The Relationship between Labor Market Conditions and Welfare Receipt in Australia: A Stock-Flow Analysis

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ANU Working Papers in Economics and Econometrics
573

April, 2012 JEL: C59, J11, I38

ISBN: 086831 573 7

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Abstract

This paper estimates the role of labor market conditions in the recent decline in welfare receipt among the working age population in Australia. A stock-flow model is used, which involves modeling the underlying welfare flows and using the results to simulate the effect of labor market conditions on the welfare stock. The simulation analysis suggests that improvements in the labor market explain the majority of the decline. A range of robustness checks are undertaken including using alternative levels of geographic disaggregation to deal with likely measurement error in labor market data.

JEL classifications: C59, J11, I38.

[+] This paper is derived from my PhD thesis. I am indebted to my supervisors Jeff Borland, John Creedy and Lixin Cai for their constructive guidance. Thanks are also due to Paul Miller, Richard Disney, Tue Gorgens, Joshua Chan and Cain Polidano for their invaluable comments. I acknowledge the Commonwealth Department of Education, Employment and Workplace Relation (DEEWR) for the sample of the LDS data and the assistance provided in using the sample. The research findings and the views expressed in this paper are my own, and should not be attributed to the Commonwealth department.

1 Introduction

Like in many other developed countries, there was a substantial increase in welfare reliance in Australia in the last three decades of the 20th century. In the 1990s, when the number of long-term welfare recipients remained persistently high despite improving labor market conditions, concerns were raised that the growth in recipient numbers may have been caused by 'passive' welfare policy whereby recipients are generally not required to undertake any activity in return for the payments they received.

In response, it has been on the government welfare reform agenda to shift welfare policy towards a more active model in which recipients are increasingly subject to activity testing. In contrast with the radical welfare reforms in the U.S, the pace of welfare reforms in Australia has been gradual in nature. These reforms have taken place in a period of sustained improvements in labor market conditions and welfare use has since continually declined. From its peak of 19.5% in 1996, the rate of income support receipt among the population aged 15-59 has fallen to 15% in 2005.[1]

It is plausible that labor market conditions and welfare reforms have both been responsible for the decline in welfare reliance. This paper focuses on examining the contribution of labor market conditions to the decline in welfare reliance over the period 1997-2005. The paper does not try to estimate the contribution of welfare reforms because, with welfare policy being uniform nation-wide, there is no plausible estimation strategy to separate welfare reform effects from the effects of unobserved time-varying factors. As it will be shown however, there is sufficient geographic variation in labor market conditions to identify the

[1]Statistics exclude payments to full-time students and are based on the author's calculations using administrative data.

effects of labor market conditions. Understanding the impact is of great policy implication. For example, it will provide answers to the question of whether strong labor market conditions can significantly reduce welfare reliance, which can be vital in designing optimal welfare policy. Understanding the role of labor market conditions is also useful in forecasting and planning welfare budget.

The main contribution of this paper is that it provides insights into the relationship between welfare reliance and labor market conditions in Australia. Thus far, the literature has been mainly focused on welfare reliance in the United States. This paper enriches the literature by providing insights from the context of a small country that has a rather distinct welfare system. The focus of the Australian welfare system is poverty alleviation, not income maintenance, which is the primary objective in most developed countries. Accordingly, Australia does not provide social insurance payments that are typically available elsewhere. Instead, the core component of the welfare system consists of a number of means-testing "income support" payments that are relatively low in payment levels and only available to people on low incomes. Given the differences, the Australian income support system is more sustainable than the current welfare models in most OECD countries. Given its unique and sustainable welfare system, insights from Australia are useful in analyzing alternative welfare policy for other countries.

The second contribution of this paper comes from its sophisticated econometric approach in accounting for the persistence of welfare receipt. Most studies model the aggregate stock measures of welfare receipt directly and hence can only model the persistence in welfare receipt using lagged variables. This paper utilizes recently available longitudinal administrative data on welfare receipt that allow a better way to control for the persistence in welfare receipt. In particular, this paper uses a stock-flow approach proposed by Klerman and Haider (2004), which involves modeling the welfare entry and continuation rates and then using the results to simulate the impact on the welfare stock. By modeling the entry and continuation rates separately, I explicitly account for “state dependence” in welfare receipt. Furthermore, by allowing the continuation rate to vary with time on welfare, I explicitly account for the possibility of “duration dependence” in welfare receipt. With the ability to account for the sources of persistence of welfare receipt in such an explicit way, the paper avoids the biases associated with modeling the persistence in a reduced form.

The third contribution of this paper is in its approach in mitigating data issues. This paper relies on local labor market data to identify the model because there is not enough variation in the national-level data to distinguish the effects of labor market conditions from those of welfare reforms and other factors. Local labor market data also arguably reflect employment opportunities better than data at the national level. As survey estimates, however, local labor market data are measured with substantial sampling error, which can bring about attenuation bias to the estimates. For sensitivity analysis, I explore several estimation approaches that vary in the extent of attenuation bias.

The results from this paper show that that the level of welfare reliance is closely related to labor market conditions. Welfare flows are shown to be strongly related to labor market conditions and simulation results suggests that labor market improvements explain the majority of the recent decline in welfare receipt among the people of working age. The findings from this paper are broadly in line with findings presented in international literature, highlighting the importance of improving labor market conditions in reducing the level of welfare reliance.

The results also provide important insights into econometric modeling. The estimated impacts of labor market conditions on income support receipt increase substantially as the extent of measurement error in the data decreases. By contrast, the estimates are robust to alternative measures of labor market conditions. These findings underscore the importance of undertaking robustness checks in empirical studies when data are measured with errors.

The rest of the paper proceeds as follows. Section 2 presents the key features of the Australian welfare system and a quick review of the international literature. Section 3 describes the stock-flow model. Section 4 discusses the data used in the analysis. Section 5 discusses the different model specifications and their results. Section 6 provides a robust check of the results. Finally, Section 7 provides concluding remarks.

2 Background and Related Literature

2.1 The Australian Income Support System

As noted by Whiteford and Angenent (2002), the income support system serves as an eventual safety net, focusing on protecting individuals and families against poverty. The focus of poverty relief makes the Australian income support system distinct from most other developed countries where income maintenance across an individual's life cycle is the primary objective and poverty relief is an additional objective.

As a consequence, government income support payments in Australia differ from those in most other developed countries. Benefits are flat-rate and paid from general government revenue. Benefits are effectively available on an indefinite basis, subject to the means tests. The coverage of the system is universal in a sense that payments are non-contributory. The core component of the welfare system consists of a number of "income support" payments, of which the maximum benefit levels are set to ensure subsistence living standards for recipients and their families.[2] These diverse and mutually exclusive payments are similar in their

[2] According to Harmer (2008), the payment rate for a single income support recipients is above 50% of the take-home earnings of an individual working full-time on minimum wage.

payment levels but are targeted to different categories of individuals in need. For example, the Age Pension is provided to the aged and the main payment types that are available for the working age population include Disability Support Pension, Unemployment Benefits, Parenting Payments and Carer Payment.

There is also an extensive range of supplementary payments called non-income support payments that are available to low-income individuals and families with children. With relatively low benefit levels and relaxed means-tests these payments are intended to supplement, not to provide the principal source of income for individuals. With the main interest in welfare reliance, this paper focuses on income support receipt.

Recent changes to income support payments: toward a more active model

Income support payments are traditionally based on needs; except for the means-test, income support recipients typically did not face any requirement in return for payments. Up to late 1990s, activity testing was only limited to the unemployed of young age. In response to a growing concern that this passive welfare model may have contributed to the increase in welfare dependency among people of working age, the government commissioned an extensive review of the welfare system in 1999. Based on the report of this review (McClure, 2000), in 2000 the government outlined a welfare reform agenda that aims to shift the welfare policy toward a more active model whereby more and more recipients are subject to activity testing.

In contrast to the radical welfare reforms occurred in the United States in the 1990's, the pace of the welfare reform in Australia has been gradual and the most dramatic changes have only taken place after 2006. The notable changes that occurred during the period considered in this paper (prior to 2006) include tightening eligibility criteria for Disability Support Pension, stricter activity tests to Unemployment Benefits, a gradual introduction of activity testing to Parenting Payments, and closing residual payments. While it would be of interest to the policy makers to understand the effects of these changes on the number of recipients, this paper does not try to explicitly estimate their effects, because with welfare policy being uniform nation-wide, there is no plausible estimation strategy to separate welfare reform effects from the effects of unobserved time-varying factors.

This paper focuses on the relationship between labor market conditions and income support receipt. By income support (or welfare), I refer to all income support payments, implicitly treating them as an integrated payment. This treatment is to provide a complete picture of welfare reliance and to avoid any complication arising from the high level of movement between payments. The focus of the paper is on welfare reliance among people of working age, and hence it considers only individuals below the age of 60.

2.2 Literature review

There is a vast literature in the United States attempting to explain the relative role of economic conditions and welfare policy in the decline in welfare caseloads during the 1990s (Blank, 2001; Council of Economic Advisers (CEA), 1997; Council of Economic Advisors (CEA), 1999; Figlio, Gundersen, & Ziliak, 2000; Figlio & Ziliak, 1999; G. Wallace & Blank, 1999; Ziliak, Figlio, Davis, & Connolly, 2000; Ziliak, Gundersen, & Figlio, 2003). Most of these studies utilize the variation in welfare receipt across states to distinguish the effects of welfare policies and the role of economic conditions. In particular, using the time series cross-section data, these studies model the aggregate welfare stock at the state level as a function of the state unemployment rate (the proxy for economic conditions), welfare policy variables, time effects and state fixed effects. Moreover, with the growing literature providing both theoretical and empirical support for the presence of state and duration dependence in welfare receipt (see Blank, 1989 ; Moffitt, 1992), most studies account for the persistence in welfare receipt by including lagged values of either the dependent variable or the independent variables .

