ISSN 0819-2642
ISBN 0 7340 2649 8

THE UNIVERSITY OF MELBOURNE

DEPARTMENT OF ECONOMICS

RESEARCH PAPER NUMBER 991

APRIL 2007

Common Cycles in Labour Market Separation Rates for Australian States

by

Robert Dixon

Department of Economics
The University of Melbourne
Melbourne Victoria 3010
Australia.

COMMON CYCLES IN LABOUR MARKET SEPARATION RATES FOR AUSTRALIAN STATES

Robert Dixon[1]

Department of Economics, The University of Melbourne, VIC 3010

ABSTRACT: There is a considerable body of evidence showing that it is the inflow into unemployment that drives the unemployment rate up and down and so from a policy point of view an important question is whether or not movements in state inflow reflect the impact of state-specific shocks or common shocks affecting the entire economy This paper reports the results of using principal components analysis to search for a common cycle in time series data for the rate at which people are leaving employment and moving to unemployment in the six states of Australia. It is concluded that there is a common cyclical component to each of the state's separation rates but that it accounts for only a small part of the total variation we observe in the data set. In addition there are large idiosyncratic variations especially in the case of three of the six states. These findings strengthen the case for regional labour market policy in Australia.

Keywords: Unemployment Cycles Principal components analysis Australia

JEL Codes: J21 J64 R23

[1] I am grateful to the referees for helpful comments.

1. INTRODUCTION

The aim of this paper is to examine the time series characteristics of the rate at which people flow into unemployment in each of the six Australian states, with a view to determining whether movements in state inflow over time reflect the impact of state-specific shocks or common shocks affecting the entire economy. If the behaviour of regional inflow is largely explained by common 'national' factors, it suggests that policies to reduce unemployment in the regions are indistinguishable from national macroeconomic policies designed to affect general demand and supply conditions across the economy.[2] In contrast, if there are strong region-specific components explaining the behaviour of regional inflow, the case for region-specific (un)employment policies is that much stronger.

As mentioned, the paper focuses on the rate at which people enter or 'flow into' unemployment. I focus on *flows* (rather than 'stocks') because I believe that, in order to develop an understanding which will assist economic policy, variables such as the rate of unemployment must be looked at in their dynamic context. In relation to unemployment this means looking at the flows between labour market states rather than on the number in each state at any moment in time, as these 'stocks' are merely the (net) outcome of the flows. Another way to put all this is to say that policy effects the stocks only because it impacts upon the flows. So to ask questions about appropriate policy we need to examine the flows.

I focus on *the flow into unemployment* because there is a large (and growing) body of research which supports the notion that the inflow into unemployment is the key 'driver' of the unemployment rate (by this I mean its level, and not just its rate of change). For example, numerous studies of causality indicate that inflow into unemployment Granger causes outflow from unemployment while outflow does not Granger cause inflow. Dixon, Freebairn & Lim (2003) find this for Australia; Balakrishnan & Michelacci (2001) find the same for the US, Germany, France and Spain while Burgess & Turon (2005) and Dixon & Mahmood (2006) find this for the UK.

Since it is the inflow into unemployment that drives the state unemployment rate up and down, from a policy point of view an important question is whether or not movements in state inflow reflect the impact of state-specific shocks or common shocks affecting the entire economy

[2] In this paper "region" and "state" are used interchangeably.

The paper is structured as follows. In the next section I use a standard model of flows into and out of the unemployment pool to show that movements in the inflow rate is the key driver of movents in the unemployment rate over time. In the third section I explain the source of the data used and the way in which inflow is measured. The fourth and fifth sections are devoted to a discussion of the concept of common cycles and to the use of principal components analysis to test for the presence of a common cycle. The final section concludes.

