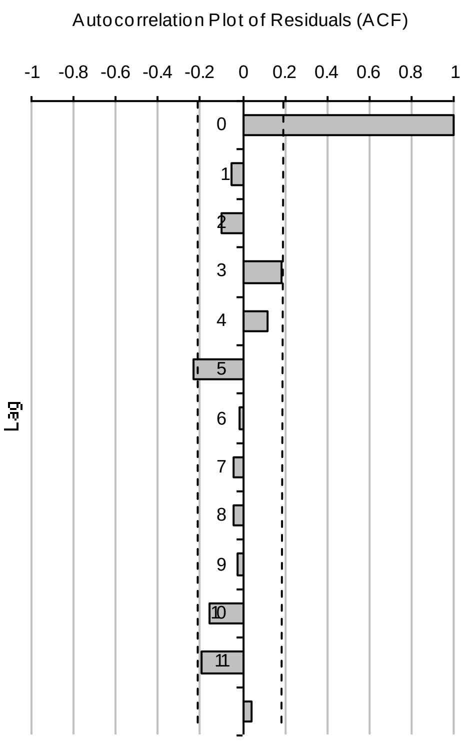
*: significant at 90%, **: significant at 95%, *** significant at 99%

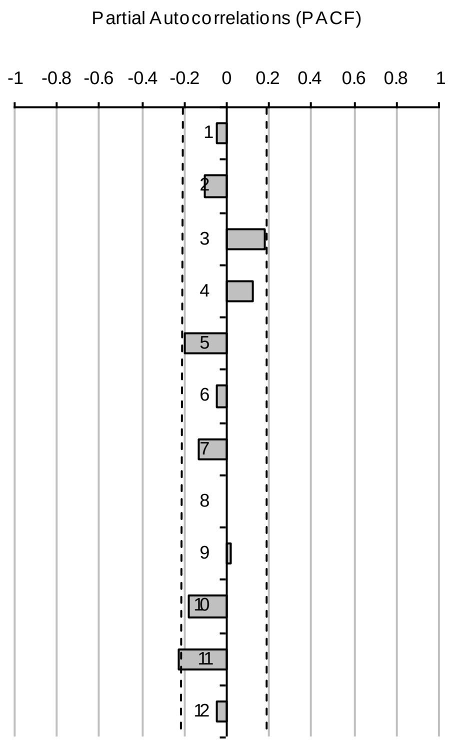
Figure 29: Plot of log quarterly sickness-related benefit grants regression plus ARIMA model residuals



Orginal series mean: 7,585, Standard deviation: 1,810

Figure 30: ACF and PACF log quarterly sickness-related benefit grants regression plus ARIMA model residuals





5, Analysis of the Job Search Service impact

Having arrived at the full model to describe quarterly sickness-related benefit grants; the discussion turns to interpretation of the model results. From the modelling process we find that Job Search Service is both insignificant in the model and its inclusion reduces the overall model fit. On this basis we conclude Job Search Service did not have a substantial impact on increasing the number of Sickness Benefit grants.

TRANSFERS FROM UNEMPLOYMENT TO SICKNESS BENEFIT

The final model examines the trend in transfers between Unemployment and Sickness Benefit. Transfers to Sickness make up the majority of transfers from unemployment-related benefit to other benefits.

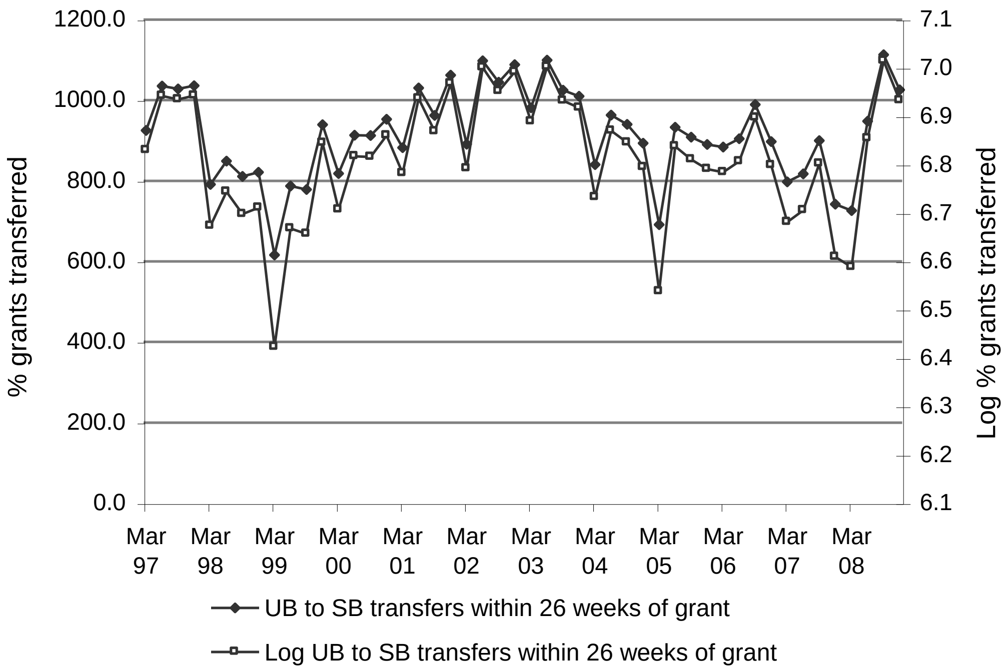
1, Exploratory data analysis

Figure 31 shows the quarterly trend in the number of transfers to Sickness Benefit within 26 weeks of a grant (excluding transfers) of an unemployment-related benefit.