With respect to the impacts of economic conditions, these studies have reached widely varying conclusions. For example, CEA (1997) includes one lag of the annual unemployment rate in the regression and attributes 44% of the decline in welfare use during 1993-1996 to the improving economic conditions. Ziliak *et al*. (2000) using a dynamic model with lagged dependent variables attribute nearly two-thirds of the same decline to economic conditions. Figlio and Ziliak (1999) attempt to reconcile these results and conclude that the differences are partly due to differences in accounting for the persistence in welfare receipt; whether lagged values of the dependent variable are included. CEA (1999), an update of the CEA (1997), also reports that their estimates are sensitive; by including a second lag of the unemployment rate the estimated role of the economic conditions is reduced by half.

The varying estimates highlight the caveats of modeling the persistence in welfare stock using lagged variables: the estimates are sensitive to model misspecification and a lack of data variation. Achen (2000) shows that in the presence of omitted variables and heavy trending exogenous variables, the coefficients of lagged dependent variables are likely to be over-estimated while the coefficient estimates for independent variables are likely to be imprecise. According to the author, the coefficients on lagged dependent variables are large because they pick up the effects of omitted variables and the imprecise estimates for other variables are due to the fact that the lagged dependent variables capture much of variation in the data, leaving little to identify the effects of the remaining variables.

Similarly, the approach of including only lagged unemployment rates has its own identification problem. As implied by Klermain and Haider (2004), whenever welfare receipt exhibits state and duration dependence, welfare caseload at a given period depends on the lagged values of all time-varying independent variables, not just on the lagged values of the unemployment rate. Furthermore, the high level of serial correlation in the unemployment rate can lead to the imprecise estimates of the current unemployment rate and its lags.

There are several possible explanations for the widespread usage of these stock models despite their caveats. First, these models are straightforward to implement and their estimated coefficients are easily interpreted. Second, and perhaps more importantly, data on welfare receipt are available mostly in stock measures.

Klermain and Haider (2004) propose an alternative estimation method when data on flows onto and off welfare are available. Instead of estimating the stock level directly, they propose to model the underlying flows onto and off welfare and then use the estimated model to simulate the impact on the stock levels. This stock-flow model is quite complicated to implement and the coefficient estimates from the flow models do not relate to the stock levels directly. Its main advantage over the stock methods, however, is that the stock-flow model can account for the sources of persistence including state and duration dependence directly. As a result, the stock-flow approach avoids the biases arising from accounting for these sources of persistence using lagged variables.

Klerman and Haider (2004) also estimate the stock-flow model using Californian administrative data and they conclude that about half of the welfare caseload decline in California can be attributed to declining unemployment. Unlike the sensitive results obtained from the stock models, their estimates are robust to the number of lags of the unemployment rate included in the regressions. The robustness of the stock-flow model is also found by Klerman, Haider and Roth (2003), who reconsider the model using richer specifications.

There have also been a number of studies that use household panel survey data to study the evolution of aggregate welfare caseload. For example, Gittleman (2001) and Grogger(2004) and Wallace (2007) use data from the Survey of Income and Program Participation (SIPP) to evaluate the impacts of policy changes and economic conditions on the welfare flows and aggregate caseloads in various periods in the United States. Cappellari & Jenkin (2009) use data from the British Household Panel Survey (BHPS) to explain the trend in welfare reliance in Britain during the period 1991-2005. Being able to control for extensive variables, these studies minimize the omitted variable bias. However, because of small sample size, their estimates are found to be sensitive to different model specifications.

3 Econometric Framework: A Stock-Flow Model

This paper uses the stock-flow approach that was proposed by Klerman and Haider (2004). The model follows simply from writing down the stock-flow identities that describe how the number of individuals in different welfare receipt statuses evolves over time.

Consider a simple situation, where individuals are distinguished by either being on welfare or being off-welfare. Formally, let $S_{r,t}$ be the number of welfare recipients, E_t be the number of welfare entrants, and L_t be the number of welfare leavers (exits) in period t. The current number of welfare recipients can be expressed as:

$$S_{r,t} = S_{r,t-1} - L_t + E_t. \tag{1}$$

To express the welfare flows in terms of proportions, let $S_{n,t}$ be the number of individuals not on welfare (non-recipients). Dividing and multiplying the first two terms of the right hand side of Equation (1) by $S_{r,t-1}$ and the third term by $S_{n,t-1}$, we have :

$$S_{r,t} = \frac{S_{r,t-1} - L_t}{S_{r,t-1}} S_{r,t-1} + \frac{E_t}{S_{n,t-1}} S_{n,t-1}. \tag{2}$$

Let e_t be the welfare entry rate $e_t = E_t / S_{n,t-1}$, and c_t be the continuation rate $c_t = (S_{r,t-1} - L)/S_{r,t-t}$, Equation (2) can be expressed more compactly as:

$$S_{r,t} = c_t S_{r,t-1} + e_t S_{n,t-1}. \tag{3}$$

Equation *(3)* describes how the recipient stock evolves over time for a general population, whereby changes in the stock are limited to the flows onto and off welfare. However, this paper focuses on the incidence of welfare receipt amongst people of working age (aged 15-59), whereby changes in the recipient stock are also brought about by excluding welfare recipients aged 60 or older. It is necessary to make adjustments to Equation (3) to reflect this exclusion.

Let O_t^{60} be the number of welfare recipients in the previous period who turn 60 and remain on welfare in the current period. Due to the age restriction, O_t^{60} is not counted in the current welfare stock and should be treated as part of the outflow. The stock-flow identity for the welfare stock of the population aged 15-19 is given by:

$$S_{r,t} = (c_t S_{r,t-1} + e_t S_{n,t-1} - O_t^{60}). \tag{4}$$

For notational brevity, let:

$$r_t = \frac{c_t S_{r,t-1} + e_t S_{n,t-1} - O_t^{60}}{c_t S_{r,t-1} + e_t S_{n,t-1}}. \tag{5}$$

Using this notation, Equation (4) becomes:

$$S_{r,t} = r_t(c_t S_{r,t-1} + e_t S_{n,t-1}). \tag{6}$$

We can express the number of non-recipients among the population aged 15-59, $S_{n,t}$, in a similar way. Let P_t denote the size of the population aged 15-59, we have:

$$S_{n,t} = P_t - S_{r,t} = \frac{P_t}{P_{t-1}} * \left(S_{n,t-1} + S_{r,t-1}\right) - S_{r,t} \tag{7}$$

Combining Equations (6) and (7), the number of non-recipients aged 15-59 can be rewritten as:

$$S_{n,t} = (1 + p_t - r_t c_t) S_{r,t-1} + (1 + p_t - r_t e_t) S_{n,t-1} \tag{8}$$

, where $p_t = \frac{P_t - P_{t-1}}{P_{t-1}}$.

Combining Equations (7) and (8), the stock-flow relationships for the population aged 15-59, distinguished by either being on welfare and off welfare can be represented in a matrix form as follows:

$$\begin{bmatrix} S_{r,t} \\ S_{n,t} \end{bmatrix} = \left\{ \begin{bmatrix} 0 & 0 \\ 1 + p_t & 1 + p_t \end{bmatrix} + \begin{bmatrix} r_t & 0 \\ 0 & r_t \end{bmatrix} \begin{bmatrix} c_t & e_t \\ -c_t & -e_t \end{bmatrix} \right\} \begin{bmatrix} S_{r,t-1} \\ S_{n,t-1} \end{bmatrix}. \tag{9}$$

Equation (9) serves as the basis for a simple stock-flow model, allowing separate models for the entry and continuation rates and hence allowing for state dependence in welfare receipt. It can be extended to account for duration dependence by differentiating recipients further by their duration on welfare. Let S_t^k denote the number of recipients who have been on welfare continuously for k periods and c_t^kdenote the proportions of S_{t-1}^k, who remain on welfare in period t. The population aged 15-59, differentiating by duration on welfare, can be represented as follows:

$$\begin{bmatrix} S_t^1 \\ S_t^2 \\ S_t^3 \\ \vdots \\ S_t^K \\ S_{n,t} \end{bmatrix} = \left\{ \begin{bmatrix} 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 0 & 0 \\ 1 + p_t & 1 + p_t & \dots & 1 + p_t & 1 + p_t & 1 + p_t \end{bmatrix} \right.$$

$$\left. + \begin{bmatrix} 1 & 0 & \dots & 0 & 0 & 0 \\ 0 & r_t^1 & \dots & 0 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & r_t^K & 0 \\ r_t^1 & r_t^{21} & \dots & r^{K-1} & r_t^K & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 & \dots & 0 & 0 & e_t \\ c_t^1 & 0 & \dots & 0 & 0 & 0 \\ 0 & c_t^2 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & c_t^{K-1} & c_t^K & 0 \\ -c_t^1 & -c_t^2 & \dots & -c_t^{K-1} & -c_t^K & -e_t \end{bmatrix} \right\} \begin{bmatrix} S_{t-1}^1 \\ S_{t-1}^2 \\ S_{t-1}^3 \\ \vdots \\ S_{t-1}^K \\ S_{n,t-1} \end{bmatrix} \tag{10}$$

, where K denotes welfare spells being equal to and greater than K periods, $r_t^k = S_t^k / c_t^{k-1} S_t^{k-1}$ for $k = 1 \dots K-1$, $r_t^K = S_t^K / (c_t^{K-1} S_t^{K-1} + c_t^K S_{t-1}^K)$. These ratios, r_t^k reflect the difference between the actual size of the stock and the number deriving from the stock-flow relationship without accounting for the outflow due to the age restriction.

By grouping individuals who have been on income support continuously for K periods or longer together, I assume the continuation probability to be constant after K periods. This assumption is necessary to handle an initial conditions problem, which will be discussed further in the data section.

