Cyclical Flows in Australian Labour Markets

By

Natalia Ponomareva and Jeffrey Sheen
Department of Economics
Macquarie University

Abstract

We show that Australian labour markets became more flexible after 1980, but most gains occurred before 1993. We find large and significant procyclical effects in the transition probabilities from unemployment to jobs, which contribute significantly to the variations of unemployment. Transitions from jobs to unemployment are countercyclical, but the effects are small and insignificant. Job-losing and job-finding are both important for the evolution of unemployment over the whole business cycle, but during recessions, job-finding is a bigger issue. For women, part-time transitions are more important.

Keywords: Labour market flows, unemployment, transition probabilities, business cycles

Mailing Address:
Department of Economics
Macquarie University,
North Ryde, NSW, Australia

Date: 20 September 2009

Acknowledgements: We thank Robert Dixon for useful suggestions.

1. Introduction

An understanding of the key empirical facts about the cyclical flows of people between labour market states is vital for the design of macroeconomic models and policy. During downturns in the business cycle, unemployment rises quickly, and it can remain high for some time after the cycle of economic activity has bottomed out. This rise and its persistence may occur for a number of reasons. Maybe people begin to lose their jobs and flow into the unemployment pool; maybe those who are already unemployed find it harder to get a job; or maybe in a downturn, people previously inactive in the labour market are forced to actively seek hard-to-find work, while fewer unemployed can afford to become inactive. It is not uncommon to find economists and policy-makers that take for granted that job loss is the major explanation for rising unemployment in a downturn. While this might be true for very deep downturns like the Great Depression of the early 1930s, there is growing evidence that this is not the case for recessions in the course of the normal business cycle. It is the declining outflows from unemployment, rather than the inclining inflows, that are largely responsible for the deterioration in unemployment in recessions.

In establishing this key conclusion, a substantial literature has built up to consider the probabilities of transition between states across the business cycle, extending an earlier literature that mainly focused on actual gross flows in U.S. labour markets.[1] That earlier literature came to the conclusion that job losses, or inflows to (rather than outflows from) unemployment from (to) employment, were the defining feature in recessions. The recent literature has come to the opposite conclusion. A number of authors have studied flows between labour market states in Australia[2] coming to similar conclusions.

In this paper, we extend that literature to give a more detailed analysis of the trends and cyclical behaviour of monthly transition probabilities between labour market states over a

[1] Gross flows were the focus of, *inter alia*, Poterba and Summers (1986), Abowd and Zellner(1985), Blanchard and Diamond (1990), Davis and Haltiwanger (1992). Recent work focusing on transition probabilities include Hall (2005b), Shimer (2005), Fujita and Ramey (2009), Elsby, Michaels and Solon (2009). Also see Burgess and Turon (2005)
[2] For example, see Junankar and Kapuszinski (1990), Fahrer and Heath (1992), Borland (1996), Dixon, Lim and Freebairn (2004), Chua, Dixon and Lim (2007).

thirty year sample (1980:8 to 2009:6) that includes three definitive recessions (1982-3, 1990-1, and 2008-9). For the first time in this literature, we study transition probabilities between four states of the labour market—full-time employment (*F*), part-time employment (*P*), unemployment (*U*) and not in the labour force, or inactive (*I*)[3].

Using summed labour market flows per capita, we find evidence that the increase in labour market flexibility in Australia happened only during the period of Labor governments under Hawke and Keating until 1996. There were no discernible improvements in flexibility during the period of the Coalition government of Howard until 2007. We show that there are some noticeable differences in the latest slowdown. In particular, our observation that labour markets have become much more flexible appears so far to have meant a much less severe effect on labour markets in the 2008-2009 recession, which had been widely expected to be unusually severe. Over the whole sample, we find that the inflow probabilities to Australian unemployment, from both types of employment and inactive states, have been relatively small and declining compared to the larger and growing outflow probabilities. We find that the outflow probabilities are significantly procyclical, and magnified in recessions. In all of our analysis, we compare flow outcomes for men and women in Australia over the thirty year sample. We find the important result that the gap between the genders has significantly narrowed in terms of total flows per capita and for many transition probabilities. However gender differences remain in some cyclical responses—female outflow probabilities from unemployment into part-time jobs (*UP*) are more seriously affected in recessions, while the inflows from jobs (*FU* and *PU*) tend to be more affected in recessions for men.

To address these issues, we consider two-state and four-state models. With a two-state model, we allow only for movements between full-time employment (*F*) and unemployment (*U*). This enables us to focus on the key choice between inflows and outflows for unemployment in a relatively simple model. However this ignores the possibility of interactions with labour market inactivity and with the different types of employment—full-time and part-time. Thus in the four-state version, we include flows between states of full-time and part-time employment, unemployment and inactive.

[3] Henceforth we shall use the 'inactive' descriptor in place of the conventional though more cumbersome 'not-in-the-labour force'.

We follow Shimer (2007) by assuming a continuous time model for the evolution between any states. This avoids the so-called 'time aggregation bias', which can arise because the data is necessarily observed at discrete intervals. For example, the labour force survey may miss spells of unemployment that begin and end during the interval. To deal with this, instantaneous transition probabilities are assumed to remain constant from the beginning to the end of any month. Thus the period transitions can accommodate intra-period movements between states, thus avoiding an underestimation of the flows. The instantaneous and full-period transition probabilities for each period are found by using the solution of a set of differential equations for the shares of people transitioning from one state to another. We focus on these probabilities because they play a vital role in the theory of job-finding, job-losing and labour force participation. For example, in the literature on search, the job-finding probability is driven by the vacancy to unemployment ratio, which in turn is driven by exogenous business cycle variables. Similarly job-loss probability reflects the risk of job security, which will also be driven by these exogenous variables.

We examine the business cycle properties for each transition probability series in two ways. First, we observe graphically the changes during each of the three recessions in our sample. Second, we obtain seemingly unrelated regression (SUR) estimates for each against a variable for the business cycle, the employment to population ratio, in an AR(12) model. We also test to see whether recessions amplify the effects of that cyclical variable. Our summed gross flow results suggest a sample break in 1993, and so we compare cyclicality estimates for the whole sample, and for the seventeen years since 1993. In all of our tests, we compare the regressions for men and women.

We also look at the contributions of each transition probability to a 'steady state' measure of the unemployment rate. This steady state is constructed on the basis that the total inflows into each state equal the total outflows to every other state within the month of observation. We show that this steady state measure is highly correlated with actual unemployment. The key question we address here is which of the job-finding or job-losing probabilities is most important for understanding the movements in unemployment. Does the answer differ for men and women? Is there a difference between full-time and part-time employment contributions?

Our paper has the following structure. In section 2, we discuss the stock and flow data available in Australia that can be used to measure transition probabilities. We explain the transformations needed to make the flow data consistent with the stock data, and then how to extract transition probabilities from an s-state continuous time differential equation system with observations at discrete intervals. We also explain the general structure of our regression equations. Section 3 examines the statistical properties of a two-state model, and section 4 of a four-state model. The final section provides concluding comments.

2. Data and Modelling Procedures

To calculate the probabilities of people making a transition between any two labour market states, we need either measures of stocks of people in each state for a suitably short term duration, or better, data that measures flows between states in a period.

In the case of Australia, the ABS produces unmatched stock measures of 'short term unemployment' in a month, being those people who have been unemployed for less than the relevant four weeks (see ABS6291 Table 14a) coming from a *full-time* job. Unfortunately, it does not provide data on those who came from a part-time job, nor the equivalent 'short term employment' or 'short term inactive'. Though it allows us to get some insights about movements from and into unemployment, and their relative importance for unemployment rate determination, it is somewhat restrictive since in reality there is substantial movement to and from the inactive state, I (i.e. not in the labour force) in addition to full-time and part-time employment, F and P.

Instead, matched gross flow data (sourced from ABS6202 GM1 and ABS6203 prior to October 1997) can be used. This data shows that there are large flows from being inactive to being employed or unemployed and *vice versa*, as well as significant movements to and from the two employment categories. Table 1 gives an idea of the size of the relative flows, by showing the gross monthly flows between the four states from June to July 2009, in the midst of a recession. For example, the monthly flow from full-time and part-time employment to the inactive state was 75,000 and 152,000 respectively, about twice and five times greater than the 40,000 and 32,000 flows to unemployment. The relative flows from unemployment to inactive were 131,000, again two and a half times the 53,000 and 132,000 flows to full-time and part-time employment. The movements between full- and part-time employment (270,000 and 318,000) were far larger than movements to other states. Therefore, we are able to obtain more accurate transition probabilities between the states if we can use the gross flow data that covers all four states.

However the gross flow data comes with a problem. It arises from *matched* household survey outcomes[4], whereas the stock data is for all survey outcomes, matched and unmatched. This means that the flows from and into a given state do not sum up to the changes in the relevant unmatched stock data (as obtained from ABS6291 LM8). As an example, in Table 1, the last column and last row show this stock data for the months of June 2009 and July 2009 respectively. The numbers differ substantially (on average by 18%) from the previous column and row, which give implied stock totals for each of the months from the flow data. To make the stock and flow data consistent, the gross flow data have to be transformed to match the relevant stock counterparts. We follow Dixon *et al* (2004) in applying the 'Residual Allocation System' (RAS) method, used for input-output tables, to the gross flow data to make them consistent with the stock data. This scaling adjustment assumes that the missing unmatched data has similar characteristics to the matched data[5].