2. THE IMPORTANCE OF THE RATE AT WHICH PEOPLE FLOW INTO UNEMPLOYMENT

The unemployment rate is defined as the ratio of the number unemployed (*U*) to the total labour force (*LF*). Allowing for both *U* and *LF* to vary over time, the change in the unemployment rate (*UR*) will be:

$$\Delta(UR_t) = \frac{U_t}{LF_t} - \frac{U_{t-1}}{LF_{t-1}} = \frac{\Delta U_t}{LF_t} - \left(\frac{U_{t-1}}{LF_t}\right)\left(\frac{\Delta LF_t}{LF_{t-1}}\right) \tag{1}$$

where Δ represents a discrete change operator.

Changes in the number unemployed in any period (ΔU) reflect the balance between two flows, an inflow into unemployment (*IN*) and an outflow from unemployment (*OUT*). Thus:

$$\Delta U_t = U_t - U_{t-1} = IN_t - OUT_t \tag{2}$$

Given (2), equation (1) may be written as:

$$\Delta(UR_t) = \frac{(IN_t - OUT_t) - U_{t-1}\left(\Delta LF_t / LF_{t-1}\right)}{LF_t} \tag{3}$$

The two terms in the numerator on the RHS of (3) may be given a rather interesting interpretation. The last term, $U\left(\Delta LF / LF\right)$, measures the extent to which the number unemployed can change when there is a growing labour force and yet the unemployment rate remain constant.[3] The first term, $(IN - OUT)$, is simply the balance of inflows and outflows over any period and is equal to the observed (i.e. the actual) change in the number unemployed over the period. Clearly, if the first term in the numerator (i.e. $(IN - OUT)$, the actual change)

[3] We may see this as follows: For the unemployment rate to be constant over time we require the rate of growth in unemployment to equal the rate of growth in the labour force. That is, we require: $\Delta U/U = \Delta LF/LF$. This in turn implies that the magnitude of ΔU is such that it is exactly equal to the product $U(\Delta LF/LF)$.

exceeds the second (i.e. $U\left(\Delta LF / LF\right)$, the change consistent with the unemployment rate remaining constant) the unemployment rate will rise. Only if the first term is exactly equal to the second will the unemployment rate be constant. In fact, even when $(IN - OUT)$ equals zero, the unemployment rate can rise or fall depending on the rate of growth of the labour force. This should not be surprising. If the labour force is (say) rising over time then the number unemployed must rise at the same rate to keep the ratio between the two (this is the unemployment rate, (*U/LF*)) constant. However, for the number unemployed to rise over time there must be a net inflow into unemployment, that is $(IN - OUT)$ must be positive, not zero.

Since the change in the labour force over a short period like a month or a quarter is ‘small’ and given also that the unemployment rate is itself ‘small’, it follows that $\left[\left(U/LF\right)\left(\Delta LF/LF\right)\right]$ will be very small both in absolute terms as well as relative to the other component in the equation, hence I will follow other researchers and throughout treat:

$$\Delta\left(UR\right) \approx \left(\Delta U / LF\right) = \left(\frac{IN - OUT}{LF}\right) = \frac{IN}{LF} - \frac{OUT}{LF} = INR - OUTR \tag{4}$$

where *INR* and *OUTR* are the inflow and outflow rates (that is, the absolute number of persons flowing in to and out of unemployment measured relative to the size of the labour force) respectively.

A large body of research supports the notion that the inflow into unemployment is the key causal driver of the unemployment rate. In particular, given that the inflow rate is exogenous,[4] there will be a stable monotonic relationship between the unemployment rate and past inflow rates provided only that the outflow rate is related in a stable and predictable fashion to the (inherited) stock of unemployment. This may be seen as follows:

We begin by noting that (4) implies that the unemployment rate will evolve over time according to the rule[5]

$$UR_t \;=\; UR_{t-1} + \left(INR_{t-1} - \;OUTR_{t-1}\right) \tag{5}$$

It is common to regard any flow (i.e. the number of persons per period moving between any two states) to be determined by the relevant transition probability in conjunction with the