Properties of the series

The Unemployment to Sickness benefit transfers is relatively stationary with no clear trend (Figure 31). Such a pattern is somewhat surprising since the total number of people granted Unemployment Benefit over this period has fallen dramatically (Figure 2, page 12). Logging the series does not help in reducing the change in variance over this period. The series shows an erratic seasonal pattern, with June quarter being a high point in transfers but not in all years (Figure 32). Figure 33 shows the series differenced by lag 4 to remove the seasonal pattern and show the underlying trend. The series appears to be

Figure 31: Quarterly series of Unemployment to Sickness benefit transfers within 26 weeks of grant (excluding transfers)



influenced by a series of sharp shocks (eg March 1998, March 2004, March 2007 and June 2008).

Figure 32: Quarterly Unemployment to Sickness benefit transfers within 26 weeks of grant (excluding transfers) differenced lag 1

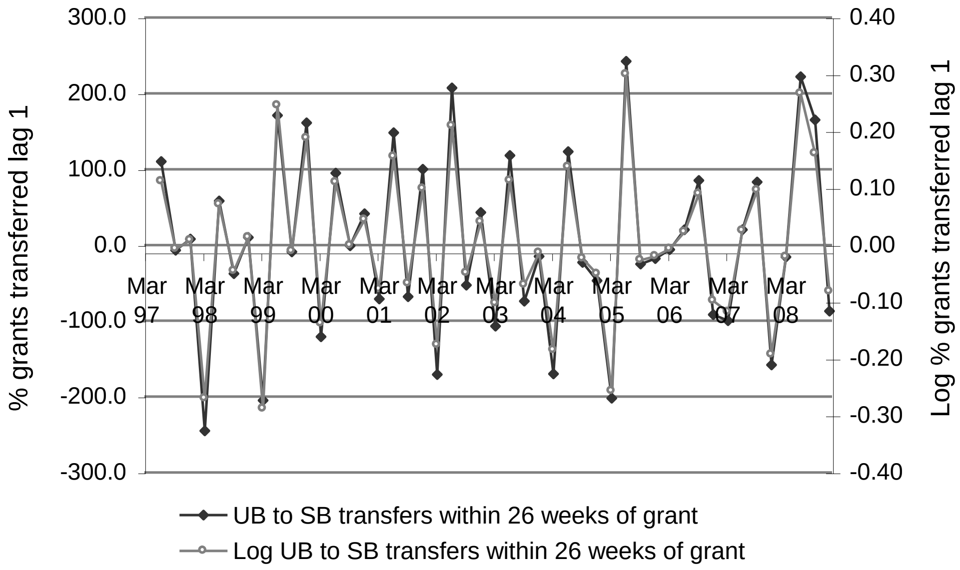
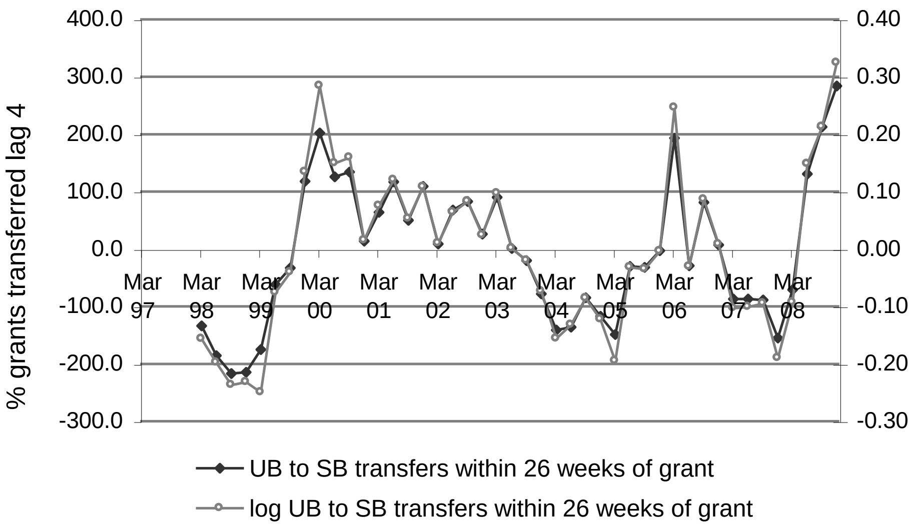


Figure 33: Quarterly Unemployment to Sickness benefit transfers within 26 weeks of grant (excluding transfers) differenced lag 4



2, Regression model selection

For discussion of the explanatory variables in the model see section on average duration on benefit after 13 weeks (page 32). In addition to these variables we also developed additional variables to represent the number of UB grants, UB stock. Other than UB grants all the trend variables have been converted into a forward three-quarter moving average with the following weightings 0.5, 1, 0.5. Table 34 provides the correlation matrix of the continuous variables included in the regression modelling, whilst Table 35 and Table 36 summarise model fit and parameters estimates for the various regression models.