Equation (10) forms as a basis for the stock-flow model that accounts for state and duration dependence in welfare receipt explicitly where the entry and continuation rates are posited as a function of labor market conditions and other control variables, $e_t = e(X_t, \theta)$, $c_t^k = c(X_t, \theta, k)$. For notational brevity, let S_t be the vector that contains the number of individuals in each welfare receipt state, $P(p_t)$ denotes the matrix that contains the population growth rate, $R(r_t)$ denotes the matrix that containing the ratios between the observed number of welfare recipients and the predicted recipients using the stock-flow relationships without accounting for the age restriction, r_t and $M(X_t, \theta)$ denotes the matrix that contains the transition rates (entry and continuation rates) between the different welfare states. The stock-flow model can be represented compactly as:

$$S_t = \{P(p_t) + R(r_t)M(X_t, \theta)\}S_{t-1}. \tag{11}$$

This equation, in conjunction with models for the entry and continuation rate, can be used to evaluate the impact of the explanatory variables on the welfare caseload. The implementation of the stock-flow model includes two steps. The first step involves estimating models for the welfare flows to obtain the estimates of the parameters θ. Then given an initial stock S_0 and any arbitrary path for explanatory variables, $\{\tilde{X}\}_{t=1}^{j}$, the implied stock in period j can be simulated as:

$$S_j = \prod_{t=1}^{j}\{P(p_t) + R(r_t)M(\tilde{X}_t, \theta)\}S_0. \quad (12)$$

To evaluate the impact of the recent improvements in the labor market, I simulate the welfare stock for a scenario of labor market conditions not improving, and compare it with the simulated welfare stock associated with the observed path of labor market conditions.

4 Data

This paper relies on geographic variation in labor market conditions for identification. This section starts with a discussion of empirical considerations in identifying local labor market regions, followed by a description of the data.

4.1 Identifying local labor market regions

To be used as geographic units of analysis, regions must have labor market data available. As will be shown below, this paper uses data from Australian Bureau of Statistics (ABS) Labor Force Survey. The Labor Force Survey (LFS) data are collected and disseminated based on the administratively-defined Labor Force Statistical Regions. The list of the Statistical Regions (SRs) is reported in Appendix A.

Since the labor market statistics at disaggregated regional levels are to be used as the proxy for labor market opportunities, each region should resemble a (functional) labor market area. Loosely speaking, labor demand in such an area should be mostly met by labor supply from within the same area, and vice versa. The requirement of self-containment in terms of labor supply and demand is to ensure that labor market data of each region reflect labor market conditions faced by its residents and thus the variation in the labor market data across regions reflect different labor market conditions.

Perhaps due to the technical complexity of delimiting local labor market regions, there is only limited attempt has been made in identifying those areas in Australia. The most comprehensive study thus far is by Mitchell and Watt (2010) who use Journal-to-Work data to identify “functional” regions in New South Wales and contrast them with the SRs. The authors find that the SRs do not necessarily correspond to functional regions. Each metropolitan SR is too small to be a single labor market while rural SRs are too large.

Accordingly, Statistical Regions need to be regrouped to resemble labor market regions. I use an ad-hoc approach, judging on distances and observed commuting patterns. Each non-metropolitan SR is treated as a single labor market. For metropolitan SRs in each of the smaller states, Western Australia, South Australia, and Queensland are treated as a single labor market. For the two capital cities of New South Wales and Victoria, Sydney and Melbourne each is posited to consist of several local labor markets.[3] Overall, 62 SRs are aggregated to 32 regions, as reported in Appendix A. Hereafter, these regions are referred to as “Local Labor Market Regions” (LLMRs).

4.2 Data

The primary data used comprise administrative payment records of a ten-percent sample of individuals who received income support payments at any stage during the period January 1995 to February 2006. For each individual in the sample, a payment record is available for every fortnight within the sample period the individual was on income support. Main

[3] For Sydney metropolitan area, the SR containing the city central and its neighboring SRs are considered one single labor market, “outer” Northern Sydney SRs another, and “outer” Western Sydney SRs the third one. This regrouping is partly based on the functional regions identified in Mitchell and Watt (2010). Melbourne region is divided into two local regions; one region consists of Inner Melbourne and its neighboring SRs and another region consists of the two outer SRs. This grouping is based on the work journey patterns reported in a paper by Victorian Department of Planning and Community Development (2008).

information included for each record includes sex, date of birth, residential postcode, family status, benefit type and benefit entitlement. The dataset however does not contain payment records to full-time students prior to May 1998 and hence this paper does not consider payments to full-time students. The population of interest in this study is people of working age and hence I restrict the sample to persons aged 15-59.

The individual identifiers and information on welfare payments makes it possible to track individual welfare receipt patterns over time. I use the residential postcode to map welfare recipients to local labor market regions. Because the data are administratively recorded, they are free from self-reported and attrition biases, enabling derivation of reliable estimates for the welfare flows and stock at regional levels.

Central to the derivation of the welfare stock and flows is the definition of a spell on welfare – that is when a stay on welfare receipt begins and when it ends. A concern is that short breaks between payments may be due to administrative errors and may not reflect genuine exits from payments. To mitigate this concern, this paper uses a 3-fortnight break rule in determining welfare spells, following Tseng et al. (2008).

As the frequencies of labor market data are monthly, the fortnightly data of welfare payments are collapsed to monthly statistics. To do so requires the entry and exit dates of each welfare spell. One complication is that the LDS dataset does not provide the exact dates but the fortnights containing these dates. As a solution, I impute the dates using the information on basic benefit entitlement.[4]

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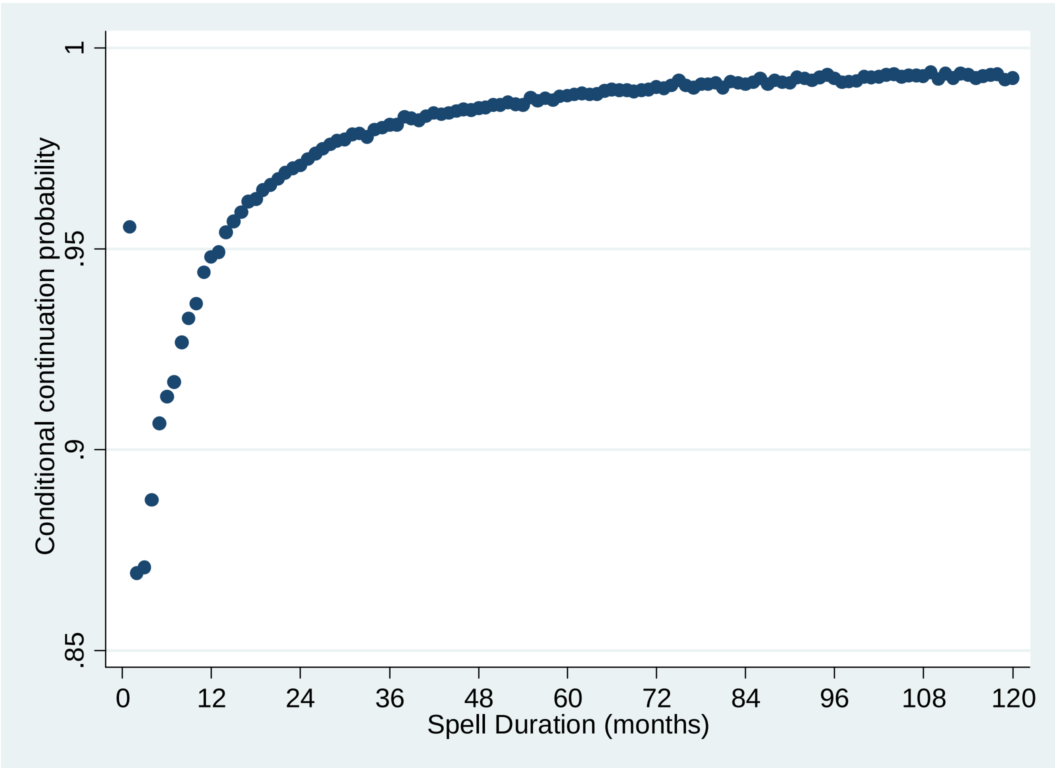
[4] The basic entitlement a person received in a fortnight is a function of the number of days the person was on income support in that fortnight and the rate of payment per day the recipient was entitled to. The number of days in receipt of welfare in the first fortnight of a welfare spell can be inferred by comparing the amount of basic entitlement received in that fortnight

Another complication is that the LDS has only information on current welfare receipt, and hence it is impossible to determine the length of welfare receipt for individuals who are on welfare at the beginning of the data. To address this form of left censoring, I assume the probability of continuation to be constant after K months on welfare and discard the first K periods of the data. Any persons continuously on welfare for K periods since the start of the data period will be in the constant part of the continuation probability and hence, making the left censoring irrelevant. For everyone else, I can derive the exact spell duration.

Figure 1: Continuation Rate by Duration on Income Support



The choice of K is based on several empirical considerations. As the probability of continuation on welfare is assumed to be constant after K months on welfare, the empirical

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and the amount received in the next fortnight. In a similar way, the number of days in receipt of welfare in the spell ending fortnight and hence the ending date is inferred by comparing the amount received in that fortnight and the amount received in the preceding fortnight.

continuation rate after K-months on welfare should be fairly constant. However, K should not be too large compared to the data period. The continuation rate of all spells commenced during the data period (Figure 1) increases strongly with duration on welfare up to about a spell length of 24 months, and becomes relatively stable thereafter. Thus, K is chosen to be 24 months and hence data from January 1997 to December 2005 are to be used in estimation.

I use data from ABS Labor Force Survey (LFS) to derive population estimates and measures of labor market conditions. It is important to note that the LFS sample is only around 0.45% of the total adult population (Australian Bureau of Statistics, 2002). With small sample size, the LFS statistics at the disaggregated regional levels are reportedly estimated with considerable sampling error. I return to the issue of sampling error later.

Using the number of individuals in each labor force state by age group, I construct the monthly estimates of the population aged 15-59 and derive the monthly estimates of the unemployment rate among adults (aged 15 and over). In addition, the statistics are also used to construct the estimates of the employment rate among the population of working age population aged 15-64. The estimates of the population aged 15-59 are used to derive the number of non-recipients and hence the welfare entry rate. The unemployment rate is used as the main measure of labor market conditions and the employment rate as an additional measure.

The LFS data contain quarterly information on the occupation and industry composition of employed persons and I use a simple linear interpolation to estimate their monthly statistics. These characteristics are used as control variables in the flow models. I also use Census 2001 data to obtain information on education and country of birth composition of the population at the regional levels. As shown later, these variables are to be used in one of the flow model specifications.