[4] As mentioned earlier, tests for causality indicate that inflow into unemployment Granger causes outflow from unemployment while outflow does not Granger cause inflow.
[5] While inflow and outflow rates are measured during a period, the unemployment rate will be measured at the beginning of the period.

size of the relevant pool at the beginning of the period. Applying this idea, the flow measured in terms of numbers of persons per period moving out of unemployment (*OUT*) is equal to the product of the (transition) probability of any one unemployed person moving out of unemployment over any period (ϕ) and the number unemployed (*U*) at the beginning of the period. So that:[6,7]

$$OUT_t = \phi \times U_t$$

where $0 < \phi < 1$

Dividing both sides by the size of the labour force gives an expression for the outflow rate (*OUTR*) in terms of the transition probability (ϕ) and the unemployment rate (*UR*):

$$OUTR_t = \phi \times UR_t \tag{6}$$

This means that (5) may be written as:

$$UR_t = INR_{t-1} + (1-\phi)UR_{t-1} \tag{7}$$

At this point I think it will be obvious to the reader that the level of unemployment at any moment in time may be written in terms of the history of inflow rates alone. A formal proof relies upon the familiar Koyck transformation. It proceeds as follows:

Given (7), we may write for UR_{t-1},

$$UR_{t-1} = INR_{t-2} + (1-\phi)UR_{t-2}$$

Substitution of the above into (7) gives

$$UR_t = INR_{t-1} + (1-\phi)INR_{t-2} + (1-\phi)^2 UR_{t-2} \tag{8}$$

Likewise, given (7) we can write for UR_{t-2}

$$UR_{t-2} = INR_{t-3} + (1-\phi)UR_{t-3}$$

Substitution of the above into (8) gives

---

6 I am simplifying things here by making the outflow rate a linear function of the unemployment rate. However, the point being made in the text (that there will be a stable monotonic relationship between the unemployment rate and past inflow rates if the outflow rate is related in a stable and predictable fashion to the (inherited) stock of unemployment) will remain even if we allow outflow and unemployment to be related in a non-linear fashion.

7 For evidence on the existence of a stable relationship between the outflow rate and the unemployment rate for Australia, see Leeves (1997) and Dixon et al (2003). Numerous studies for other countries also support the existence of such a relationship (a relationship which is implied by the 'matching model', amongst other theories).

$$UR_t = INR_{t-1} + (1-\phi) INR_{t-2} + (1-\phi)^2 INR_{t-3} + (1-\phi)^3 UR_{t-3}$$

If we continuously backwards substitute for the unemployment rate and take this further and further back in time, we will obtain

$$UR_t = \sum_{i=0}^{n} (1-\phi)^i INR_{t-1-i} + (1-\phi)^n UR_{t-n} \tag{9}$$

Given that $0 < \phi < 1$, it must be the case that as $n \to \infty$, $(1-\phi)^n$ becomes negligible leaving the expression:

$$UR_t = \sum_{i=0}^{n} (1-\phi)^i INR_{t-1-i} \tag{10}$$

which is to say that with a constant transition probability (ϕ), the level of the unemployment rate at any moment in time is simply a geometric distributed lag function of past inflow rates.

Since it is the inflow into unemployment that drives the state unemployment rate up and down, from a policy point of view the key question is whether or not there are common cycles in the rate of inflow. In the next section of the paper I explain the source of the data used to measure inflow while the fourth section of the paper examines this data to see if there are common cycles in the inflow rates.

3. THE DATA

As the measure of the inflow into unemployment in any period I will follow other authors and use what is commonly called 'the separation rate' (see Barro (1997, Ch 10) and Mankiw (1997, Ch 5) for examples), this is the rate at which people flow from employment to unemployment. The separation rate is defined as:

$$s = \frac{ETU}{E}$$

where E is the number employed at the start of any period and ETU is the number of persons who were employed at the beginning of the period but who were unemployed at the end of the period (this is the number who 'flowed from Employment To Unemployment' during the period.)