2.1 The data transformation procedure

Consider people who at time t=0 were in state i, where i is an element of the S-vector of states. These people are observed both in matched gross flow data, and in stock data. At time t=1, a share n_{row}^{ij} (i.e. row share) of these people in the flow data can be measured as having flowed through the period to state $j \neq i, j=1,..S,$ while a share n_{row}^{ii} remains in state i. Since the number of people in state i at t=0 is known from the stock data, N_{0i}, we can calculate the implied flow of people from state i at t=0 to each state j at t=1 so that their sum is consistent

[4] The gross flow data is prepared monthly by the ABS from the Labour Force Survey, which is based on a sample of representative private dwellings comprising about 0.24 per cent of the Australian population. This data *matches* respondents over consecutive months, with each household staying in the sample for eight months, and then leaving the sample permanently. This means at least one eighth of the households cannot be matched. Matching failures may occur for other reasons, like if a household is unavailable for interview in a particular month. Apart from these missing observations, which can cause bias, there is also a bias caused by classification errors when wrong answers are recorded (see Blanchard and Diamond, 1990, for a detailed explanation).

[5] The ABS warns that 'overall, those who can be matched (in the private dwelling sample) represent about 80% of all people in the survey. About two-thirds of the remaining (unmatched) 20% are likely to have characteristics similar to those in the matched group, but the characteristics of the other third are likely to be somewhat different.'

with the stock data at time t=0; this flow will be $n^{ij}_{row} N_{0i.}$ However, the transformed data is not necessarily consistent with the stock data at time t=1 and so the procedure has to be repeated. Thus consider people who are in state k at t=1. The column share n^{mk}_{column} of them got there having been in state m at t=0 where m is an element of the S-vector of states. Given the known number of people, N_{1k} in state k at t=1 from the stock data, $n^{mk}_{column} N_{1k.}$ will represent the adjusted flow of people from state m at t=0 into state k at t=1 consistent with the stock data at t=1. Again, this can be done for all states k. This column adjustment of the flow data may disrupt the previous row alignment of stocks and flows, and so the adjustment procedure to match stocks at t=0 and t=1 has to be repeated until we achieve convergence (in the sense that each subsequent complete iteration produces the same results as the previous one). Then we take the average value of the row and the column data transformations since the values of each will be close but not identical[6].

A sample of the results from the transformation procedure is shown in Table 2. Comparing with Table 1, the column and row sums of the transformed gross flows are only marginally different (at an absolute average of 0.08%) from the respective stock figures.

2.2 Getting transition probabilities

The transformed gross flow data can be used to calculate instantaneous transition probabilities between states i and j, λ_t^{ij} , following the approach described in Shimer (2007). This approach assumes that transitions occur continuously over time according to a Poisson process. However the flows are only observed over a discrete period (one month), and within that period the instantaneous transition probabilities between states are assumed to remain constant, yielding a within-period differential equation system. The probability of making a transition from state i to j over a period from t to t+1 is then given by:

$$\Lambda_t^{ij} = 1 - e^{-\lambda_t^{ij}} \tag{1}$$

[6] Dixon *et al* (2004) report that 10 complete iterations are more than enough to match the 'convergence' criterion that the ratios of the transformed data do not differ from corresponding ratios in the stock data by more than 0.001. We go beyond this criterion and do 500 iteration to ensure that convergence is achieved in the sense that the transformed data obtained from a completed iteration do not differ from the transformed data obtained from a previous iteration.

Across periods, these probabilities can differ, and we use regression analysis to understand the evolution of the probabilities. The model implies that transition probabilities only change between discrete periods, suggesting that labour market behaviour alters when monthly data is released.

Given the set of states *S*, denote $N_t^{ij}(\tau)$ as the number of people who were in state *i* at time *t* and are in state *j* at time $t+\tau$ where $\tau \in [0,1]$. Then the share of people who began in state *i* at time *t* and reached state *j* at time $t+\tau$ is:

$$n_t^{ij}(\tau) = \frac{N_t^{ij}(\tau)}{\sum_{k \in S} N_t^{ik}(\tau)} \tag{2}$$

where $N_t^{ij}(0) = n_t^{ij}(0) = 0$ for all $i \neq j$. Note that these shares are relative to the numbers in state *i* at the beginning of period *t.*

For $i \neq j,\ n_t^{ij}(\tau)$ evolves in the period from *t* to *t*+1 according to the following differential equation:

$$\dot{n}_t^{ij}(\tau) = \sum_{k \neq j} n_t^{ik}(\tau)\, \lambda_t^{kj} - n_t^{ij}(\tau) \sum_{k \neq j} \lambda_t^{jk} \tag{3}$$

with $\sum_{j \epsilon S} n_t^{ij}(\tau) = 1$. Equation (3) says that the share of people moving from state *i* to *j* at time $t+\tau$ increases because a (constant) proportion λ_t^{kj} of those that moved in the previous τ sub-periods from *i* to another state *k* arrive in *j*, and decreases because a (constant) proportion λ_t^{jk} of those that had reached *j* after τ sub-periods will exit to another state. If *s* is the number of states in *S,* then writing (3) for all $i \neq j$ gives a system of $s(s-1)$ linear differential equations, which can be solved for $s(s-1)$ fractions $n_t^{ij}(1)$ for $i \neq j$ as functions of $s(s-1)$ transition rates. Since the fractions $n_t^{ij}(1)$ can be calculated using the (transformed) gross flow data, we get a boundary value system of $s(s-1)$ differential equations that can be solved numerically to obtain the instantaneous transition probabilities λ_t^{ij}.for each period. We are interested in the corresponding full-period transition probabilities, Λ_t^{ij}.

Up to a three-state model, the differential equation system can be solved symbolically, and the transition probabilities then obtained numerically from the resulting set of simultaneous equations. This has been the practice in the existing literature. Beyond three states, this procedure is practically impossible, and so instead we use numerical boundary value techniques for differential equation systems to solve for the transition probabilities.[7]

2.3 Estimating cyclical responses

To understand better how each of our computed transition probabilities responded to business cycle impulses, we run regressions of these against a common representative cycle factor. There are a variety of time series that could be used for this factor. We use the total employment to population ratio, which is available monthly. The reason for selecting this is that Chua, Dixon and Lim (2007) have shown that for transformed gross flows from 1980 to 2003 in a three-state model for Australia, this variable has the highest correlation from a candidate set with an autoregressive latent variable that arises as a common factor in a Bayesian estimation.

We also test for an asymmetric response to the business cycle variable. To do this, we introduce a recession dummy multiplied with the cycle variable. The recessions were chosen using the classical datings of peak to trough for the Australian economy as identified by the Melbourne Institute—these are November 1981 to May 1983 and February 1990 to October 1991—and using our own assessment for September 2008 to July 2009.

We regress each computed transition probability against a constant, twelve own lags, the employment to population ratio (the 'cycle' variable) and that ratio multiplied by the 'recession' dummy, and monthly seasonal dummies:

$$\Lambda_t^{ij} = c^{ij} + \sum_{k=1}^{12} \alpha_k^{ij}\, \Lambda_{t-k}^{ij} + \left(\beta^{ij} + \gamma^{ij}\ recession\right)\frac{emp_t}{pop_t} + seasonals + v_t^{ij} \qquad (4)$$

The lags are necessary to deal with the substantial monthly dynamics. The random errors for each (v_t^{ij}) are likely to exhibit significant cross-equation correlation, since there are bound to be unspecified shocks that affect transitions between more than one pair of states, $\{i, j\}$. Therefore we do seemingly unrelated regressions (SUR)[8].

[7] See Keller (1992). As a check, we have obtained solutions using both the symbolical and the numerical method for a two- and a three-state model, and obtained identical results for the transition probabilities.
[8] In our regressions, at least a quarter of the cross-equation correlations of the residuals exceeded 15%.

3. A Two-State Model

It is useful to begin with a simple model of transitions with just two states, which, as shown by Shimer (2007), is implementable with available *unmatched stock* data on the labour market[9]. We fix one of the two states as unemployment, simply because data is available in Australia for the stock of short-term unemployment (but not for any other state). The choice of the second state depends on what assumptions are made about the labour force and employment. A common assumption for two state models[10] is that the labour force, L, is constant. This implies that the only relevant second state is employment. Any short-term (i.e. within the period) flows into unemployment must then be equivalent to short term outflows from employment, with transitions to and from the inactive state assumed irrelevant. However for Australia going back to 1978, the ABS provides data only on those short-term unemployed in a month that had a *full-time* job in the last four weeks. Therefore, for our two-state analysis on available Australian stock data, we have to assume that the only transitions are between unemployment, U_t and full-time employment, F_t, with part-time employment, P, held constant. This implies that $L - P = F_t + U_t$.

With only two possible states to move into, full-time employment and unemployment, equation (2) implies that the shares $n_t^{FU}(\tau)$ and $n_t^{UF}(\tau)$ evolve according to:

$$\dot{n}_t^{FU}(\tau) = n_t^{FF}(\tau)\lambda_t^{FU} - n_t^{FU}(\tau)\lambda_t^{UF} \tag{5}$$

$$\dot{n}_t^{UF}(\tau) = n_t^{UU}(\tau)\lambda_t^{UF} - n_t^{UF}(\tau)\lambda_t^{FU} \tag{6}$$

That is, each of these shares increases if there is a flow from the other state and decreases if there is a flow to the other state. At any instant, $n_t^{FF}(\tau) + n_t^{FU}(\tau) = 1$ and $n_t^{UU}(\tau) + n_t^{UF}(\tau) = 1$, and so these two differential equations can be solved to give at $\tau = 1$:

$$n_t^{FU}(1) = \frac{\lambda_t^{FU}}{\lambda_t^{FU} + \lambda_t^{UF}}\left(1 - e^{-(\lambda_t^{FU} + \lambda_t^{UF})}\right) \tag{7}$$

$$n_t^{UF}(1) = \frac{\lambda_t^{UF}}{\lambda_t^{FU} + \lambda_t^{UF}}\left(1 - e^{-(\lambda_t^{FU} + \lambda_t^{UF})}\right) \tag{8}$$

[9] Beyond two states, flow data becomes essential due to the unavailability of short-term measures for employment or the inactive state.