Figure 2: Welfare Recipients and Labor Market Conditions

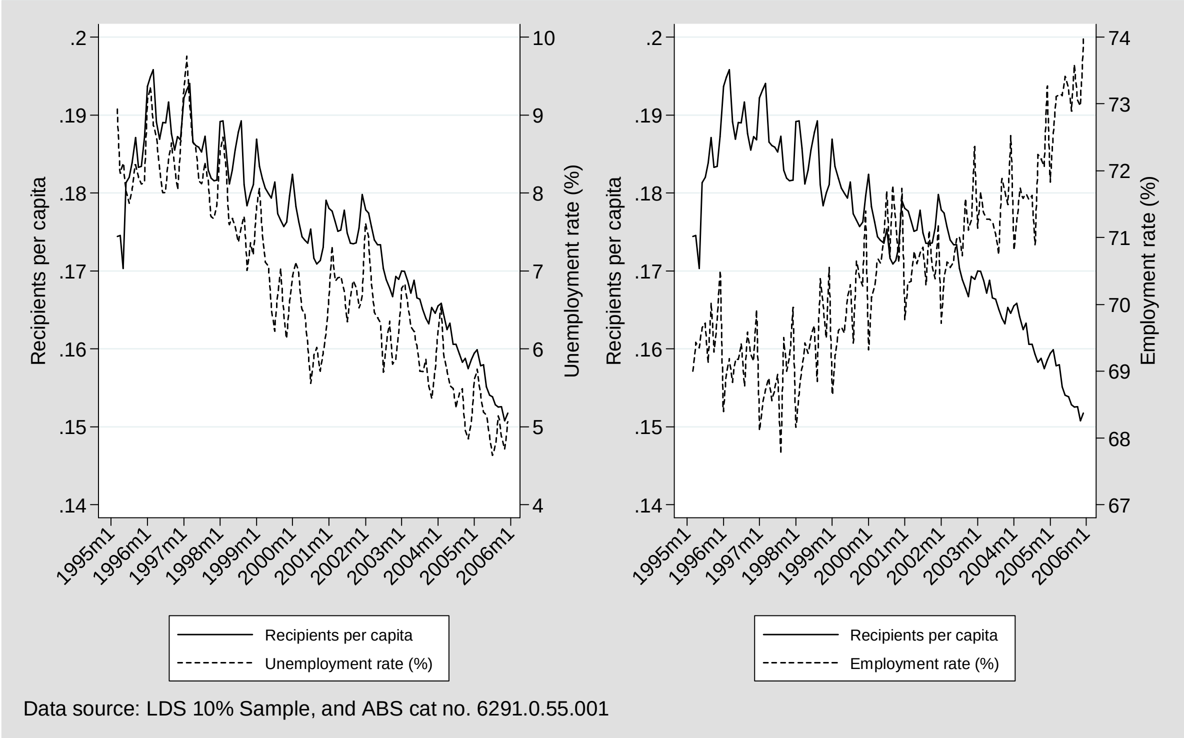

Figure 2 plots the rate of income support receipt among people aged 15-59 from 1995 to 2005, along with the unemployment and employment rates. The rate of income support receipt peaked in 1996 at around 19.5% and then declined and by the end of 2005 the rate was around 15%, 4.5 percentage points lower than its peak value. The unemployment rate increased marginally between 1995 and 1997, and then followed a downward trend. The movement in the employment rate was reflective of that in the unemployment rate. During the estimation period 1997-2005, the decline in welfare reliance is accompanied closely by the improvements in the unemployment and employment rates.

Figure 3: Welfare Flow Rates and Unemployment Rate

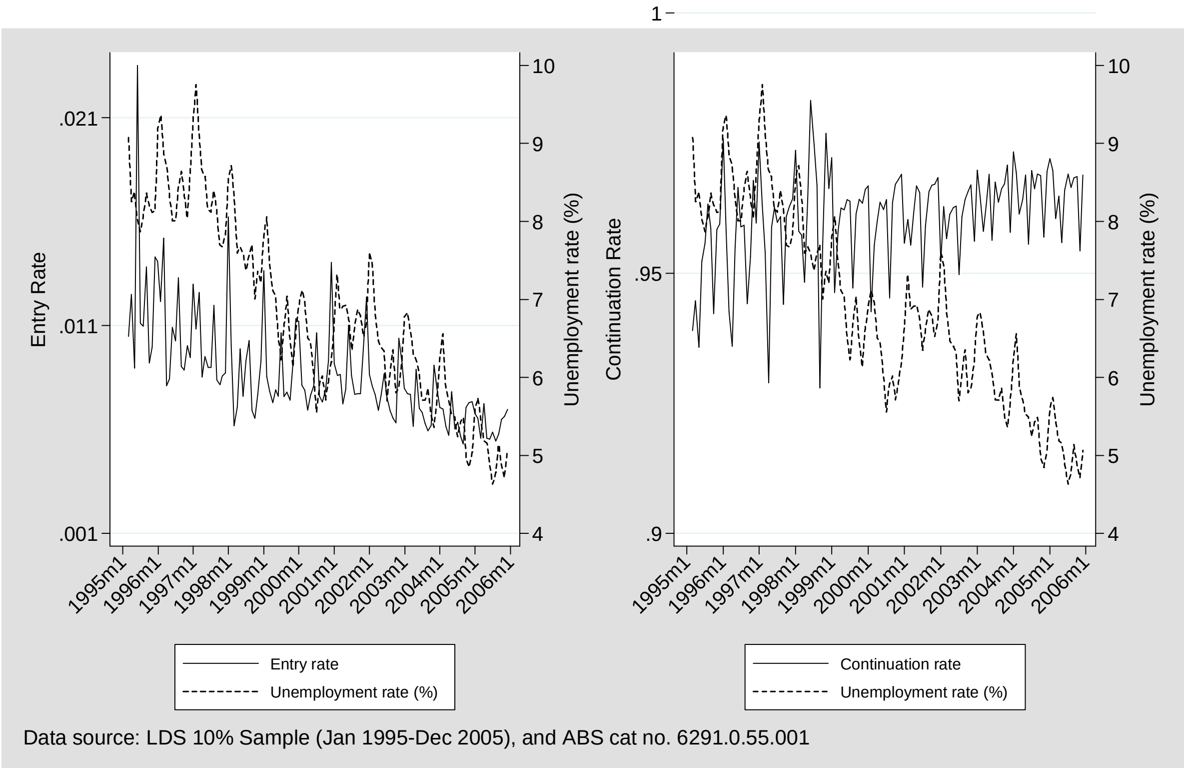

Figure 3 plots the welfare entry and continuation rates. The entry rate and unemployment rate are positively correlated; both declined over time. The continuation rate, however, marginally increased with time. A possible explanation for the pattern in the continuation rate is the change in the composition of recipients over time. Declining flows onto payments result in higher shares of recipients with long-term durations over time. This underscores the importance of accounting for duration dependence when modeling the probability of continuation on welfare.

5 Modeling Strategy and Results

5.1 Flow Model Specifications and Results

Central to the stock-flow model are the empirical models for the underlying flows. This section first presents the general models for the entry and continuation rates and then discusses three alternative specifications, along with their estimation results. As shown below, the use of different specifications is an attempt to examine the potential bias due to measurement error.

Because the LDS dataset includes information only for those on welfare, I model the entry probability using a grouped-data equivalent of the individual-level logit model. I calculate the entry rate for region j in month t, e_{jt} , as the ratio of the number of welfare entrants to the number of individuals at risk of going onto welfare (the estimated population size minus those currently on welfare). The grouped logit model for the entry rate at the region – month level is as follows

$$ln\frac{e_{jt}}{1-e_{jt}} = \alpha + X_{jt}\beta + y_t + \delta_j + \varepsilon_{jt}. \quad (13)$$

In addition to the measures of labor market conditions, X_{jt} include the regional-level shares of employed population by occupation and industry. These variables are included to account for the impacts of regional industry and occupation structures on welfare use. For the time effects, I include year dummies to capture a general time trend and calendar month dummies to capture seasonal variation. Accounting for the time effects are necessary given a number of changes in welfare policy occurred during the estimation period. Without accounting for the time effects, the estimated coefficients for the labor market variables would be over-estimated. Fixed effects for regions are also included to account for region-level unobserved heterogeneity (except for one specification).

The grouped logit model is to be estimated using weighted least squares with each observation being given an analytical weight of $(1-\hat{e}_{jt})\hat{e}_{jt}n_{jt}$ where n_{jt} refers to the number of people at risk of entering welfare (the estimated population size minus those currently on welfare) and $\hat{e}_{jt}$ is the predicted entry rate from a first-stage un-weighted regression. This analytical weight is to adjust for heteroscedasticity in error terms that is induced by differences in population size across regions (Maddala, 1983). Furthermore in regressions, standard errors are also allowed to be clustered within regions.

I estimate the continuation rate using individual-level data. Let C_{jit} be a continuation indicator which is equal to zero if this individual leaves income support and equal to one otherwise. The probability of continuing on welfare is estimated using a logit specification as follows

$$Pr\left[C_{ijt} = 1\right] = exp\{\, \alpha + X_{jt}\beta + y_t \ + \delta_j + g\left(k_{ijt}\right)\} \tag{14}$$

,where $g\left(k_{ijt}\right)$ is a flexible specification for the dependence of the continuation probability on duration on welfare. The continuation probability is assumed to be a quadratic in k, up to 24 months and constant thereafter, effectively top-coding k at 24 months. As discussed earlier, this top-coding is necessary to deal with the left-censoring problem. To account for the initial decline in the observed empirical continuation rate and the effect of top-coding, I include 4 dummy variables for k =1, 2, 3 and 24 respectively.

Using this general model framework, I estimate three specifications which differ in the geographical level of analysis and in the treatment of region-level unobserved heterogeneity. I use the unemployment rate as a proxy for labor market conditions and estimate the entry and continuation models with no lags and with lags of the unemployment rate. The latter regressions are intended to check the sensitivity of the results to accounting for lagged effects of labor market conditions on the welfare flows.

5.1.1 Specification I: Fixed Effects Estimators on the LLMR-level Data

In this first specification, I estimate equations (13) and (14), accounting for region and time fixed effects using data aggregated to the Local Labor Market Region (LLMR) level. In the absence of measurement error, this specification is the most appropriate choice. Using most disaggregated data maximizes the variation in the data used for identification. Including fixed time effects is necessary to control for the impact of welfare reforms and other time-varying factors on the welfare transition probabilities. Including region fixed effects is an effective way to control for persistent observed differences in regional characteristics.