Australian measures of gross flows between employment and unemployment are published by the Australian Bureau of Statistics and are constructed from data collected as part of their monthly Labour Force Survey. The data has its origin in the matching of responses by individuals in any month's survey with responses by the same individuals in the previous month's survey. These matched records are then 'expanded up' to yield population estimates of flows between various labour market states.[8] Unfortunately, flows (matched records) data for Australian states is only available since October 1997.

A chart of the (seasonally adjusted) separation rates over the period 1997:3 – 2005:3 for each of the states is given in Figure 1.[9] The case for an exclusively national stabilisation policy is strongest if regions have large common shocks and tend to move together. We can see in Figure 1 that while there appear to be movements which the states have in common (most obviously associated with the slowdown in the rate of economic growth in Australia in 2000), there are also idiosyncratic components and so it is both worthwhile and necessary to apply a statistical procedure to try to identify these two components and to assess their relative size. That is the task of the following section of the paper.

[FIGURE 1 NEAR HERE]

4. IS THERE A COMMON CYCLE IN THE SEPERATION RATES?

The approach followed in this paper is based on the notion that the identification of common or uncommon cycles provides important information about whether the series are driven by similar stochastic processes.[10] This information in turn provides potentially useful insight into the strength of the case for regional as opposed to purely or solely national employment policies. If common cycles are identified, it suggests that all of the regions would benefit from the implementation of any general, national counter-cyclical measures. On the other hand, if cyclical paths of the regions are very different, it suggests that national counter-cyclical measures are harder to design and have a potentially uncertain regional impact. In this

---

[8] Detailed discussions of the gross flows data and its limitations can be found in Foster (1981), Borland (1996) and Dixon (2001). A short account of the way in which the flows data is compiled is given in an Appendix to this paper.

[9] The separation rates used in this paper have been computed from gross flows data for the period 1997:10 – 2005:12 obtained from the ABS in Datacube 6291.0.55.001 Table GM1 - labour force status and gross changes (flows) by sex, state, age. We will only look at data for the six states because there are numerous missing observations in the flows data for the two Australian Territories. All figures refer to flows per *month*. I show quarterly averages to make it easier for the reader to see the relative magnitudes across states and over time. In the econometric work I will use monthly data so as to gain the greatest number of degrees of freedom.

[10] Increasingly in the macroeconomics and regional literature 'cycles' are defined as all departures from a 'trend' which results from the application of one or other filtering process to the raw data with the aid of an econometric technique. This is the approach taken in this paper but it is important that the reader understand that this involves a quite different method of analysis to that which focuses on the dating of 'business cycles' based on turning points in graphs showing (indicators) of economic activity. In this, older more descriptive approach, a cycle is thought of in terms of regular oscillations, alternating between below and above trend with a regular period of between 4 and 8 years. This is a quite different concept of cycle to that associated with the econometric approach where the term 'cycle' can be applied to any deviation from the filtered series, no matter how short and how asymmetric the deviations might be.

case, we would in principle have a case for region-specific counter-cyclical measures either instead of, or in addition to, national measures.

In this section of the paper I will investigate the existence and size or importance of any common cycle using principal components analysis. It is convenient to talk a little about the nature of principal components analysis before discussing in detail how it might be used to test for the presence of any common cycle.[11]

Essentially principal components analysis is a method for identifying patterns of linear relationships which are present in a correlation (or co-variance) matrix. The method transforms the original variables into new, uncorrelated variables or 'components' without partitioning the data set into dependent and independent variables, instead the entire data set is considered simultaneously with each variable being related to every other variable. Each component is a linear combination of the original variables and there will be as many components are there are original variables in the study. The first component is selected so as to account for the greatest amount of variance in the total data set, the second component will account for the greatest amount of the variance remaining after the first component is removed (a key feature of the method is that the components are orthogonal and the values of any two principal components will be uncorrelated with each other), and so on.