[10] For example, Hall (2005a), Shimer (2007), Elsby, Michaels & Solon (2009) start with this assumption.

The first (second) represents the share of the total employed (unemployed) at *t* that became unemployed (employed) at *t*+1, determined as a function of the two unknown instantaneous transition probabilities, which we extract from stock data in the two-state model[11].

For Australia, the stock of *short-term* unemployed is available for those who had been full-time employed but became unemployed during a month. In our model, this measure yields $\Lambda_t^{FU} F_t$. With data on the stock of full-time employment, F_t, also available, we can compute Λ_t^{FU}, and then of course λ_t^{FU}. We can use data on the total stock of unemployed people, U_t, whose period to period evolution is given by[12]:

$$\begin{aligned} U_{t+1} &= \Lambda_t^{FU} F_t + (1 - \Lambda_t^{UF}) U_t \\ &= \Lambda_t^{FU} F_t + e^{-\lambda_t^{UF}} U_t \end{aligned} \tag{9}$$

This says that the stock of unemployed at *t*+1 is given by the number of full-time employed at *t* that lose their job through the period plus the number of unemployed at *t* unable to find a job when *t*+1 arrives[13]. The only unknown in equation (9) is then λ_t^{UF}, for which we can solve at each data point. Having computed λ_t^{UF} and λ_t^{FU} from stock data, we can then solve equations (7) and (8) for the implied flow measures $n_t^{FU}(1)$ and $n_t^{UF}(1)$.

3.1 Two-State Results

We apply the method just discussed to Australian stock data from February 1978 to July 2009.

[11] For the two-state model, equations (5) to (8) are presented only for illustration. The transition probabilities are not computed using these, as explained in the next paragraph. However in the four-state model using gross flow data, the analogous flow equations are used directly to compute the transition probabilities.

[12] To derive this, note that the change in the number of unemployed at time $t+\tau$ ($\dot{U}_{t+\tau}$) is given by the number of full-time employed at $t+\tau$ that lose their jobs ($\lambda_t^{FU} F_{t+\tau}$) less the number of unemployed that find jobs ($\lambda_t^{UF} U_{t+\tau}$). However the change in short-term unemployment at $t+\tau$, ($\dot{n}_t^{FU}(\tau) E_t$), equals $\lambda_t^{FU} F_{t+\tau}$ less those unemployed then that find a job, ($\lambda_t^{UF} n_t^{FU}(\tau) F_t$). Solving the resulting differential equation yields (9).

[13] The full-period probability of an unemployed person at *t* finding a job is $\Lambda_t^{UF} = 1 - e^{-\lambda_t^{UF}}$, so the probability of remaining unemployed is $\Lambda_t^{UU} = -e^{-\lambda_t^{UF}}$.

3.1.1 Transition Probabilities: The results for men and women for the full-period transition probabilities Λ_t^{ij} are shown in Figures 1 and 2 as twelve month moving averages to reveal their smoothed paths[14].

The first thing to note is the relative large size of the job-finding probabilities (Λ_t^{UF}) to the job-losing ones (Λ_t^{FU}). The former is on average about thirteen times bigger for men, and nine times for women. These relativities are not surprising, since the number of people moving in each direction is of the same order, while the base stock of the unemployed is much smaller than that of the full-time employed.

Second, the gap between male and female full-time job-losing probabilities has declined by a third, though the job-finding probability has not changed.

Third, the job-finding probability appears to fall significantly in 'recessions'. The three identified recessions in the whole sample period are shown by the shaded columns. We note that the falls tended to happen a few months before each recession, suggesting a need for better ways to identify recessions. In regard to job-losing probabilities, men suffered a countercyclical response in the first two recessions only, and women only in the first.

3.1.2 Cyclical Estimates: Our expectation is that the full-time job-losing probability should be countercyclical—in a boom, the chance of losing one's job should fall($\beta^{FU} < 0$ in (4)). We have no prior belief about the differential effect in a recession—in a recession, the job-losing probability may or may not be amplified ($\gamma^{FU} \lesseqqgtr 0$)[15]. We would expect the job-finding probability to be procyclical($\beta^{UF} > 0$) as jobs are more plentiful in boom times. Again we have no prior belief about the possible asymmetric effect in a recession.

[14] In all of our subsequent figures, we present 12-month moving averages to smooth out the monthly seasonal factors.

[15] If recessions have an amplified effect on a transition probability, the signs of β^{ij} and γ^{ij} should differ. For all our regressions, we have instead used an intercept dummy for recessions, and we get the same parameter signs and significances as we have reported for the slope dummy..

In Table 3, we present our SUR estimates[16] for the cyclical parameters (β^{ij} and γ^{ij}) on male and female transition probabilities. We show results for the whole sample period (1980:8 to 2009:6) and for the last seventeen years (1993:1 to 2009:6).

The first result to note in Table 3 is that the job-finding responses to the business cycle are far larger than the job-losing ones, especially for women. The second is that these responses have become much bigger in the last seventeen years. Third, recessions have a significant amplifying effect on job-finding probabilities. For men, the estimated sign on the cycle variable on the job-losing probability is not as expected, but is significant at 1% only prior to 1993. Perhaps this sign problem might be due to the overly restrictive assumptions on the labour force and part-time employment in the two-state model. When we relax these assumptions in the four-state model introduced in the next section, we find that these sign problems on job-losing probabilities disappear, while the job-finding probabilities retain their qualitative effects.

4. A Four-State Model

Although the two-state model provided some useful results, the fixed labour force and part-time employment assumptions are too strong. For the first time in this strand of the literature, we will now implement a four-state model of full-time employment, part-time employment, unemployment and inactive transitions, and instead use matched and transformed gross flow data (as described in section 2). The set of states S is now $\{F, P, U, I\}$. The procedure for extracting the twelve full-period transition probabilities, Λ_t^{ij} for $\{i, j\} \epsilon S$ is given in section 2.2.

4.1 Four-State Results

4.1.1 Total Flows: The first issue we examine is how the overall mobility of the Australian labour market has changed over the last thirty years. To do that, we sum up all the transformed gross flows between the three states in each month and divide by the total civilian population. In Figure 3, we show these results for men and women. Three points are worth noting. First, female mobility is much greater than male mobility by almost 3

[16] For each SUR regression, we present Hoskins' multivariate test for serial correlation. We show in Table 3 that only the SUR model for men over the whole sample cannot reject multivariate serial correlation. More lags in that regression did not correct the problem.

percentage points, though the gap has narrowed. Second, there was a positive trend in overall mobility for both men and women from 1980 to 1993, after which there was no trend. The positive trend occurred during the Labor governments of Hawke and Keating, and their labour market reforms evidently had positive effects on mobility. The Coalition government under Howard from 1996 to 2007 evidently had no effect on mobility. Third, it is interesting to observe how male mobility spiked upwards in the recessions, while female mobility hardly changed in the first two episodes and even fell in the most recent one. This suggests that recessions might affect women more by the hours they work than by moving between the four measured states.

4.1.2 Transition Probabilities: Next, we present the full-period transition probabilities between each state for men and women. These are given in Figures 4 to 15.

Figures 5 and 10 are for *FU* and *UF* transitions, which can be compared to the two-state measures in Figures 2 and 1. The patterns of transition probabilities from full-time employment to unemployment and *vice-versa* seem to be quite different in a two-state and four-state models especially for women. This indicates that being inactive (or not in the labour force) or employed part-time are important states, which cannot be ignored.

Comparing Figures 8 and 9, we can see that the probability of moving from part-time employment to the inactive state (*PI)* is higher on average than moving from employment to unemployment (*PU*), especially for women. At the same time, the probabilities of moving from full-time employment to unemployment (*FU*) and the inactive state (*FI*) are comparable (as can be observed from Figures 5and 6). Overall, the probability of moving from part-time employment to being inactive (*PI*) almost halved for both genders over the thirty year period, while the probability of moving from full-time employment to the inactive state (*FI*) decreased for women, though was unaffected for men. Figures 13 to 15 generally indicate that men exit the inactive state to join all other states with higher probability than women, with the exception of going to part-time employment (*IP*) for which women have a higher probability of finding a job than men.

There seems to be a significant gender effect in transitions to part-time and full time employment. The probabilities of moving from any state to part-time employment are significantly higher for women (as can be seen from Figures 4, 11 and 14) while transition probabilities from any state to full-time employment are larger for men (as shown in Figures 7, 10 and 13). Figures 5 and 8 indicate that the probability of losing a part-time job is much higher than the probability of losing a full-time job and both probabilities are higher for men compared to women.

From Figures 10, 11, 13 and 14, we see that chances of getting a job for both the unemployed (*UF* and *UP*) and the inactive (*IF* and *IP*) have decreased dramatically during recessions, though the decrease has been relatively mild in the most recent recession, possibly because it was not yet over. At the same time, Figures 5, 8 and 15 show the probability of becoming unemployed (*FU, PU* and *IU*) increased during recessions both because some workers are losing jobs and because the cost of inactivity rises, leading those who return to the labour force into unemployment because it has become harder to find a job. However this increase in probability of becoming unemployed has been relatively mild in the recent recession, again possibly because it is not yet over.