Table 34: Correlation matrix for log quarterly Unemployment to Sickness benefit transfers within 26 weeks of grant (excluding transfers) and selected continuous independent variables

	UB to SB	UBgrants	UBstockMA	EmployedPerMA	UnemployedPerMA
UB to SB	1.00	0.18	0.03	0.09	-0.08
UBgrants	0.18	1.00	0.95	-0.90	0.86
UBstockMA	0.03	0.95	1.00	-0.95	0.86
EmployedPerMA	0.09	-0.90	-0.95	1.00	-0.95
UnemployedPerMA	-0.08	0.86	0.86	-0.95	1.00

Trend variables

Unlike the previous models in this report, there are no strong correlations between trend variables and transfers between UB and SB. It appears UB to SB transfers is not greatly influenced by economic conditions, population change or the total number of people coming onto unemployment-related benefits.

MSD interventions

Of the four MSD interventions, the alignment of SB UB benefit rates, Work for You and SBIB changes under Working New Zealand are significant (model 5).

Table 35: Regression model summary fit statistics for log quarterly Unemployment to Sickness benefit transfers within 26 weeks of grant (excluding transfers)

Model	Model variables	Log(L)	SBC	Parameters	Observations
1	Trend: Employed%	-295.0	594.0	1	48
2	MSD: SBIBwnz Trend NI	-291.1	590.0	2	48
3	MSD: WRK4U Trend	-288.7	589.0	3	48
4	MSD: WRK4U JSS Trend	-288.1	591.7	4	48
5	MSD: WRK4U SBIBwnz SBUBRateAlign Trend	-282.3	584.0	5	48
6	MSD: WRK4U SBIBwnz Trend	-285.0	585.6	4	48
7	MSD: WRK4U SBUBRateAlign Trend	-286.5	588.5	4	48
8	Seasonal: DecQtr Trend MSD	-280.0	583.2	6	48
9	Seasonal: MarchQtr Trend MSD	-274.9	573.0	6	48
10	Trend: Employed Seasonal MSD	-274.6	572.3	6	48
11	Trend: Employed Unemployed% Seasonal MSD NI	-272.3	567.9	6	48
12	Final Regression Variables	-272.3	567.9	6	48

Not all models tested are shown in the table.
NI: no intercept term.

Seasonal dummies

Including each separately showed March and December quarters are significant and produce lower SBC scores (models 8 and 9). When we then combine these quarter dummies into a single model December becomes significant (results not shown).

Table 36: Parameter estimates for alternative regression model specifications

Model	Intercept (MU)	Labour market variables			Seasonal dummies		MSD interventions			
		EmployedPerMA	EmployedMA	UnemployedPerMA	MarchQtr	DecQtr	WRK4U	JSS	SBUBRateAlign	SBIBwnz
1		*** 1,266								
2		*** 1,279								*** -220
3	** -2,647	*** 5,063					*** -222			
4	** -2,842	*** 5,338					*** -213	-51		
5	*** -3,665	*** 6,621					*** -237		** -107	*** -195
6	*** -2,750	*** 5,209					*** -209			** -192
7	*** -3,537	*** 6,436					*** -249		** -104	
8	*** -3,801	*** 6,800				** 62	*** -244		** -114	*** -210
9	*** -3,158	*** 5,943			*** -106		*** -218		** -107	*** -162
10	** -783		*** 1		*** -110		*** -270		*** -116	*** -198
11			*** 1	*** -3,923	*** -116		*** -274		*** -145	*** -182
12			*** 1	*** -3,923	*** -116		*** -274		*** -145	*** -182

*: significant at 90%, **: significant at 95%, *** significant at 99%

Not all models tested are shown in the table.

Retesting trend, MSD and seasonal variables

Once the MSD and seasonal variables are included we retested trend variables (models 10 and 11). The inclusion of Unemployment rate and changing Employed percentage to a count produced a better overall fit (model 11). We retested seasonal and MSD intervals, but there was no change in the model (results not shown).

3, Selection of ARIMA models

Table 37 and Table 38 summarise the testing of alternative ARIMA models. ACF PACF plots indicate autocorrelation. Of the ARIMA models tested, ARIMA$(1,0,0)_2(0,0,1)_1$ without Unemployment and SB-UB rate alignment variables was most successful in generating a random residual series.