However, because the labor market data are measured with errors, this specification has a major drawback: the estimated effects of labor market conditions are subject to considerable attenuation bias. With labor market data at the Statistical Regional level being reportedly measured with a substantial degree of sampling errors (Pfeffermann, Feder, & Signorelli, 1998), the labor market data used in this specification should also have a high degree of measurement errors. Moreover, the identification strategy used exacerbates the impact of measurement error. With region fixed effects being included, differences in labor market conditions across regions are not used to identify the effects of labor market conditions. With time fixed effects being included variation due to a general trend is not used for identifying the effects, either. This identification strategy effectively uses only part of variation in labor market conditions that is most subject to measurement error to identify the effects of labor market conditions.

Table 1 presents estimation results based on monthly data from January 1997 to December 2005. In both entry and continuation models, the coefficients on the unemployment rate are statistically significant and positive in sign. These results suggest that favorable market conditions reduce the probability of receiving welfare; a higher unemployment rate causes more people to enter welfare and less people to leave it. The coefficients on lagged unemployment rates are very small in size and statistically insignificant for both entry and continuation rates, suggesting that there is little dependence on lagged labor market conditions.

Table 1: Flow Estimation Results-Specification I

	Entry rate (grouped logit)				*Continuation rate (logit)*			
	no lags		*3 lags*		*no lags*		*3 lags*	
	Coef.	*S.E.*	Coef.	*S.E.*	Coef.	*Robust S.E.*	Coef.	*Robust S.E.*
U. Rate	0.0211***	0.0037	0.0175***	0.0036	0.0204***	0.0038	0.0213***	0.005
UR-1st lag			0.0047*	0.0026			0.0054	0.0053
UR-2nd lag			0.0050	0.0042			-0.0086	0.0057
UR-3rd lag			-0.0044	0.0035			-0.0001	0.0067
∑***UR***	0**.0211**		**0.0228**		**0.0204**		**0.1800**	
year 1998	-0.0732***	0.0102	-0.0721***	0.0105	0.0718***	0.009	0.0704***	0.0087
year 1999	-0.0449***	0.011	-0.0430***	0.0111	-0.0254**	0.0129	-0.0281**	0.0127
year 2000	-0.0432***	0.0128	-0.0400***	0.0142	-0.0300*	0.0154	-0.0346**	0.0151
year 2001	-0.0562***	0.0144	-0.0540***	0.0155	0.0111	0.014	0.0068	0.0136
year 2002	-0.1702***	0.0185	-0.1669***	0.0194	-0.0566***	0.0166	-0.0607***	0.0166
year 2003	-0.2367***	0.0187	-0.2332***	0.0194	0.0363*	0.0205	0.0313	0.0202
year 2004	-0.3345***	0.0217	-0.3300***	0.0227	0.0609***	0.0195	0.0549***	0.0195
year 2005	-0.3925***	0.0296	-0.3873***	0.0309	0.0227	0.0211	0.0152	0.021
Duration variables								
1st month	-	-	-	-	1.3168***	0.0131	1.3168***	0.0131
2nd month	-	-	-	-	0.0428***	0.0081	0.0428***	0.0081
3rd month	-	-	-	-	-0.0720***	0.0056	-0.0720***	0.0056
Duration	-	-	-	-	0.1415***	0.0026	0.1415***	0.0026
Duration^2	-	-	-	-	-0.0026***	0.0001	-0.0026***	0.0001
24+ months	-	-	-	-	0.9853***	0.0158	0.9853***	0.0158
Adj. R^2	79.2%		79.2%		11.1%		11.1%	
No. of obs.	3,456		3,456		22,687,650		22,687,650	

Notes: ***, **, and * indicate significance at the 1%, 5% and 10% level respectively. Standard errors for the continuation rate equation are clustered-robust standard errors. Other control variables include calendar month dummies, and occupational and industrial composition (see Appendix B).

The coefficients on the year dummies for the entry rate show a downward trend in the entry rate, with the rate of decline accelerating in later years. This time pattern suggests that there are other time-varying factors contributing to the reduction in the entry rate. By contrast, the year effects for the continuation rate do not show a clear time pattern. As for duration dependence, the coefficients on the duration variables are strongly significant, and their sign implies that the probability of continuation on welfare increases with time on payments. Hence, it is important to account for duration dependence in income support receipt.

5.1.2 Specification II: "Pooled" Estimators on the LLMR level data

As discussed, one concern with Specification I is that its estimates are subject to considerable attenuation bias. For sensitivity analysis, I consider other specifications that aim to reduce the impact of measurement error.[5] One alternative is to re-estimate the models, using the same data but dropping the region dummies. This specification effectively uses "pooled estimators" that utilize both variations in labor market conditions across and within regions for identification. Compared to the variation within regions, variation across regions does not face measurement error to the same degree since it reflects long-term underlying differences in labor market conditions. Thus, estimates from this specification should suffer less attenuation bias compared to the estimates from Specification I.

Estimates from this specification, however, are subject to the so-called heterogeneity bias because unobserved time-invariant regional differences are not properly controlled for. To minimize heterogeneity bias, I include extra regional variables, including regional education and country of birth composition of the population that obtained from the (cross-sectional) census data.

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[5] One way to reduce the extent of measurement error is to "extract signal", filtering out sampling errors. However, this is a very complicated task given that sampling errors are auto-correlated due to the rotating panel sampling scheme employed in the LFS survey. To filter out errors requires knowledge of the auto-correlation structure of errors (see Bell and Hilmer, 2008; Pfeffermann, Feder and Signorelli 1998). The knowledge of autocorrelation of the LFS survey data is not available and will need to be estimated using panel data of the LFS survey. This method is beyond the scope of this paper.

Table 2: Flow Estimation Results-Specification II

Variable name	Entry rate (grouped logit)				Continuation rate (logit)			
	no lags		3 lags		no lags		3 lags	
	Coef.	*S.E.* *	Coef.	*S.E.* *	Coef.	*S.E.* *	Coef.	*S.E.* *
U. Rate	0.0387***	0.0051	0.0243***	0.004	0.0217***	0.0026	0.0223***	0.0048
UR-1st lag			0.0078***	0.0028			0.0060	0.0055
UR-2nd lag			0.0096**	0.004			-0.0084	0.0058
UR-3rd lag			0.0015	0.0039			0.0011	0.0064
$\sum$***UR***			**0.0432**				**0.0210**	
year 1998	-0.0808***	0.0109	-0.0774***	0.0113	0.0743***	0.0084	0.0738***	0.0083
year 1999	-0.0509***	0.018	-0.0451**	0.0179	-0.0136	0.0113	-0.0141	0.0108
year 2000	-0.0419**	0.0168	-0.0323*	0.0177	-0.0281*	0.0149	-0.0296**	0.0143
year 2001	-0.0734***	0.0202	-0.0632***	0.0206	0.0111	0.0124	0.0095	0.0118
year 2002	-0.1937***	0.0235	-0.1835***	0.024	-0.0588***	0.0163	-0.0601***	0.0162
year 2003	-0.2640***	0.023	-0.2522***	0.0242	0.0475**	0.0213	0.0459**	0.0213
year 2004	-0.3508***	0.0237	-0.3376***	0.0253	0.0694***	0.0189	0.0676***	0.0189
year 2005	-0.4106***	0.0273	-0.3937***	0.0289	0.0335*	0.0201	0.0311	0.0197
Duration Variables								
1st month	-	-	-	-	1.3170***	0.0131	1.3170***	0.0131
2nd month	-	-	-	-	0.0429***	0.0081	0.0429***	0.0081
3rd month	-	-	-	-	-0.0719***	0.0056	-0.0719***	0.0056
Duration	-	-	-	-	0.1417***	0.0025	0.1417***	0.0025
Duration^2	-	-	-	-	-0.0026***	0.0001	-0.0026***	0.0001
24+ months	-	-	-	-	0.9874***	0.0157	0.9874***	0.0157
R^2	75.1%		75.0%		11.1%		11.1%	
No. of obs.	3,456		3,456		22,687,650		22,687,650	

Notes: Standard errors (SE) are clustered-robust standard errors. ***, **and * indicate significance at the 1%, 5% and 10% level respectively. Other control variables include region dummies, calendar month dummies, occupational and industrial composition, and regional profile by country of birth and education (see Appendix B).

Regression results for Specification II are reported in Table 2. For the entry rate, the estimated effect of the unemployment rate is twice as large as the effect obtained from Specification I. By contrast, for the continuation rate, the estimated effect is only marginally larger.

One plausible explanation for the difference in the results between the entry and continuation rate models is that the latter includes duration variable. Recipients with more favorable employment characteristics are likely to move off welfare faster and thus those stay longer on average have greater employment disadvantage. Duration variables, therefore, capture in part the heterogeneity in the population across regions. Consequently, the residual heterogeneity that is unaccounted for in the continuation rate model should be less substantial compared to that in the entry rate model.[6]

As for the lagged effect of the unemployment rate, the coefficients on the unemployment rate lags for the entry rate are positive but still significantly smaller than the contemporaneous effect. The aggregate effect, as the sum of the coefficients on the unemployment rate and its lag, is slightly higher than the effect from the model without lags. The coefficients on lagged unemployment rates are not statistically significant in the continuation rate model, however.

5.1.3 Specification III: Fixed Effects Estimators on the Major SR level data

Another way to reduce attenuation bias is to use labor market data at a more aggregated regional level. There are several considerations in choosing a particular broader level of geographical disaggregation. As sampling errors are inversely related to sample size, the more aggregated the labor market data are, the less sampling errors the estimates are measured with. However, the geographic disaggregation should be not too broad so that the labor market data still offer reasonable variation to identify the models.

Based on these considerations, I choose to disaggregate the labor market data by Major Statistical Regions. As shown in Appendix B, there are 13 Major Statistical Regions in Australia. Each state typically consists of two Major Statistical Regions, one comprising of the whole capital city and the other comprising of the remaining non-urban Statistical Regions. With this grouping, the labor market data at the Major Statistical Region level retain cross-state variation in the labor market and much of the differential movements in the labor

[6] When duration variables are omitted from the regressions, the estimated effect of the unemployment rate indeed becomes substantially larger.

market across urban and rural regions within states. As a result, the data should still offer reasonable variation to identify the models.