4.1.3 Cyclical Estimates: To understand better how each of our computed transition probabilities has responded to business cycle impulses, we regress (using SUR) each of the twelve full-period transition probabilities against a constant, twelve own lags, seasonals, the employment to population ratio, and a multiplicative recession dummy, as in equation (4).

We expect that job-finding probabilities should be procyclical—their estimated βs should be positive, while job-losing ones should be countercyclical. This is because in boom phases of the business cycle, it should be easier to find and hold a job. We expect that transition probabilities from full-time to part-time work would be countercyclical, while the reverse should be procyclical. That is, in a boom, fewer full-time jobs should be converted to part-time. We would expect inactive to unemployment transitions to be countercyclical (and *vice versa*) probably because households' wealth and other income is procyclical.

The results are shown in Table 4. First, we note that our estimates show that *UF* and *UP* (or job-finding) transitions indicate consistently large and statistically significant procyclicality (especially in the 1993:1-2009:06 sample[17]), with absolute values much higher than all other transition cases. Second, the cycle has a stronger effect on the probability of finding a part-time job compared to a full-time job. Third, as in the two-state model, there is an additional and significant amplifying recession effect on the job-finding probabilities. Fourth, the *UF* and *UP* parameters have increased in value for the last fifteen years relative to the first fifteen for both genders; the probability of finding a full-time job has recently become significantly procyclical for men and women. Fifth, though *PU* (or part-time job-losing) transitions used to be significantly countercyclical, their response to the phases of the cycle are no longer significant (except for the effect of the 2008-2009 downturn); also their parameter sizes are much smaller than the *UP* ones. Sixth, for women, the full-time (but not the part-time) job-losing probability has become significantly countercyclical with no significant additional recession effect. Finally, we find significant multivariate serial correlation in the whole sample, but can reject it for men only in the sample from 1993.

Overall it seems that responsiveness of the job-finding probabilities to the cycle phases is much greater than responsiveness of the job-losing probabilities for both genders. In recessions, the procyclical job-finding responses are significantly amplified for both genders, and are only now marginally significant for male job-losing.

In addition, there are small cyclicality results for transitions involving the inactive state. For women, especially in the last seventeen years, we can reject acyclicality at 1% for *FI* and *IU*. For men, only *IP* and *IU* do not show acyclicality. *IU* shows significant countercyclicality (and *UI* procyclicality in the whole sample only), suggesting that procyclical wealth and household income effects might be influencing the decision to be inactive.

In regard to transitions between full-time and part-time employment (*FP* and *PF*), we note that there is a significant reduction in the probability of women moving from part-time to full-time jobs in a recession.

4.1.4 Contributions of transition probabilities to the unemployment rate: It is interesting to look at the contribution to the actual unemployment rate of each transition probability through the implied ‘steady state’ unemployment rate. The latter can be calculated by

[17] The *UF* probability does not seem to respond to the cycle variable significantly in the whole (1980:08-2009:06) sample, except in recessions.

assuming that the flows from and into any state are equal within a month. This resulting steady state measure has been shown to closely approximate the evolution of the actual unemployment rate in the US, albeit using two- and three-state models—for example, see Shimer (2007)[18] and Elsby, Michaels and Solon (2009).

To compute the steady state unemployment rate, we have to solve the following four-equation system[19] for $j = F_t, P_t, U_t, I_t$

$$\left(\sum_{k \neq j} \Lambda_t^{jk}\right) j = \sum_{k \neq j} \Lambda_t^{kj} k \tag{10}$$

where $F_t + P_t + U_t + I_t = Pop_t$, which is the civilian population.

Each of these equations simply says that the flows out of state j to the other three states equals the flows in to that state from the other three in a month. This set of equations can be solved [20] for $\{F_t^*, P_t^*, U_t^*, I_t^*\}$ as a function of the twelve computed transition probabilities and the civilian population. The steady state unemployment rate becomes:

$$u_t^* = \frac{U_t^*}{F_t^* + P_t^* + U_t^*} \tag{11}$$

which is independent of the population. Note that this measure is computed using all the transition probabilities, which vary throughout the sample[21].

In Figure 16, we plot this (unconditional) steady state measure and the actual unemployment rate for both men and women. The first thing to note is that the series are highly correlated (77% in the case of women, and 80% for men). Second, the steady state measures always exceed the actuals during recessions, while during booms there is much less difference.

Following Shimer (2007), we now calculate the contributions of each transition probability to the steady state rate in equation (11) by assuming only that particular probability varies in the

[18] Shimer (2007) reports a 99% correlation between these for US data in a three-state model of employment, unemployment and inactive.
[19] In fact, we used three of the equations in (10) and the population identity.
[20] For a four-state model, the solution is too large to do by hand, and so we used *Mathematica* to solve it.
[21] If the transition probabilities are evaluated at their whole sample means, the average steady state unemployment rate is 7% for men and 7.3% for women.

sample, whilst leaving all others fixed at their average values for the sample. We call these the conditional steady state unemployment rates. The results are shown in Figures 17a-d for men and Figures 18a-d for women. The figures show the unconditional unemployment rate and the conditional steady state rates computed for one particular transition probability contribution. The correlations of each of these conditional steady state unemployment rates with the unconditional ones over the whole sample are shown in Table 5. Note that the means of the graphed series in Figures 17and 18 will be the same. Therefore we are interested in the relative variations of the actual unemployment rate and the contributing conditional steady state transition measure, which is captured by the correlations given in Table 5

For men, we see that the biggest contributors to the unconditional steady-state unemployment, and thus to actual unemployment, are full-time and part-time job-loss to unemployment (*FU* and *PU)* and full-time job-finding (*UF*).

For women, the biggest contributors are part-time job-loss to unemployment (*PU*) and part-time job-finding from unemployment (*UP*), as well as job-loss to the inactive state (*FI* and *PI*). Full-time job-finding is a minor contributor.

5. Concluding Comments

The characteristics of the short-term dynamics between different states of the Australian labour market are crucial for the design of macroeconomic and labour policies. They also matter substantially for the design of macroeconomic models.

In this paper, we have established that Australian labour markets have become much more flexible since 1980, but that almost all of these gains occurred before 1993. We have noticed a narrowing of the gender gap for many transition probabilities. Though some gender differences remain, the convergence is worth noting.

Transitions from employment to unemployment are countercyclical, but the effects are insignificant and small. That is, in a recession, the problem of workers losing their job is not a large one. However we have shown that large and significant procyclical effects arise in the probability of transitions from unemployment to employment. These effects are significantly amplified in a recession, which implies that the main problem is that the unemployed cannot find jobs. This transition problem contributes significantly to the variations of unemployment.

Over the whole business cycle, our ‘steady state’ analysis for unemployment has shown that job-finding and job-losing probabilities are both important, though for women these only involve part-time jobs, while for men, it is both full-time and part-time jobs.

These results indicate that policy-makers need to focus on both job-losing and job-finding issues over the whole business cycle, but primarily on job-finding ones in recessions. These results also have implications for the design of macroeconomic models. The importance in size and cyclical contribution of the unemployment to jobs transition probability suggests the need for business cycle models that further emphasise job-finding issues.

References

Abowd, J. and Zellner, A. (1985) "Estimating gross labor force flows. *Journal of Business and Economic Statistics*, July, 3:254–83, 1985

Blanchard, O.J. and Diamond, P. (1990), "The Cyclical Behavior of the Gross Flows of U.S. Workers," *Brookings Papers on Economic Activity*, 2: 85-143.

Borland, J. (1996) "Labour Market Flows Data for Australia", *Australian Economic Review*,29, 225-235.

Burgess and Turon (2005) "Unemployment Dynamics, Duration and Equilibrium: Evidence from Britain" *Economic Journal*, April 2005

Chua, C.L., Dixon, R. and Lim,G.C. (2007) "What Drives Worker Flows?" Melbourne Institute Working Paper No. 34/07.

Davis, S. and Haltiwanger, J (1992) "Gross job creation, gross job destruction and employment reallocation". *Quarterly Journal of Economics*, 107(3):819–863.

Dixon, R., Freebairn, J. and Lim, G. C. (2004), "A framework for understanding changes in the unemployment rate in a flows context: an examination net flows in the Australian labour market" [http://repository.unimelb.edu.au/10187/788], 28 pages

Elsby, M.W.L., Michaels, R., and Solon, G,. (2009). "The Ins and Outs of Cyclical Unemployment." *American Economic Journal: Macroeconomics*, 1(1): 84–110.

Fahrer, J and Heath, A (1992) "The Evolution of Employment and Unemployment in Australia", Reserve Bank of Australia Research Discussion Paper, RDP 9215,

Fujita, S. and Ramey, G. (2009), "The Cyclicality of Separation and Job Finding Rates" *International Economic Review*, Vol 50–2, May.

Hall, R.E. (2005a), "Employment Efficiency and Sticky Wages: Evidence from Flows in the Labor Market," *Review of Economics and Statistics*, August, 87(3): 397-407

Hall, R.E. (2005b), "Job loss, job finding, and unemployment in the U.S. economy over the past fifty years". *NBER Macroeconomics Annual*, pages 275–310.

Junankar, P.N. and Kapuscinski C.A. (1990), "The Duration of Unemployment in Australia: Memory and Measurement", ANU Centre for Economic Policy Research Discussion Paper No 238

Keller, H.B. (1992), Numerical Methods for Two-Point Boundary Value Problems, Dover, New York.