Table 37: Model fit for competing ARIMA models

			White noise test (p values)			
Model	**Model parameters**	**SBC**	**6**	**12**	**18**	**24**
ARIMA(1,0,0)2 Drop Unemployed RateAlign	5	558.4	0.002	0.006	0.007	0.017
ARIMA(0,0,1)	7	565.0	0.145	0.253	0.062	0.189
ARIMA(1,0,0)2(0,0,1)1 Drop Unemploy RateAlign	6	547.3	0.751	0.682	0.850	0.844

Not all models tested are shown in the table.

Table 38: Variable parameters of competing ARIMA models

Model	Intercept (MU)	EmployedMA	UnemployedPerMA	WRK4U	SBUBRateAlign	SBIBwnz	MA(1)	AR(2)
		Regression variables					Autoregressive and moving average parameters	
ARIMA(1,0,0)2 Drop Unemployed RateAlign	*** -106.5	*** 0.55		*** -165.11		*** -157.08		*** 0.63
ARIMA(0,0,1)	*** -116.8	** 0.71	*** -3,391.11	*** -258.63	*** -133.51	*** -164.67	*** -0.31	
ARIMA(1,0,0)2(0,0,1)1 Drop Unemploy RateAlign	*** -107.6	*** 0.58		*** -139.76		*** -135.44	*** -0.65	*** 0.86

*: significant at 90%, **: significant at 95%, *** significant at 99%

Not all models tested are shown in the table.

4, Specification of full model

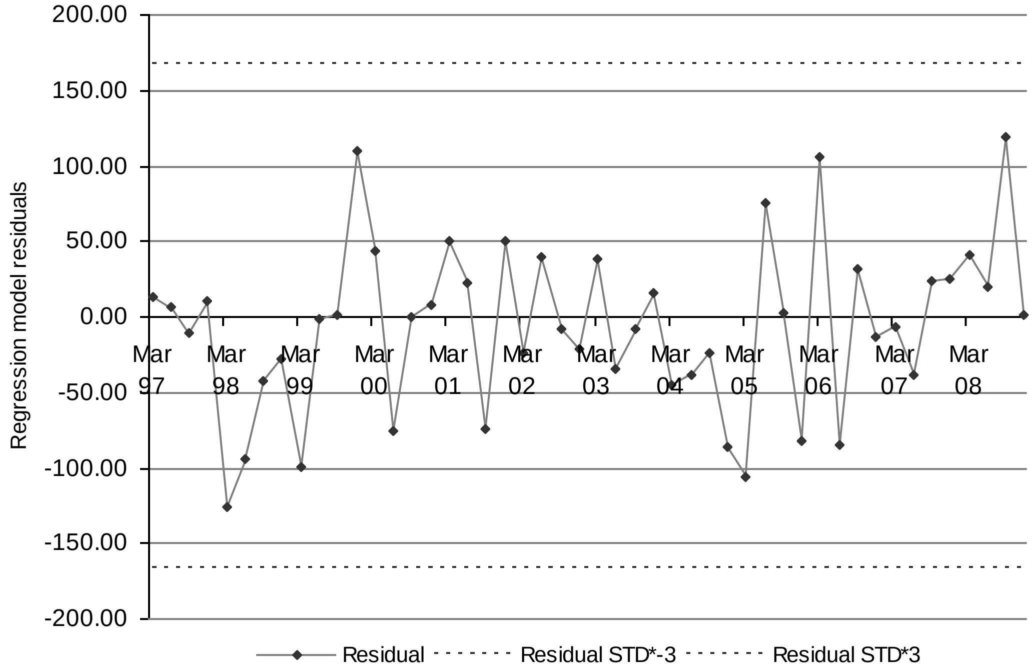
Table 33 summarises the model statistics and the beta estimates for each of the parameters in the full model with Job Search Service. Including Job Search Service does diminishes overall model fit and reduces the significance of WRK4U variable. Figure 29 provides the model residuals with Figure 30 showing the autocorrelation plots. The autocorrelation plots are satisfactory.

Table 39: Model of log quarterly Unemployment to Sickness benefit transfers within 26 weeks of grant (excluding transfers) model fit

	Model
Observations	48
Log(l)	-260.9
AIC	535.9
SBC	549.0
Parameters	7
Estimate	
Intercept	*** 0.59
MA(1)	*** -0.65
AR(2)	*** 0.88
MarchQtr	*** -105.39
WRK4U	* -120.78
JSS	-117.53
SBIBwnz	*** -136.22