Table 3: Flow Estimation Results-Specification III

	Entry rate (grouped logit)				Continuation rate (logit)			
	no lags		3 lags		no lags		3 lags	
Variable name	Coef.	*S.E.*	Coef.	*S.E.*	Coef.	*S.E.*	Coef.	*S.E.*
Unemp. Rate	0.0404***	0.0077	0.0330***	0.0096	0.0369***	0.0103	0.0463***	0.0171
UR-first lag			0.0165*	0.0079			0.0107	0.0087
UR-second lag			0.0098	0.0150			-0.0257*	0.0136
UR-third lag			-0.0184	0.0112			-0.0027	0.0181
$\sum$***UR***			0.0410				0.0286	
year 1998	-0.0617***	0.0135	-0.0613***	0.0130	0.0775***	0.0152	0.0720***	0.0121
year 1999	-0.0239	0.0224	-0.0232	0.0216	-0.0147	0.0288	-0.0244	0.0237
year 2000	-0.0053	0.0272	-0.0038	0.0269	-0.0218	0.0308	-0.0375	0.0272
year 2001	-0.0348	0.0245	-0.0361	0.0248	-0.0031	0.0311	-0.0196	0.0268
year 2002	-0.1438***	0.0312	-0.1406***	0.0311	-0.0748*	0.0445	-0.0899**	0.0404
year 2003	-0.2093***	0.0322	-0.2080***	0.0300	0.0214	0.0506	0.0032	0.0449
year 2004	-0.2923***	0.0419	-0.2897***	0.0410	0.0597	0.0501	0.0369	0.0439
year 2005	-0.3439***	0.0491	-0.3416***	0.0466	0.0271	0.059	-0.0013	0.0515
Duration Variables								
1st month	-	-	-	-	1.3167***	0.0137	1.3167***	0.0137
2nd month	-	-	-	-	0.0426***	0.0105	0.0426***	0.0105
3rd month	-	-	-	-	-0.0720***	0.0061	-0.0720***	0.0061
Duration	-	-	-	-	0.1416***	0.0037	0.1416***	0.0037
$Duration^2$	-	-	-	-	-0.0026***	0.0001	-0.0026***	0.0001
24+ months	-	-	-	-	0.9867***	0.0227	0.9866***	0.0227
R^2	81.0%		81.0%		11.1%		11.1%	
Number of obs.	1,404		1,404		22,687,650		22,687,650	

Notes: ***, **, and * indicate significance at the 1%, 5% and 10% level respectively. Standard errors are clustered-robust standard errors. Other control variables include region dummies, calendar month dummies, regional occupational and industrial composition (see Appendix B).

To isolate the improvement in the estimates due to a reduction in the extent of measurement error in the labor market data, I also use the same identification strategy as Specification I, including region dummies to account for fixed region effects. Table 3 reports the estimation results for Specification III. Focusing on the entry model without lags, the coefficient on the unemployment rate is strongly significant and the estimate is substantially larger than the corresponding estimate based on the LLMR level data. Similarly, for the continuation rate model, the coefficient on the unemployment rate is also substantially larger compared to the estimate based on the LLMR level data. Altogether, the results suggest attenuation bias is quite serious in Specification I.

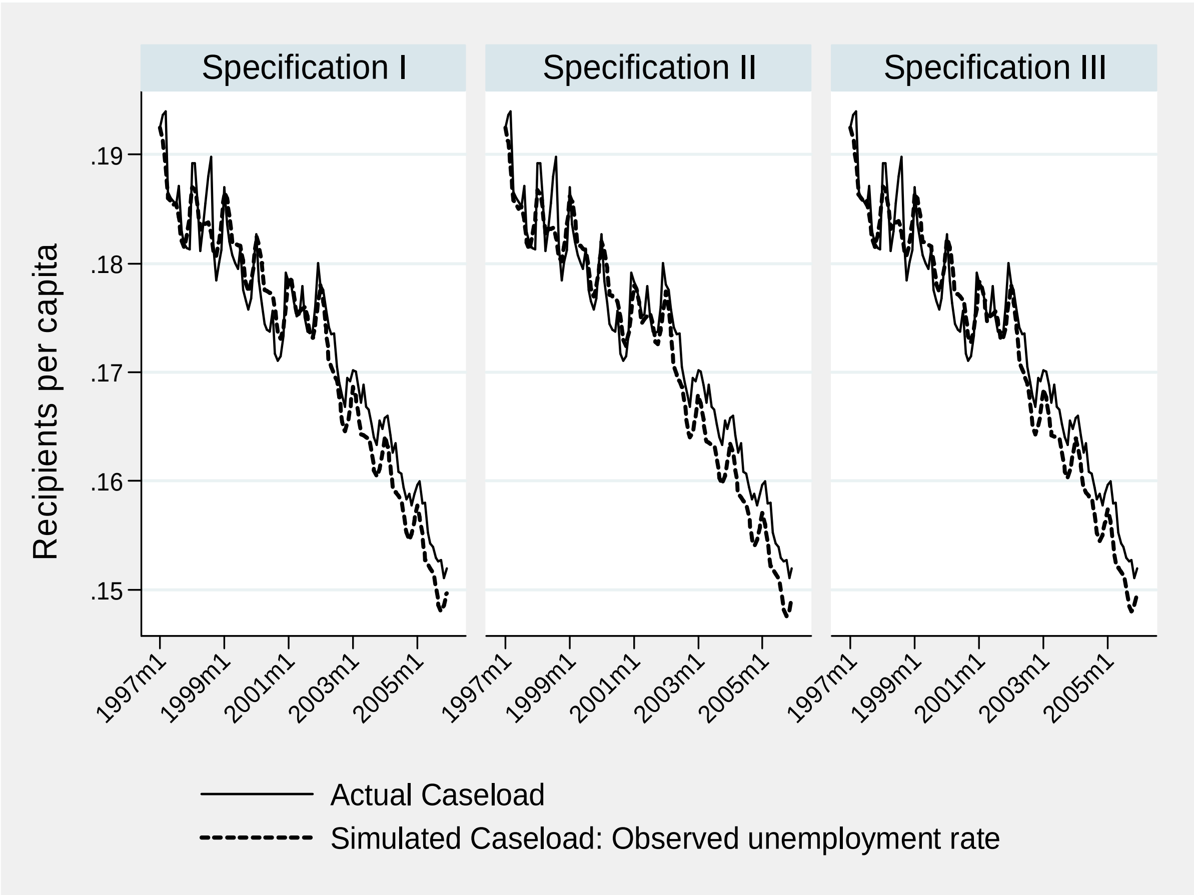
As for the lags of the unemployment rate, the estimates vary in sign, significance and magnitude. This volatile pattern is likely due to the combination of limited variation in the unemployment rate at the Major Statistical Region level and high serial correlation in the unemployment rate. The aggregate impact of the unemployment rate on the entry probability, measured as the sum of the coefficients of the unemployment rate and its lags, is in similar magnitude as the estimate obtained from the model without lags. By contrast, for the continuation rate, the aggregate effect obtained from the model with lags is considerably smaller.

5.2 Recovering the effects on the welfare caseload: simulation results

Once the flow models are estimated, the next step of the stock-flow model is to simulate the implications of the changes in the regressors on the stock using the stock-flow relationship described in Equation (12). To evaluate the fitness of the stock-model, Figure 4 presents the simulated path of the (per-capita) caseload based on the observed path of the unemployment rate for the models without lags. In every specification, the simulated caseload follows closely the actual path indicating that the stock-flow model predicts the evolution of the caseload reasonably well.

The main focus of the paper is to measure the role of the improvements in labor market conditions during 1997-2005 in explaining the decline in the welfare stock during the same period. To assess this, I simulate the path of welfare stock for a counter-factual path of the unemployment rate that represents a situation where the labor market conditions did not improve. The implied effect of the improvements in labor market conditions on the welfare caseload is given by the difference between this simulated path and the simulated path following the observed path of unemployment rate.

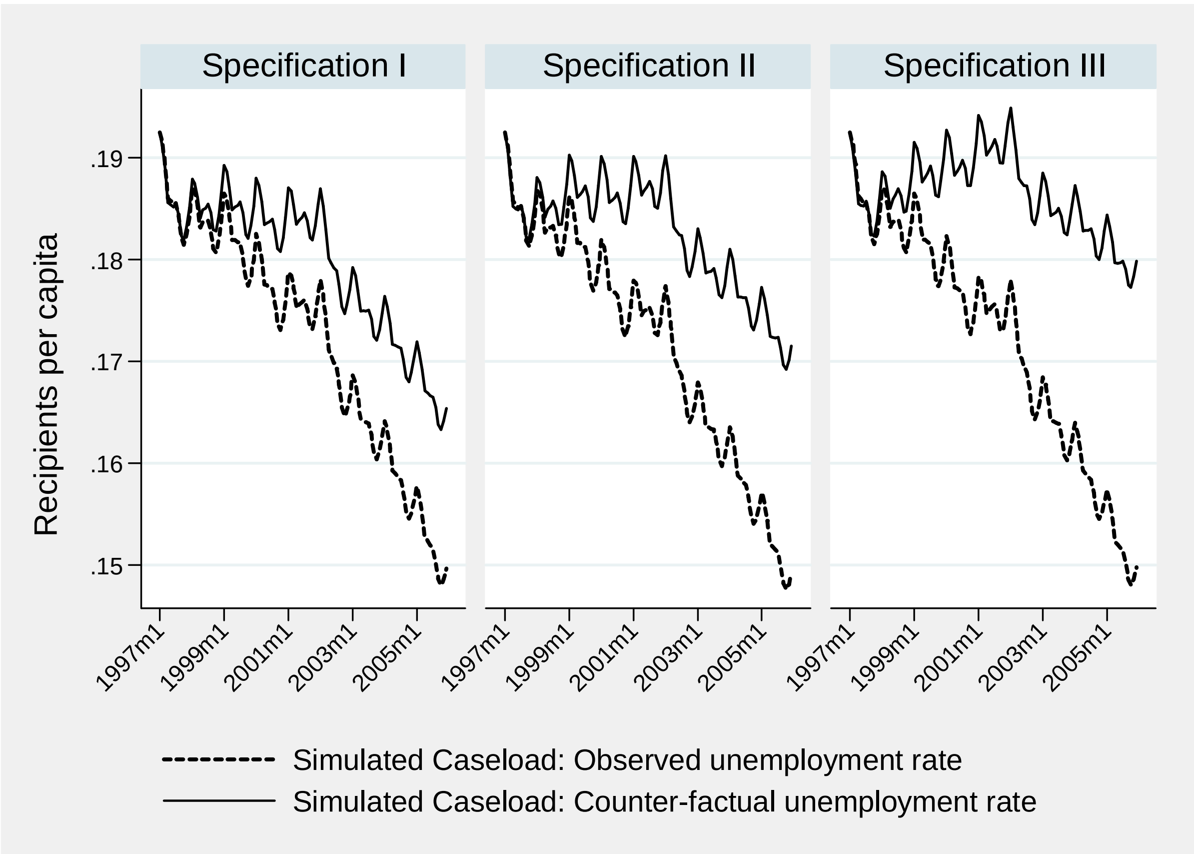
Figure 4: The Actual and Simulated Income Support Caseload