Poterba, J. and Summers, L. (1986) "Reporting errors and labor market dynamics" *Econometrica,* 54(6):1319–1338, November

Shimer, R. (2005) "The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, March, 95(1), 25–49

Shimer, R.(2007), "Reassessing the Ins and Outs of Unemployment," http://www.nber.org/papers/w13421, 41 pages

Figure 1

Λ^{UF}: Job-finding Probabilities (2 states)

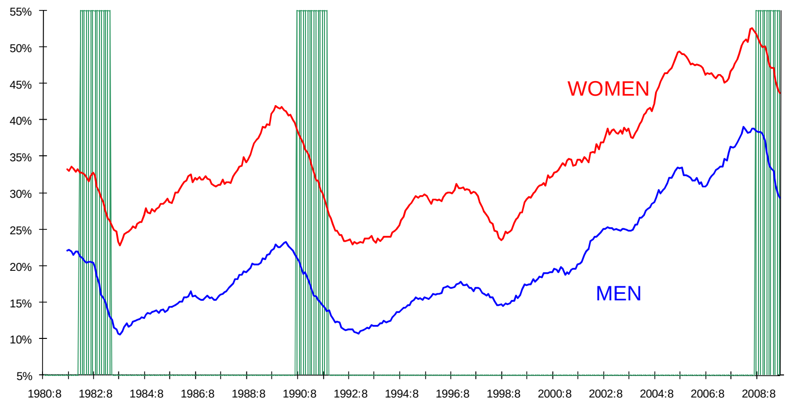

Figure 2

Λ^{FU}: Job-losing Probabilities (2 states)

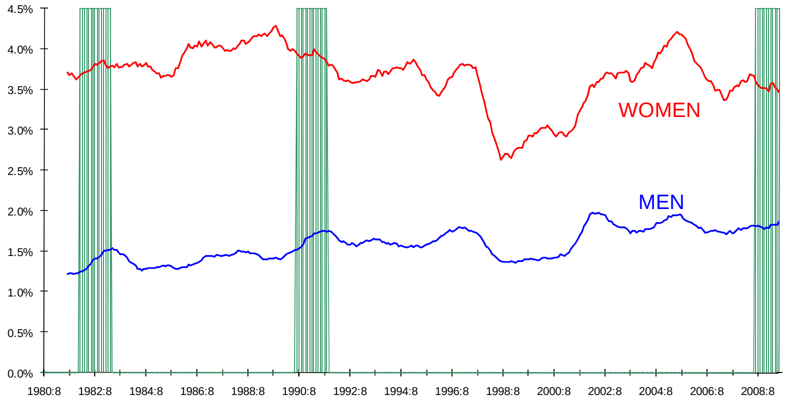

Figure 3

Total Gross Flows of Labour per Capita (4 states)