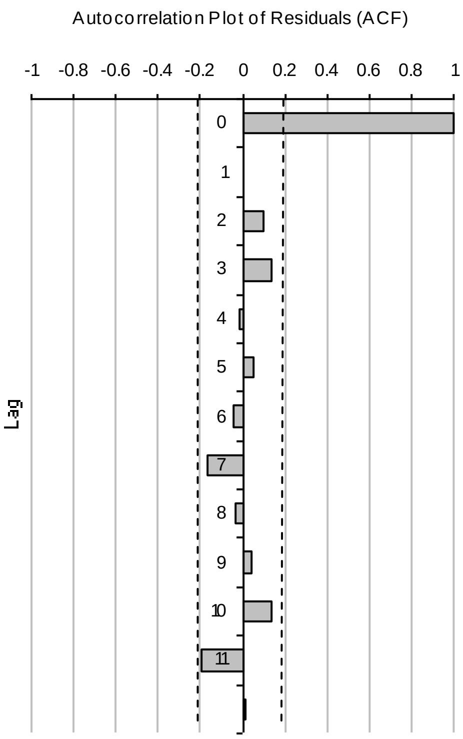
*: significant at 90%, **: significant at 95%, *** significant at 99%

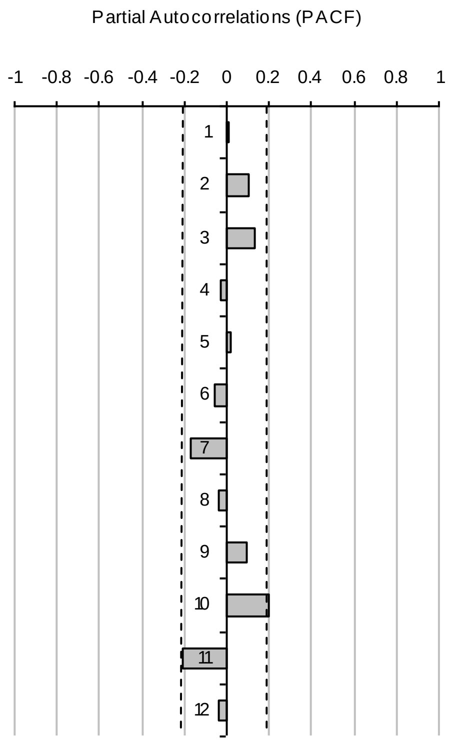
Figure 34: Plot of log quarterly Unemployment to Sickness benefit transfers within 26 weeks of grant (excluding transfers) regression plus ARIMA model residuals



Orginal series mean: 916.38, Standard deviation: 113.43

Figure 35: ACF and PACF log quarterly Unemployment to Sickness benefit transfers within 26 weeks of grant (excluding transfers) regression plus ARIMA model residuals





5, Analysis of the Job Search Service impact

Having arrived at the full model to describe quarterly Unemployment to Sickness benefit transfers within 26 weeks of grant (excluding transfers); the discussion turns to interpretation of the model results. From the modelling process we find that Job Search Service is both insignificant in the model and its inclusion reduces the overall model fit. On this basis we conclude Job Search Service did not have a substantial impact on the number of transfers to Sickness Benefit within the first 26 weeks of being granted an unemployment-related benefit.

DEPENDENT AND INDEPENDENT DATA SERIES

Dependent series

Table 40: Dependent variables

Quarter	UB related benefit grants	Average benefit duration within 13 weeks	Average benefit duration within 26 weeks	Average benefit duration within 52 weeks	SB related benefit grants	UB to SB transfers
September 1996	33,795			211.83	6,628	
December 1996	36,976			207.23	6,687	
March 1997	27,840		127.60	213.96	5,621	925
June 1997	31,578	78.74	136.86	225.11	6,488	1,035
September 1997	34,555	78.05	135.19	223.32	6,831	1,028
December 1997	38,888	79.26	133.86	219.52	6,699	1,036
March 1998	31,274	77.33	133.65	223.72	5,838	791
June 1998	35,382	79.31	137.15	223.89	5,836	849
September 1998	36,088	77.88	134.03	218.52	5,516	811
December 1998	41,079	78.90	132.03	214.15	5,542	821
March 1999	30,804	76.79	132.74	220.81	4,951	616
June 1999	32,164	79.37	137.92	223.14	5,494	787
September 1999	31,744	76.69	132.13	212.96	5,662	778
December 1999	39,680	77.39	126.05	200.28	5,912	939
March 2000	29,170	74.30	126.06	206.75	5,436	818
June 2000	31,482	76.90	131.40	212.26	5,705	913
September 2000	31,561	75.21	128.19	205.66	6,075	912
December 2000	37,056	76.62	124.81	197.21	6,408	953
March 2001	27,260	73.71	124.11	203.61	5,585	882
June 2001	29,259	75.24	127.43	205.61	6,067	1,030
September 2001	29,741	74.40	126.04	200.48	6,415	962
December 2001	35,619	76.97	124.45	195.36	7,001	1,062
March 2002	26,212	72.52	120.45	194.94	6,046	891
June 2002	27,772	75.42	127.29	203.24	6,792	1,098
September 2002	29,090	75.27	127.08	200.35	7,227	1,045
December 2002	31,561	76.65	123.66	193.08	7,312	1,088
March 2003	23,523	72.81	120.95	192.93	6,288	981
June 2003	24,725	75.52	126.07	195.34	7,183	1,099
September 2003	24,742	74.33	123.14	187.57	7,581	1,025
December 2003	23,908	75.59	120.05	182.49	8,308	1,010
March 2004	18,087	71.29	115.40	180.85	7,173	840
June 2004	18,038	74.24	123.70	191.90	7,950	963
September 2004	20,026	73.76	120.64	184.33	8,735	940
December 2004	20,862	75.20	118.89	182.76	8,931	893
March 2005	14,549	70.53	114.02	182.78	7,053	691
June 2005	16,347	74.54	124.25	196.68	8,696	933