As depicted in Figure 2, the unemployment rate steadily declined during the estimation period. The counterfactual path representing the situation of labor market conditions not improving hence should be a path where the unemployment rates fixed at a level close to the levels observed in the initial months of 1997. One concern with fixing the unemployment rates at the value of a particular month is that the unemployment rate exhibits strong seasonal movements, being higher in summer months and lower in winter months. To mitigate the impact of seasonality, I fix the unemployment rates at the average value of a 12 month period from July 1996 to June 1997, which is equal to 8.7%.

Figure 5 presents the simulations for the counterfactual path where the unemployment rate is fixed at the July 1996-June1997 level of 8.7%, based on the models without lags. As expected, the receipt rate does not decline as much for the counter-factual history of the unemployment rate when compared to the decline in the simulated receipt rate associated with the actual path of the unemployment rate. In line with the differences in the coefficients in the flow models, the estimated effect of the labor market improvements on the receipt rate- the gap between the two simulated paths, varies strongly across the three specifications.

Figure 5: Simulated Caseload: Counter-Factual Scenarios of UR



The corresponding estimates for the implied effects of declining unemployment during the entire simulation period also summarized in Table 4. Based on Specification I, the decline in the welfare receipt that is associated with the counter-factual scenario is 0.0271, in contrast with the simulated decline of 0.0428 that is associated with the observed path of the unemployment rate. Together, these two estimates imply that 36.7% ([0.0428-0.0271]/0.0428) of the decline during the period January 1997-December 2005 can be attributed to the improvements in the unemployment rate. The estimates from other specifications are substantially higher. At 47.6%, the estimate from Specification II is around one third higher and at 70.4%, the estimate from Specification III, almost twice as large.

In the contrast with the varying estimates across the three alternative specifications, within each specification, adding lags of the unemployment rate does not change the estimated effects of the unemployment rate substantially. Thus, I conclude that the estimated effects of labor market conditions are robust to including lags of the unemployment rate.

Table 4: Simulation Results

	Models with no lags			**Models with 3 lags**		
	Spec. I	**Spec. II**	**Spec. III**	**Spec. I**	**Spec. II**	**Spec. III**
Simulations with actual unemployment rates						
Simulated Dec-2005 level	0.1497	0.1492	0.1497	0.1498	0.1491	0.1503
Simulated decline	0.0428	0.0423	0.0427	0.0427	0.0433	0.0421
Simulations with counter-factual unemployment rates						
Simulated Dec-2005 level	0.1654	0.1715	0.1789	0.1651	0.1727	0.1769
Simulated decline	0.0271	0.0210	0.0126	0.0273	0.0198	0.0155
Decline attributable to labor market conditions	36.7%	51.6%	70.4%	35.9%	54.3%	63.1%

Several substantive points emerge from these simulations. First, the estimated role of labor market conditions varies significantly across flow specifications. While being subject to attenuation bias, the flow estimates from Specifications I and III do not face any obvious upward bias, and hence their simulation results can be thought of as lower bound estimates of the true effect of labor market conditions, and their large differences can be attributed to a reduction in measurement error. In other words, the estimates from Specification I suffer serious attenuation bias, and the estimates from Specification III suffer less attenuation bias and thus are closer to the true effect. As a result, Specification III is our preferred specification.

Second, labor market conditions are found to play a dominant role in the decline in the number of individuals on income support. Based on the results from the preferred specification, up to 70% of the total decline occurred during the simulation period can be attributed to the improvements in labor market conditions that occurred during the same period.

6 Additional Measure of Labor Market Conditions

Thus far, this paper has used the unemployment rate as its proxy for labor market conditions for the unemployment rate is the most important labor market indicator. However, the unemployment rate might be an incomplete proxy for a number of reasons. First, the unemployment rate can be an inaccurate measure of labor market conditions in certain situations, because the way it is constructed. The unemployed by definition include only people who are actively seeking for work. However, not all individuals who want work are looking for work; in particular, individuals may decide to not to seek jobs simply because of the lack of employment opportunities. When this “discouraged worker” phenomenon is significant, the unemployment rate may be declining even though the labor market conditions are deteriorating.

Second, as emphasized by Haider, Klerman and Roth (2003), labor market conditions should be viewed as a multiple-dimensional concept. Labor market conditions may change differently for different groups of people while the overall unemployment rate can only capture the average changes. For example, if the decline in the overall unemployment rate is mainly driven by a reduction in the unemployment rate among the highly-skilled persons, the decline in the overall unemployment rate then will understate the improvements in employment opportunities for the low-skilled individuals, a group at most risk of entering income support. Moreover, other aspects of employment such as earnings and working conditions are also important factors in individual employment decisions. To the extent changes in these dimensions diverge from changes in the employment probability, the unemployment rate alone will not capture these divergences.

For a robust check, I consider alternative measures of labor market conditions. It would be ideal to consider all other relevant indicators of labor markets including the employment rate, earnings overall and by sector, and the unemployment rate by educational attainment as additional measures. To be included in the regressions, however, relevant indicators would need to be available at the regional level and measured without too high a degree of measurement errors. Based on this requirement, the employment rate is the only indicator that can be included in the regressions.

Table 5: Flow Estimation Results: with an Alternative Measure of LMCs

	Entry rate (grouped logit)			Continuation rate (logit)		
	Spec I	Spec II	Spec III	Spec I	Spec II	Spec III
Unemployment rate	0.0197***	0.0257***	0.0392***	0.0185***	0.0075**	0.0305**
	(0.0032)	(0.0049)	(0.0076)	(0.0046)	(0.0035)	(0.0119)
Employment rate	-0.0017	-0.0101***	-0.0014	-0.0021	-0.0110***	-0.0073
	(0.0020)	(0.0035)	(0.0054)	(0.0025)	(0.0024)	(0.0063)
R-squared	79.2%	75.2%	80.1%	11.2%	11.2%	11.2%

Notes: Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% level respectively.

Accordingly, I re-estimate the stock-flow model, including the employment rate as an additional measure of labor market conditions. With the employment rate being included, the estimates of the role of labor market conditions should be less sensitive to a discouraged worker effect, as discussed earlier.

The estimation results are reported in Table 5 for the models without lags. The coefficients for the employment rate have the expected sign but mostly insignificant, except for the specification II where the estimates are strongly significant. The coefficients on the unemployment rate become marginally smaller in size compared to the previous estimates, except for the Specification II, where the coefficient for the entry rate is reduced by around 40% and the coefficient for continuation rate is reduced by around 80%.

The main focus of the analysis is, however, on the role of labor market conditions in the decline in the receipt rate. Table 6 reports simulations based on the flow estimates presented in Table 5 for the actual path of the unemployment and employment rates and an counter-factual scenario where both unemployment and employment rates are fixed at their average level during July 1996-June 1997. The estimates for the percent of the total decline attributable to improvements in labor market conditions for Specifications I, II and III are 37.5%, 44.9% and 71.9% respectively. These estimates are similar to the corresponding estimates from the previous section, suggesting that during the period considered in this paper the estimated role of labor market conditions is robust to the worker discouraged effect.

Table 6: Simulation Results with Alternative Measure of Labor Market Conditions

	Spec I	**Spec II**	**Spec III**
January 1997 (initial period) level	0.1925	0.1925	0.1925
Simulations with actual labor market conditions			
Simulated December 2005 level	0.1496	0.1490	0.1496
Simulated decline	0.0429	0.0434	0.0428
Simulations with count-factual labor market conditions			
Simulated December 2005 level	0.1656	0.1685	0.1804
Simulated decline	0.0268	0.0239	0.0120
Decline attributable to labor market conditions (%)	37.5%	44.9%	71.9%
Corresponding results from previous section	36.7%	51.6%	70.4%

Another concern with the estimates obtained in this paper is that changes in welfare policy during the period considered may induce changes in labor supply among welfare recipients.

Due to the lack of appropriate instrumental variables to account for this type of endogeneity, I decided not to examine the extent of the resulting bias. However, the welfare policy changes during the estimation period were mild in nature and empirical evidence also suggests that the welfare changes have moderate impacts on labor supply (for example, see Cai, Kalb, Tseng, & Vu, 2008; Borland & Tseng, 2007; Richardson, 2002). Therefore, this type of endogeneity bias, if present, is unlikely to change the substantive findings of this paper.

7 Conclusion

This paper has applied a stock-flow model to estimate the relationship between the rate of income support receipt and labor market conditions during 1997-2005 in Australia. Central to the analysis are the empirical relationships between the underlying welfare flows and labor market conditions. There are two main empirical issues in estimating the relationships including measurement error in the labor market data and finding adequate proxies for labor market conditions.

The paper has addressed each of these issues accordingly. It has considered different strategies that vary in the extent of measurement error and the estimated effects of labor market conditions increase substantially as the extent of measurement error decreases. In terms of proxies for labor market conditions, the simulation results are found to be robust to alternative measures of labor market conditions.