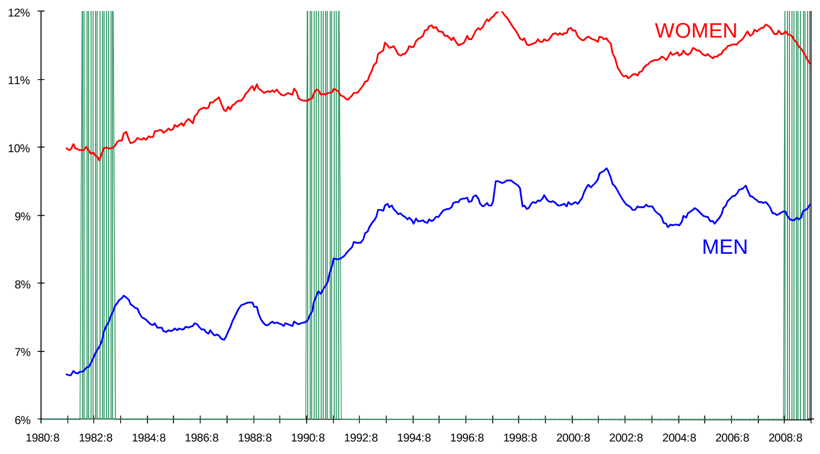

Figure 4

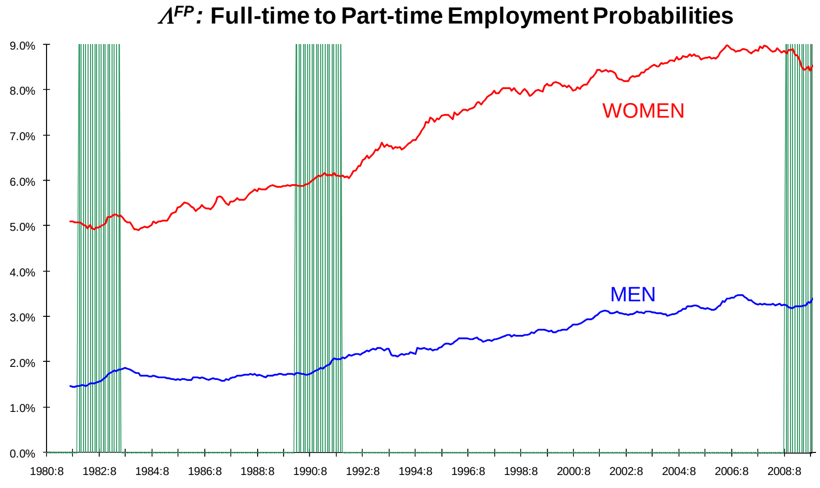

Figure 5

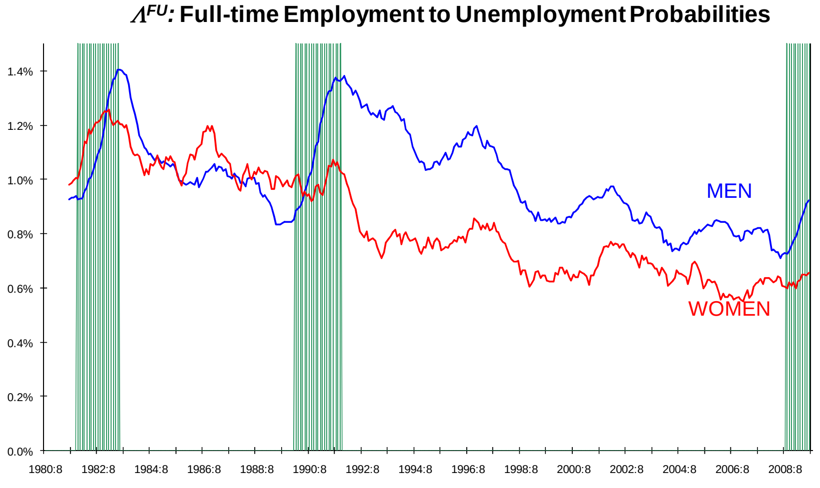

Figure 6

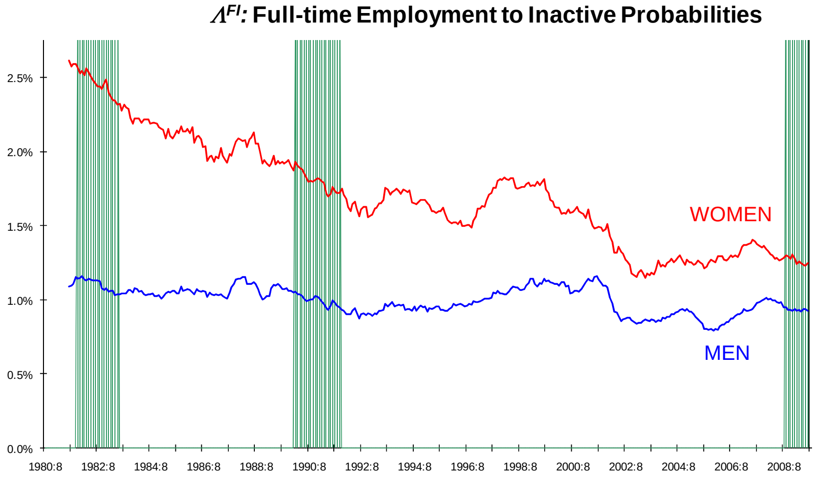

Figure 7

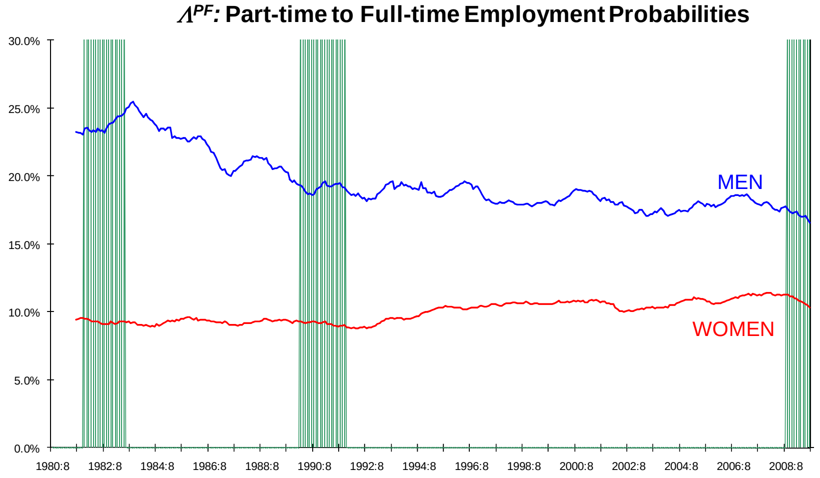

Figure 8

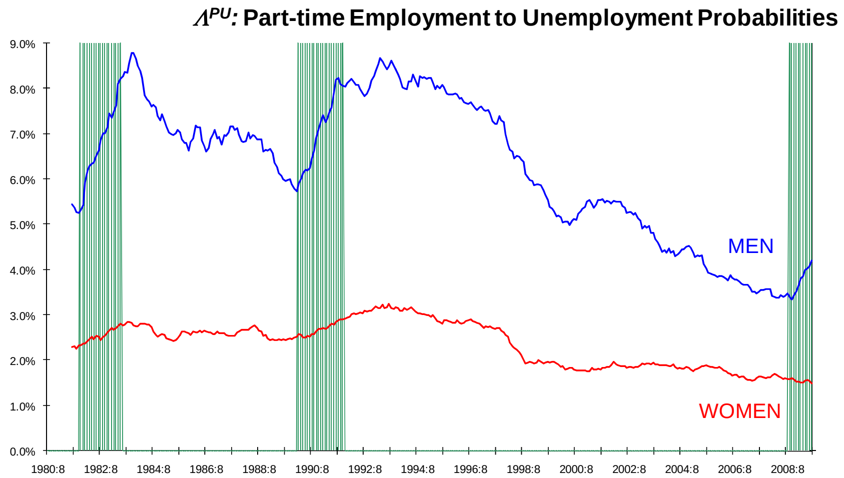

Figure 9

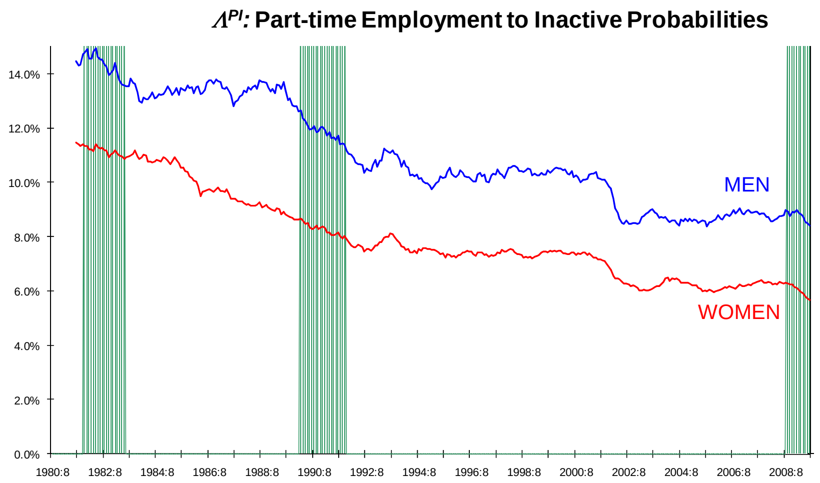

Figure 10

Λ^{UF}: Unemployment to Full-time Employment Probabilities

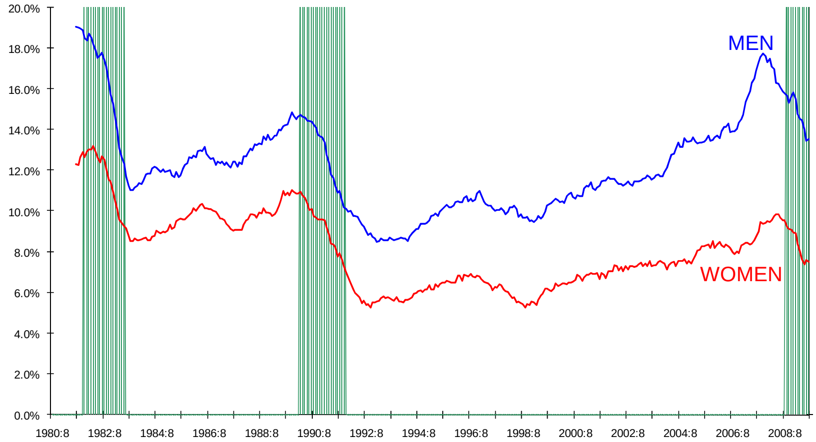

Figure 11

Λ^{UP}: Unemployment to Part-time Employment Probabilities

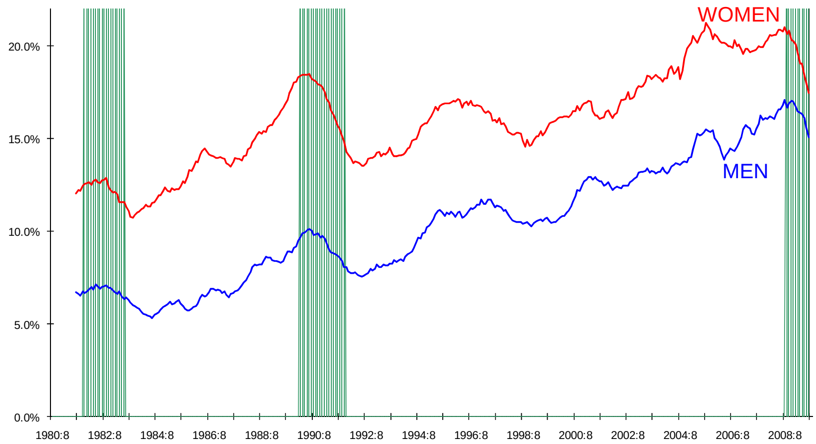

Figure 12

Λ^{UI}: Unemployment to Inactive Probabilities

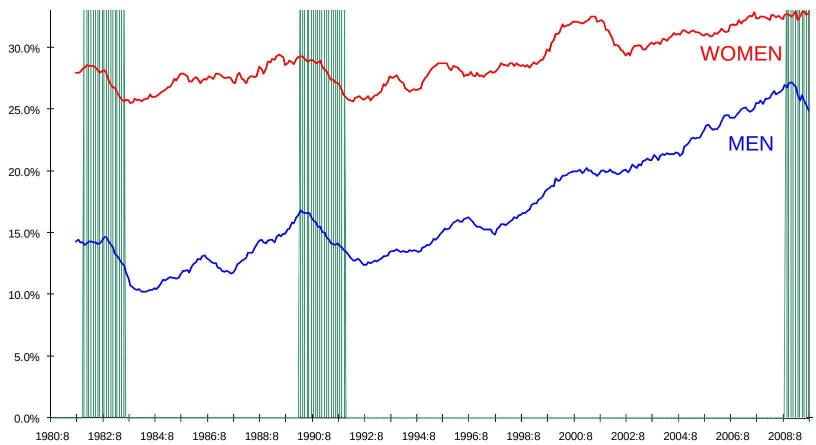

Figure 13

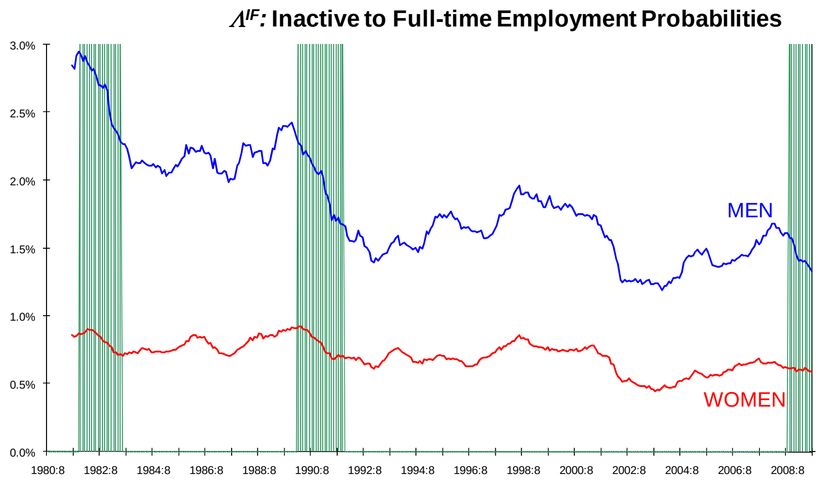

Figure 14

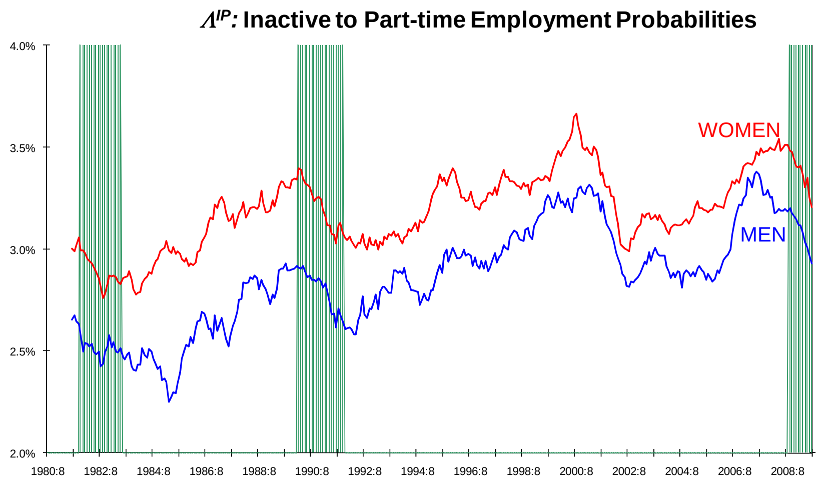

Figure 15

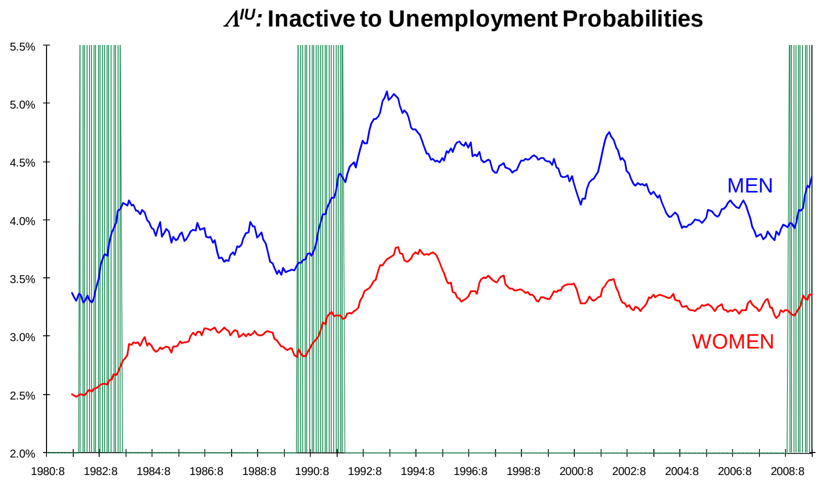

Figure 16

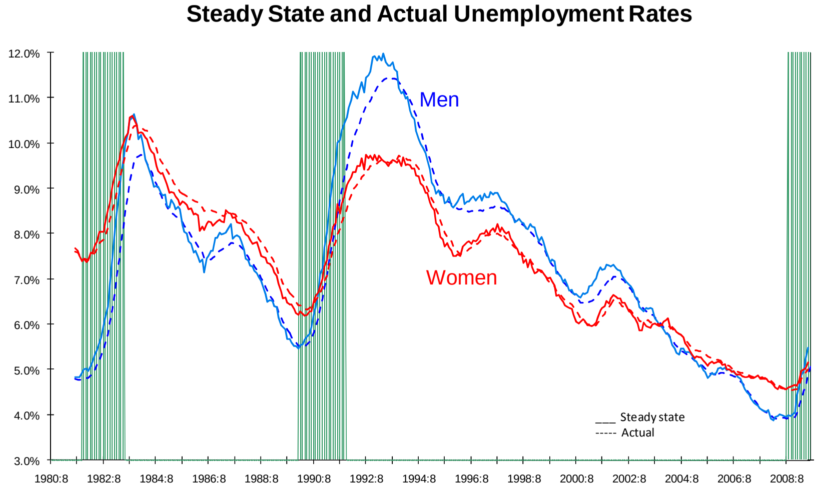

Figure 17a

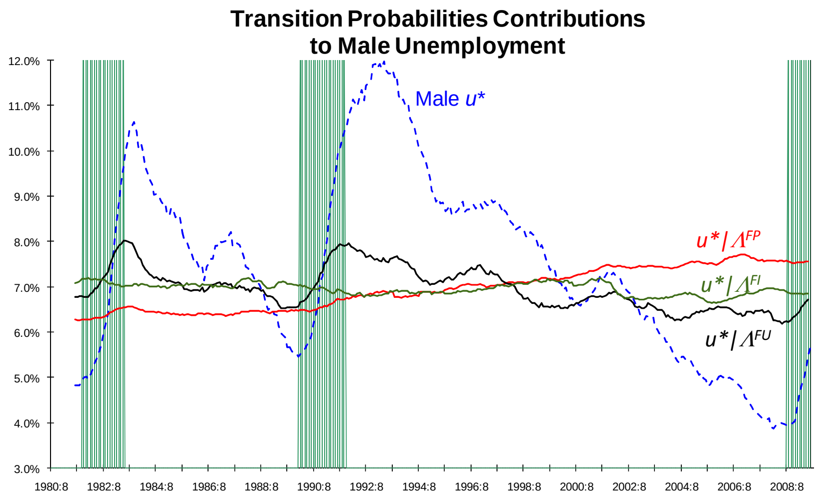

Figure 17b

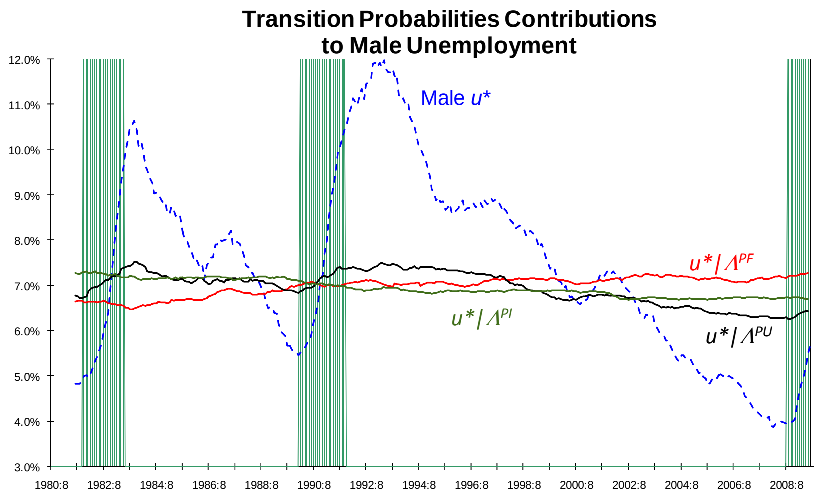

Figure 17c

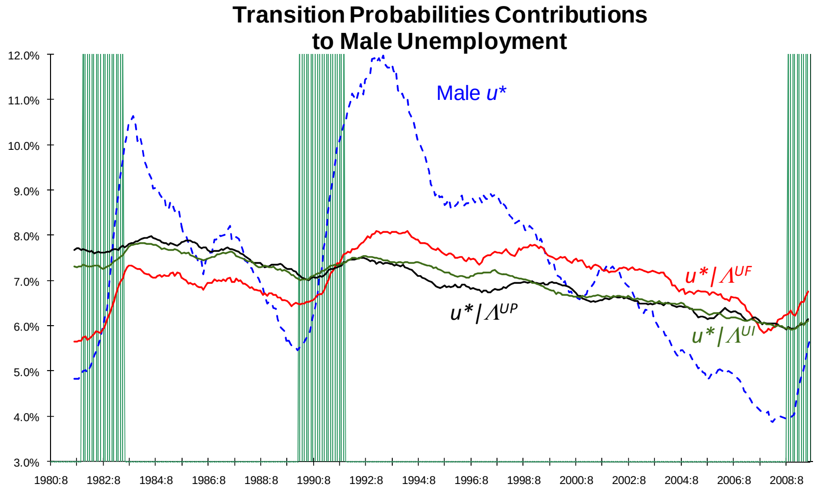

Figure 17d

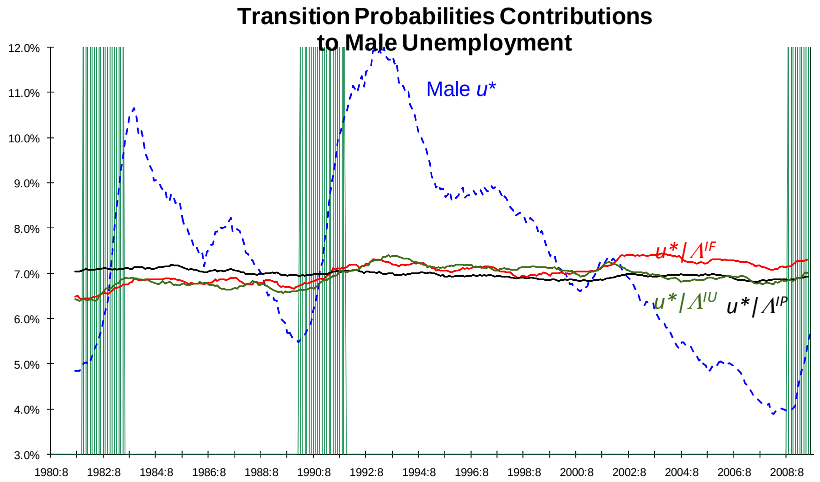

Figure 18a

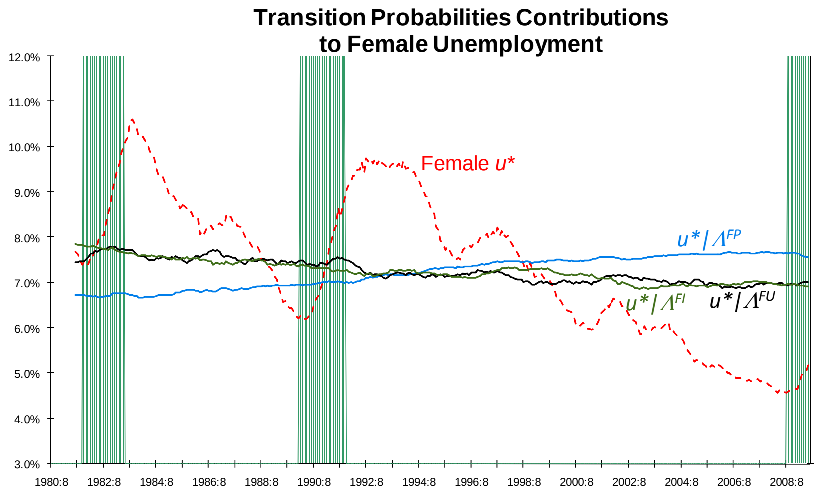

Figure 18b

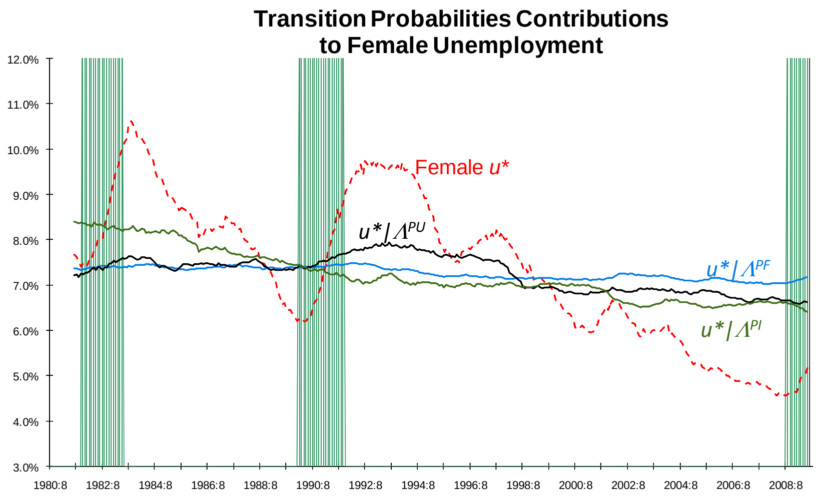

Figure 18c

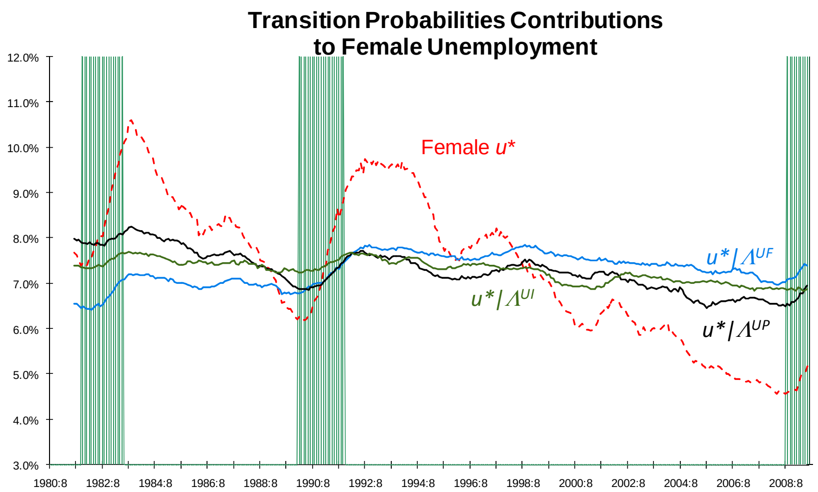

Figure 18d

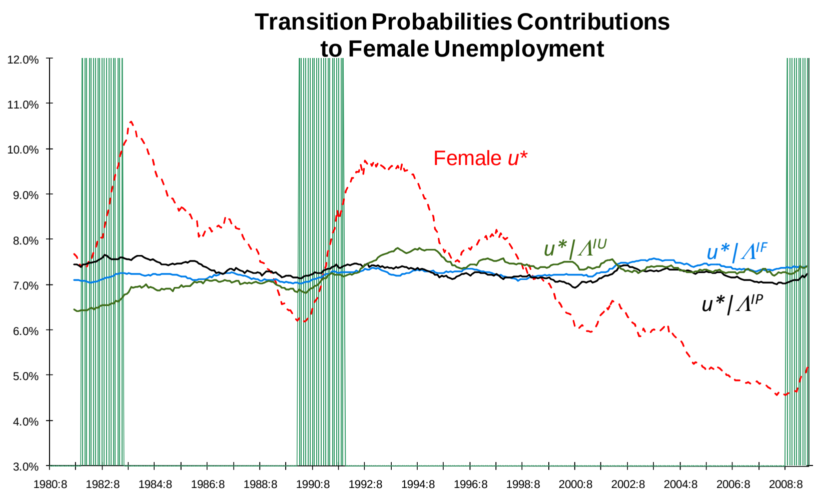

Table 1: Actual Gross Flow and Stock Data

Persons ('000s) July 2009 / June 2009	Actual Gross Flow Data: Full-time employed	Part-time employed	Unemployed	Inactive	Flow totals June 2009	Stock data June 2009
Full-time employed	5,847	270	40	75	6,231	7,546
Part-time employed	318	2,182	32	152	2,684	3,223
Unemployed	48	62	308	131	549	654
Inactive	53	132	123	4,317	4,625	6,082
Flow totals July 2009	6,266	2,645	503	4,676		
Stock data July 2009	7,606	3,201	606	6,121		

Note: The flow data is from ABS6202 GM1, and corresponding stock data from ABS6291 LM8.

Table 2: Transformed Gross Flow and Actual Stock Data

Persons ('000s) July 2009 / June 2009	Transformed Gross Flow Data: Full-time employed	Part-time employed	Unemployed	Inactive	Flow totals June 2009	Stock data June 2009