Quarter	UB related benefit grants	Average benefit duration within 13 weeks	Average benefit duration within 26 weeks	Average benefit duration within 52 weeks	SB related benefit grants	UB to SB transfers
September 2005	18,414	74.66	122.28	188.68	9,268	908
December 2005	16,992	76.45	122.30	189.06	9,089	890
March 2006	15,035	71.65	115.53	180.13	8,133	884
June 2006	14,269	75.58	124.34	189.73	9,162	904
September 2006	16,739	73.23	115.89	170.15	9,242	989
December 2006	13,895	73.49	113.00	168.19	9,541	897
March 2007	11,190	67.38	104.10	160.40	8,604	797
June 2007	10,179	70.04	111.78	171.83	9,373	817
September 2007	12,724	70.56	108.86	165.17	10,380	900
December 2007	10,715	72.18	112.30	177.38	10,299	742
March 2008	9,572	69.70	110.88	183.20	8,582	726
June 2008	11,105	74.45	123.49	205.35	10,188	948
September 2008	16,228	74.98	122.95		11,565	1,113
December 2008	17,093	78.72	131.34		11,592	1,026
March 2009	22,978	77.28			10,094	
June 2009	29,355				11,630	

Source: Information Analysis Platform, data extracted 30 September 2009 (research data, not official MSD statistics)

Independent series

Table 41: HLFS derived explanatory variables

Quarter	Working age population (15-64) WorkingAge	Employed (15-64) Employed	% working age in employment EmployedPer	Employed full time (15-64) EmployedFT	% working age in full time employment EmployedFTPer	Unemployed (15-64) Unemployed	% working age in unemployment UnemployedPer	Not in the labour force (15-64) NotInLabFrce	Labour force (15-64) LabourForce	Average age of working age population AvgAge	% working age over 55 years Prop55Plus
March 1996	2,359	1,698	70.3%	1,197	49.8%	123	6.8%	593	1,820	36.8	9.0%
June 1996	2,367	1,709	70.6%	1,192	49.4%	113	6.2%	600	1,822	36.8	9.2%
September 1996	2,375	1,720	70.8%	1,195	49.3%	117	6.4%	593	1,837	36.8	9.2%
December 1996	2,386	1,728	70.8%	1,182	48.6%	115	6.2%	598	1,843	36.9	9.2%
March 1997	2,424	1,720	70.2%	1,208	49.5%	131	7.1%	599	1,852	36.9	9.4%
June 1997	2,430	1,721	70.0%	1,220	49.8%	126	6.8%	611	1,846	37.0	9.6%
September 1997	2,435	1,721	69.9%	1,211	49.3%	128	6.9%	614	1,848	37.0	9.5%
December 1997	2,443	1,740	70.4%	1,219	49.5%	129	6.9%	601	1,868	37.1	9.4%
March 1998	2,449	1,724	69.7%	1,250	50.6%	146	7.8%	605	1,871	37.1	9.6%
June 1998	2,452	1,706	68.8%	1,259	50.9%	147	7.9%	627	1,852	37.2	9.9%
September 1998	2,455	1,706	68.7%	1,252	50.5%	140	7.6%	636	1,846	37.3	10.0%
December 1998	2,460	1,722	69.2%	1,269	51.1%	147	7.8%	619	1,868	37.3	10.1%
March 1999	2,492	1,726	69.3%	1,313	52.8%	149	7.9%	617	1,875	37.4	10.4%
June 1999	2,493	1,720	69.0%	1,320	53.0%	137	7.4%	637	1,856	37.5	10.5%
September 1999	2,496	1,730	69.3%	1,321	53.0%	128	6.9%	638	1,858	37.5	10.5%
December 1999	2,502	1,771	70.8%	1,327	53.2%	120	6.3%	612	1,890	37.6	10.2%
March 2000	2,508	1,757	70.1%	1,362	54.4%	130	6.9%	621	1,887	37.6	10.2%
June 2000	2,509	1,743	69.5%	1,365	54.5%	118	6.4%	648	1,862	37.7	10.5%