Several insights can be drawn from the analysis. The first insight is that the level of welfare reliance is closely related to labor market conditions. Labor market conditions are shown to affect both welfare inflows and outflows, and be the main explanation for the recent decline in welfare reliance among people of working age. This finding highlights the importance of the welfare system in providing assistance to individuals who are in need of assistance because of cyclical movements in the labor market. Equally, it is important to improve employment opportunities for all to reduce the level of welfare dependency.

The second insight is more related to econometric knowledge. Substantial differences in the estimates across specifications illustrate that measurement error can cause significant attenuation bias, and hence can lead to misleading conclusions. It thus underscores the importance of undertaking a thorough robustness check in empirical studies when data are measured with error.

As a final note, I would like to point out that the findings of this paper should be interpreted with caution because the data period is rather short and coincides with a period of improving labor market conditions. While the estimates capture the relationship between strong labor market conditions and welfare participation, they may not reflect the relationship between deteriorating labor market conditions and welfare participation.

References

Achen, C. (2000). *Why Lagged Dependent Variables Can Supress the Explanatory Power of Other Independent Variables*. Paper presented at the the Annual Meeting of Political Methodology (July 20-22, 2000).

Australian Bureau of Statistics. (2002). *Information Paper: Labour Force Survey Sample Design, November 2002, Cat. No. 6269.0*. Canberra: Australian Bureau of Statistics.

Bell, W. R., & Hillmer, S. C. (1990). The Time Series Approach to Estimation for Repeated Surveys. *Survey Methodology, 16,* 195-215.

Blank, R. M. (1989). Analyzing the length of welfare spells. *Journal of Public Economics, 39*(3), 245-273.

Blank, R. M. (2001). What Causes Public Assistance Caseloads to Grow? *The Journal of Human Resources, 36*(1), 85-118.

Borland, J., & Tseng, Y.-P. (2007). Does a Minimum Job Search Requirement Reduce Time on Unemployment Payments? Evidence from the Jobseeker Diary in Australia. *Industrial and Labor Relations Review, 60*(3), 357-378.

Cai, L., Kalb, G., Tseng, Y.-P., & Vu, H. (2008). The Effect of Financial Incentives on Labour Supply: Evidence for Lone Parents from Microsimulation and Quasi-Experimental Evaluation. *Fiscal Studies, 29*(2), 285-325.

Cappellari, L., & Jenkins, S. P. (2009). The Dynamics of Social Assistance Receipt: Measurement and Modelling Issues, with an Application to Britain. *SSRN eLibrary*.

Council of Economic Advisers (CEA). (1997). *Explaining the Decline in Welfare Receipt, 1993-1996*. Washington, DC: Excutive Office of the President.

Council of Economic Advisors (CEA). (1999). *The Effects of Weflare Policy and Economic Expansion on Welfare Caseload: An Update*. Washington, DC: Executive Office of the President.

Figlio, D. N., Gundersen, C., & Ziliak, J. P. (2000). The Effects of the Macroeconomy and Welfare Reform on Food Stamp Caseloads. *American Journal of Agricultural Economics, 82*(3), 635-641.

Figlio, D. N., & Ziliak, J. P. (1999). Welfare Reform, the Business Cycle, and the Decline in AFDC Caseloads. In S. H. Danziger (Ed.), *Economic Conditions and Welfare Reform* (pp. 17-48). Kalamazoo, MI: W.E. Ujohn Insitute for Employment Research.

Gittleman, M. (2001). Declining Caseloads: What Do the Dynamics of Welfare Participation Reveal? *Industrial Relations: A Journal of Economy and Society, 40*(4), 537-570.

Grogger, J. (2004). Welfare transitions in the 1990s: The economy, welfare policy, and the EITC. *Journal of Policy Analysis and Management, 23*(4), 671-695.

Haider, S. J., Klerman, J., & Roth, E. (2003). The Relationship between the Economy and the Welfare Caseload: A Dynamic Approach *Research in Labor Economics* (Vol. 22, pp. 39-69).

Harmer, J. (2008). *Pension Review Background Paper*. Canberra: Department of Families, Housing, Community Services and Indigenous Affairs.

Klerman, J. A., & Haider, S. J. (2004). A Stock-Flow Analysis of the Welfare Caseload. *The Journal of Human Resources, 39*(4), 865-886.

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics*. Cambridge: Cambridge University Press.

McClure, P. (2000). *Participation Support for a More Equitable Society: The Final Report of the Welfare Reform Working Group*. Canberra: The Australian Department of Family and Community Services.

Mitchell, W., & Watts, M. (2010). Identifying Functional Regions in Australia Using Hierarchical Aggregation Techniques. *Geographical Research, 48*(1), 24-41.

Moffitt, R. (1992). Incentive Effects of the U.S. Welfare System: A Review. *Journal of Economic Literature, 30*(1), 1-61.

Pfeffermann, D., Feder, M., & Signorelli, D. (1998). Estimation of Autocorrelations of Survey Errors with Application to Trend Estimation in Small Areas. *Journal of Business & Economic Statistics, 16*(3), 339-348.

Richardson, L. L. (2002). Impact of the Mutual Obligation Initiative on the Exit Behaviour of Unemployment Benefit Recipients: The Threat of Additional Activities. *Economic Record, 78*(243), 406-421.

Tseng, Y.-P., Vu, H., & Wilkins, R. (2008). Dynamic Properties of Income Support Receipt in Australia. *Australian Economic Review, 41*(1), 32-55.

Victorian Department of Planning and Community Development. (2008). *2006 Census Paper: Travel to Work Patterns in Melbourne*. Melbourne: Victorian Department of Planning and Community Development.

Wallace, G., & Blank, R. (1999). What Comes Up Must Come Down? Explaining Recent Changes in Public Assistance Caseloads. In S. H. Danziger (Ed.), *Economic Conditions and Welfare Reforms* (pp. 49-90). Kalamazoo, MI: W.E. Upjohn Insititute for Employment Research

Wallace, G. L. (2007). Welfare Flows and Caseload Dynamics *Journal of Applied Economics 10*(2), 415-442.

Whiteford, P., & Angenent, G. (2002). *The Australian system of social protection: an overview*. Canberra: Department of Family and Community Services.

Ziliak, J. P., Figlio, D. N., Davis, E. E., & Connolly, L. S. (2000). Accounting for the Decline in AFDC Caseloads: Welfare Reform or the Economy? *The Journal of Human Resources, 35*(3), 570-586.

Ziliak, J. P., Gundersen, C., & Figlio, D. N. (2003). Food Stamp Caseloads over the Business Cycle. *Southern Economic Journal, 69*(4), 903-919.

Appendix A: Region Classification

ABS MSR	LLMR	ABS Statistical Regions
Sydney	"Inner" Sydney	Inner and Inner Western Sydney, Eastern Suburbs, Canterbury-Bankstown, Central Western Sydney, Lower Northern Sydney
	Outer "Western" Sydney	St George-Sutherland, Fairfield-Liverpool and Outer South Western Sydney
	Outer "Northern" Sydney	Northern Beaches, North Western, Central Northern Sydney, Gosford-Wyong
Balance of NSW	Hunter	Hunter
	Illawarra and South Eastern	Illawarra and South Eastern
	Richmond-Tweed and Mid-North Coast	Richmond-Tweed and Mid-North Coast
	Northern, Far West-North Western and Central West	Northern, Far West-North Western and Central West
	Murray-Murrumbidgee	Murray-Murrumbidgee
Melbourne	"Inner" Melbourne	North Western Melbourne, Outer Western Melbourne, Inner Melbourne, North Eastern Melbourne, Southern Melbourne, Inner Eastern Melbourne , Outer Eastern Melbourne
	"Outer" Melbourne	South Eastern Melbourne, Mornington Peninsula
Balance of VIC	Barwon-Western District	Barwon-Western District
	Central Highlands-Wimmera	Central Highlands-Wimmera
	Loddon-Mallee	Loddon-Mallee
	Goulburn-Ovens-Murray	Goulburn-Ovens-Murray
	All Gippsland	All Gippsland
Brisbane	Brisbane	Brisbane City Inner Ring, Brisbane City Outer Ring, South and East BSD Balance, North and West BSD Balance
Balance of QLD	South and East Moreton	South and East Moreton
	North and West Moreton	North and West Moreton
	Wide Bay-Burnett	Wide Bay-Burnett
	Mackay-Fitzroy-Central West	Mackay-Fitzroy-Central West
	Darling Downs-South West	Darling Downs-South West
	Northern-North West	Northern-North West
	Far North	Far North
Adelaide	Adelaide	Northern Adelaide, Western Adelaide Eastern Adelaide, Southern Adelaide
Balance of SA	Southern and Eastern SA	Southern and Eastern SA
	Northern and Western SA	Northern and Western SA
Perth	Perth	Central Metropolitan, East Metropolitan, North Metropolitan, South West Metropolitan, South East Metropolitan
Balance of Perth	Lower Western WA	Lower Western WA
	Remainder-Balance WA	Remainder-Balance WA
Tasmania	Tasmania	Tasmania
NT	Northern Territory (NT)	Northern Territory

Appendix B: Variable Description- Regional Characteristics

Variable	Description
Post school education	
	Bachelor degree or higher
	Diploma
	Certificate
	No post school qualification (omitted category)
Country of birth	
	Australian born (omitted category)
	Foreign born in an English Speaking country
	Foreign born in a non-English Speaking country
Industry	
	Agriculture, forestry, fishery and; Mining
	Manufacturing
	Construction
	Transport &storage; Electricity, gas & water; Wholesale trade; Communication services
	Finance &insurance; Property &business services
	Government administration; Health & community services
	Education
	Retail trade; Cultural & recreational; Personal & other services
	Accommodation, restaurants(omitted category)
Occupation	
	Professionals
	Associate Professionals
	Tradespersons and Related Workers
	Advanced Clerical and Service Workers
	Managers and Administrators
	Intermediate Clerical, Sales and Service Workers
	Intermediate Production and Transport Workers
	Elementary Clerical, Sales and Service Workers
	Laborers and Related Workers (omitted category)