Full-time employed	7,088	326	47	91	7,552	7,546
Part-time employed	382	2,624	38	182	3,226	3,223
Unemployed	59	75	363	159	654	654
Inactive	71	174	158	5,684	6,087	6,082
Flow totals July 2009	7,599	3,199	605	6,116		
Stock data July 2009	7,606	3,201	606	6,121		

Note: The RAS procedure is used to transform the data. The difference between transformed flow totals and the stock data is less than .08%.

Table 3: SUR Regressions of Λ^{ij} in the Two-State Model

Dependent variables = transition probabilities

Each of the 2 equations includes 12 own lags, monthly seasonal dummies, the cycle variable (employment/ population) and the cycle variable multiplied by a recession dummy. Parameter estimates of the last two only are shown in the table.

1980:8 - 2009:6

MEN	Λ^{FU}	Λ^{UF}
cycle: β^{FU}	***0.015***	**0.073**
cycle*recession : γ^{FU}	**0.001**	**-0.056**
Multivariate Test for Serial Correlation Q(48) =		227.22
WOMEN		
cycle: β^{FU}	**-0.007**	**0.398**
cycle*recession : γ^{FU}	**0.000**	**-0.059**
Multivariate Test for Serial Correlation Q(48) =		195.61

1993:1 - 2009:6

MEN	Λ^{FU}	Λ^{UF}
cycle: β^{FU}	***0.009***	**0.133**
cycle*recession : γ^{FU}	**0.001**	**-0.094**
Multivariate Test for Serial Correlation Q(48) =		199.49
WOMEN		
cycle: β^{FU}	***0.003***	**0.968**
cycle*recession : γ^{FU}	**-0.001**	**-0.071**
Multivariate Test for Serial Correlation Q(48) =		178.84

NB1: 1% marginal significance -- White font on dark background

NB2: 5% marginal significance -- Black font on grey background

NB3: Italicised numbers indicate unexpected sign

Table 4: SUR Regressions of Λ^{ij} in the Four-State Model

Dependent variables = full-period transition probabilities

Each of the 12 equations includes 12 own lags, monthly seasonal dummies, the cycle variable (employment/ population) and the cycle variable multiplied by a recession dummy. Parameter estimates of the last two only are shown in the table.

1980:8-2009:6