Quarter	Working age population (15-64) WorkingAge	Employed (15-64) Employed	% working age in employment EmployedPer	Employed full time (15-64) EmployedFT	% working age in full time employment EmployedFTPer	Unemployed (15-64) Unemployed	% working age in unemployment UnemployedPer	Not in the labour force (15-64) NotInLabForce	Labour force (15-64) LabourForce	Average age of working age population AvgAge	% working age over 55 years Prop55Plus
September 2000	2,512	1,768	70.4%	1,359	54.1%	111	5.9%	634	1,879	37.7	10.9%
December 2000	2,518	1,804	71.6%	1,343	53.5%	109	5.7%	605	1,913	37.8	11.0%
March 2001	2,524	1,795	71.1%	1,382	54.9%	112	5.9%	617	1,907	37.8	11.2%
June 2001	2,526	1,794	71.0%	1,377	54.5%	103	5.5%	629	1,897	37.9	11.3%
September 2001	2,533	1,801	71.1%	1,356	53.7%	101	5.3%	631	1,902	37.9	11.7%
December 2001	2,548	1,846	72.5%	1,343	53.0%	107	5.5%	595	1,953	37.9	11.6%
March 2002	2,563	1,857	72.4%	1,375	54.0%	113	5.8%	594	1,970	37.9	11.8%
June 2002	2,576	1,851	71.8%	1,375	53.6%	103	5.3%	622	1,954	38.0	12.3%
September 2002	2,590	1,857	71.7%	1,333	51.7%	107	5.5%	626	1,964	38.0	12.4%
December 2002	2,607	1,895	72.7%	1,331	51.4%	99	5.0%	613	1,994	38.0	12.3%
March 2003	2,625	1,890	72.0%	1,352	51.9%	109	5.5%	625	1,999	38.0	12.4%
June 2003	2,640	1,893	71.7%	1,357	51.7%	96	4.8%	652	1,988	38.0	13.0%
September 2003	2,653	1,919	72.3%	1,339	50.7%	89	4.5%	644	2,008	38.0	12.9%
December 2003	2,667	1,946	73.0%	1,359	51.2%	95	4.6%	626	2,041	38.0	13.0%
March 2004	2,680	1,948	72.7%	1,398	52.4%	97	4.8%	635	2,045	38.1	13.0%
June 2004	2,690	1,947	72.4%	1,402	52.3%	84	4.2%	659	2,031	38.1	13.5%
September 2004	2,699	1,970	73.0%	1,367	50.8%	78	3.8%	650	2,049	38.1	13.7%
December 2004	2,710	2,028	74.8%	1,393	51.6%	77	3.7%	605	2,105	38.1	13.5%
March 2005	2,721	2,012	73.9%	1,436	53.0%	91	4.3%	618	2,103	38.2	13.8%
June 2005	2,728	2,008	73.6%	1,447	53.2%	79	3.8%	642	2,086	38.2	14.0%
September 2005	2,735	2,035	74.4%	1,412	51.7%	79	3.7%	621	2,114	38.2	14.1%

Quarter	Working age population (15-64) WorkingAge	Employed (15-64) Employed	% working age in employment EmployedPer	Employed full time (15-64) EmployedFT	% working age in full time employment EmployedFTPer	Unemployed (15-64) Unemployed	% working age in unemployment UnemployedPer	Not in the labour force (15-64) NotInLabForce	Labour force (15-64) LabourForce	Average age of working age population AvgAge	% working age over 55 years Prop55Plus
December 2005	2,746	2,068	75.3%	1,415	51.7%	78	3.6%	599	2,146	38.2	14.0%
March 2006	2,757	2,065	74.9%	1,463	53.3%	98	4.5%	594	2,163	38.2	14.1%
June 2006	2,766	2,073	74.9%	1,476	53.5%	78	3.6%	615	2,152	38.3	14.4%
September 2006	2,773	2,068	74.6%	1,451	52.5%	81	3.8%	624	2,149	38.3	14.2%
December 2006	2,783	2,088	75.1%	1,457	52.5%	80	3.7%	614	2,169	38.3	14.1%
March 2007	2,792	2,097	75.1%	1,504	54.0%	96	4.4%	599	2,193	38.3	14.5%
June 2007	2,796	2,096	75.0%	1,509	54.0%	79	3.6%	620	2,176	38.3	14.8%
September 2007	2,801	2,092	74.7%	1,484	53.1%	78	3.6%	631	2,170	38.4	14.7%
December 2007	2,810	2,133	75.9%	1,505	53.7%	75	3.4%	602	2,208	38.4	14.6%
March 2008	2,818	2,085	74.0%	1,550	55.2%	95	4.4%	638	2,180	38.4	15.1%
June 2008	2,823	2,111	74.8%	1,566	55.6%	86	3.9%	626	2,197	38.4	15.0%
September 2008	2,829	2,108	74.5%	1,541	54.6%	94	4.2%	627	2,202	38.5	15.1%
December 2008	2,836	2,138	75.4%	1,564	55.3%	102	4.5%	596	2,240	38.5	15.0%
March 2009	2,844	2,092	73.5%	1,608	56.7%	128	5.8%	625	2,219	38.5	15.4%
June 2009	2,852	2,084	73.1%	1,621	57.0%	132	6.0%	635	2,217	38.5	15.6%

Source: Statistics New Zealand (Household Labour Force Survey Quarterly series).

Table 42: Non HLFS explanatory variables

	NZIER			Statistics New Zealand		MSD	
	% reporting unskilled labour is hard to find	Net difference between % reporting unskilled labour hard to find	% reporting labour as main constraint on firm growth			Average stock over the quarter	Total number of grants over the quarter (excluding transfers)
Quarter	UnskilledHard	UnskilledNet	LabourAsAConstraint	GDPprod	GDPpexp	UBStock	UBgrants
March 1996	13%	95%	7%	23,661	23,509	0	0
June 1996	9%	101%	7%	23,443	23,913	120,879	0
September 1996	10%	106%	5%	23,667	22,767	124,847	33,795
December 1996	8%	105%	5%	25,429	25,618	129,897	36,976
March 1997	6%	108%	4%	24,128	23,986	129,833	27,840
June 1997	6%	115%	4%	24,218	24,791	122,895	31,578
September 1997	5%	117%	4%	24,254	23,613	127,333	34,555
December 1997	5%	119%	4%	25,662	26,200	134,217	38,888
March 1998	4%	119%	3%	24,201	24,498	138,817	31,274
June 1998	3%	132%	2%	24,014	24,639	135,831	35,382
September 1998	2%	137%	2%	24,151	23,583	143,850	36,088
December 1998	3%	126%	2%	25,857	26,610	150,553	41,079
March 1999	7%	110%	5%	24,820	25,463	152,776	30,804
June 1999	5%	111%	3%	24,641	25,584	146,962	32,164
September 1999	5%	107%	4%	25,544	24,958	150,288	31,744
December 1999	10%	96%	6%	27,496	27,945	151,729	39,680
March 2000	15%	91%	8%	26,415	26,976	150,194	29,170
June 2000	12%	100%	5%	25,796	26,623	139,502	31,482
September 2000	12%	97%	6%	26,249	25,689	139,837	31,561
December 2000	14%	91%	7%	27,918	28,655	140,273	37,056
March 2001	17%	89%	9%	26,589	27,039	136,601	27,260
June 2001	21%	84%	9%	26,473	27,303	126,560	29,259
September 2001	18%	88%	8%	26,984	26,437	126,475	29,741
December 2001	16%	92%	7%	29,133	29,777	126,298	35,619
March 2002	19%	86%	11%	27,816	28,296	123,714	26,212
June 2002	22%	81%	12%	27,719	28,220	113,730	27,772
September 2002	23%	81%	12%	28,380	27,822	114,221	29,090
December 2002	23%	82%	16%	30,634	31,427	112,602	31,561
March 2003	24%	79%	14%	29,096	29,921	109,423	23,523
June 2003	20%	86%	14%	28,771	29,561	99,364	24,725
September 2003	24%	79%	16%	29,655	29,056	98,002	24,742
December 2003	29%	73%	20%	31,750	32,248	91,794	23,908
March 2004	27%	75%	23%	30,636	31,170	84,373	18,087
June 2004	31%	71%	20%	30,460	31,138	70,425	18,038
September 2004	35%	66%	22%	30,933	30,359	67,887	20,026
December 2004	39%	60%	25%	32,614	33,438	64,610	20,862

	NZIER			Statistics New Zealand		MSD	
	% reporting unskilled labour is hard to find	Net difference between % reporting unskilled labour hard to find	% reporting labour as main constraint on firm growth			Average stock over the quarter	Total number of grants over the quarter (excluding transfers)
Quarter	UnskilledHard	UnskilledNet	LabourAsAConstraint	GDPprod	GDPpexp	UBStock	UBgrants
March 2005	46%	51%	26%	31,353	31,827	61,283	14,549
June 2005	30%	74%	24%	31,405	32,070	51,703	16,347
September 2005	26%	77%	20%	31,908	31,421	51,137	18,414
December 2005	23%	83%	19%	33,490	34,339	49,698	16,992
March 2006	17%	91%	19%	32,276	32,718	48,948	15,035
June 2006	14%	96%	15%	31,858	32,699	41,555	14,269
September 2006	16%	93%	14%	32,311	31,990	41,890	16,739
December 2006	17%	89%	19%	34,208	35,697	38,271	13,895
March 2007	24%	79%	22%	33,061	33,884	33,238	11,190
June 2007	28%	74%	19%	32,924	34,118	25,064	10,179
September 2007	24%	81%	20%	33,423	32,787	23,770	12,724
December 2007	33%	67%	21%	35,458	36,154	21,832	10,715
March 2008	27%	78%	23%	33,737	33,987	21,197	9,572
June 2008	15%	106%	18%	33,182	33,696	17,800	11,105
September 2008	9%	116%	10%	33,294	32,106	22,138	16,228
December 2008	6%	143%	5%	34,697	35,667	26,074	17,093
March 2009	2%	163%	4%	32,855	33,527	35,468	22,978
June 2009	2%	167%	3%	32,480	33,707	46,116	29,355

Source: Statistics New Zealand, 2009, NZIER quarterly employer survey 2009, Ministry of Social Development 2009 (research data not official statistics).

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