MEN	Λ^{FP}	Λ^{FU}	Λ^{FI}	Λ^{PF}	Λ^{PU}	Λ^{PI}	Λ^{UF}	Λ^{UP}	Λ^{UI}	Λ^{IF}	Λ^{IP}	Λ^{IU}
cycle: β^{FU}	-0.003	-0.010	-0.008	*-0.076*	-0.110	-0.076	0.089	0.336	0.279	0.004	0.033	-0.005
cycle*recession : γ^{FU}	0.001	0.002	0.000	0.007	0.016	-0.004	-0.022	-0.016	-0.025	-0.004	-0.003	0.004
Multivariate Test for Serial Correlation Q(48) =		7790										

WOMEN												
cycle: β^{FU}	-0.020	-0.010	-0.033	0.003	-0.026	-0.076	0.036	0.497	0.289	*-0.004*	0.026	-0.006
cycle*recession : γ^{FU}	-0.002	0.001	0.000	-0.005	0.002	-0.001	-0.018	-0.026	-0.017	-0.001	-0.003	0.001
Multivariate Test for Serial Correlation Q(48) =		7823										

1993:1-2009:6

MEN	Λ^{FP}	Λ^{FU}	Λ^{FI}	Λ^{PF}	Λ^{PU}	Λ^{PI}	Λ^{UF}	Λ^{UP}	Λ^{UI}	Λ^{IF}	Λ^{IP}	Λ^{IU}
cycle: β^{FU}	*0.010*	-0.013	-0.008	*-0.112*	-0.021	-0.101	0.499	0.907	0.328	*-0.012*	0.026	-0.107
cycle*recession : γ^{FU}	0.001	0.002	0.000	-0.015	0.009	-0.009	-0.028	-0.019	-0.042	-0.002	-0.004	0.005
Multivariate Test for Serial Correlation Q(48) =		7057										

WOMEN												
cycle: β^{FU}	*0.020*	-0.020	-0.035	0.094	-0.020	-0.069	0.496	0.530	0.220	*-0.008*	0.017	-0.057
cycle*recession : γ^{FU}	-0.007	0.001	0.000	-0.013	0.000	-0.005	-0.026	-0.049	-0.002	0.000	-0.003	0.003
Multivariate Test for Serial Correlation Q(48) =		7735										

Note 1: 1% marginal significance -- White font on dark background

Note 2: 5% marginal significance -- Black font on grey background

Note 3: Italicised numbers indicate unexpected sign

Table 5: Correlations with the Unconditional Steady State Unemployment Rate

CORRELATIONS WITH THE UNCONDITIONAL STEADY STATE UNEMPLOYMENT	u	$u^* \mid \Lambda^{FP}$	$u^* \mid \Lambda^{FU}$	$u^* \mid \Lambda^{FI}$	$u^* \mid \Lambda^{PF}$	$u^* \mid \Lambda^{PU}$	$u^* \mid \Lambda^{PI}$	$u^* \mid \Lambda^{UF}$	$u^* \mid \Lambda^{UP}$	$u^* \mid \Lambda^{UI}$	$u^* \mid \Lambda^{IF}$	$u^* \mid \Lambda^{IP}$	$u^* \mid \Lambda^{IU}$
MEN	80%	-4%	78%	49%	-3%	76%	46%	74%	47%	38%	10%	41%	22%
WOMEN	77%	-25%	60%	72%	24%	78%	75%	21%	68%	21%	-14%	39%	-5%