The set of coefficients which connect each of the original variables with the components are often referred to as an 'eigenvector' or 'latent vector'. These coefficients are chosen so as to maximise the sum of the squared correlations of the component with the original variables. For each component the sum of the squared values of these coefficients is referred to as an 'eigenvalue' or 'latent root'. It is in the nature of the method that the first component will be the linear combination with the largest variance and so it will have the largest eigenvalue.

The coefficients linking each of the original variables with the components can be converted into correlations (or 'factor loadings') summarising the relationship between each of the components and each of the original variables.[12] This allows us to easily see the relative amounts of the variation *in each of the original variables* (in our case, in each state) which is

[11] I will give only a very brief summary of principal components analysis here. Detailed expositions may be found in Afifi and Clark (1996), Dunteman (1989), Griffith and Amrhein (1997) and Taylor (1977). Carvalho and Harvey (2005) give an example of the application of principal components analysis to look at common cycles in US regional per capita incomes while Western et al (2005) use it to characterise and measure 'social capital'.

[12] The correlations will equal the value of the coefficients multiplied by the square root of the variances of the associated principal component – i.e. each of the elements of a particular latent vector are multiplied by the square root of the associated latent root or eigenvalues. As a result, the elements in this matrix of correlations will be proportional to the corresponding elements in the matrix of eigenvalues.

'explained' by the principal components. These correlations or loadings will have the properties that:[13] (i) the sum of the squared correlations for each column will equal to the amount of the variance explained by the associated principal component; (ii) the sum of the squared correlations for each row (ie for each state) will equal unity, and; (iii) the relative size of each squared correlation as we read across each row tells us about the relative contribution of each of the components towards explaining the variation in the separation rate for that state.

One advantage of using principal components analysis to investigate common cycles is that it is that it is usual to assume that the common and idiosyncratic components are additive and uncorrelated (orthogonal). Thus the search for a common cycle becomes a search for an (orthogonal) principal component which exhibits the features of a cycle which the states have in common.[14] In addition, it may be that we can account for the groupings found in the data with reference to explanatory variables involving spatial constructs. I will argue later that the sub-sets identified by the principal components method are indeed related to distances between the states measured in economic space (specifically, a measure of the extent to which their industrial structure differs from each other).

What do we mean by a 'common cycle' and how can the definition be made operational in this context? In the specific context of principal components analysis I propose that a common cycle exists if the component with the largest variance (the first principal component) has loadings for all states which are statistically significant and are of the same (positive) sign. I think we would also want this common cycle component to explain a statistically significant proportion of the total variation present in the data set and (desirably) that it also accounts for a 'large' portion of the movement over time in each state's separation rate.

Table 1 shows the eigenvectors and eigenvalues (the software package used is EViews 5.1) for the separation rates for the six states over the period 1997:10-2005:12. Although there are no particularly strong trends in the data, to avoid potentially spurious correlation I look at the series with the Hoderick-Prescott trend removed.[15] In practice the de-trended series (which are depicted in Figure 2) for most states is little different to the raw series as depicted in Figure 1

[13] To aid interpretation all variables are standardised. This is achieved by dividing each variable by its standard deviation. Another way to put this is to say that the principal components analysis is applied to the correlation matrix rather than the co-variance matrix.
[14] It is usual to refer to shocks which affect all regions simultaneously.
[15] All of the series which remain are I(0) using the ADF and Phillips-Peron tests. An alternative to de-trending would be to first-difference the data. The results obtained from applying principal components analysis to the de-trended series is essentially the same as those found if it is applied to the first-differenced series except that the common cycle component (the contribution of the first component) is a smaller proportion of the total variance in the case of first-differenced data.

and the results from applying principal components analysis to the de-trended series is essentially the same as those found if it is applied to the original series.

[FIGURE 2 NEAR HERE]

[TABLE 1 NEAR HERE]

If we scan down the coefficients which make up the first eigenvector (these are in the column headed Component 1 in Table 1) we notice that they are all the same (positive) sign and that the first eigenvalue (this is given near the foot of the table) is 1.731. Now, if the original variables were completely uncorrelated, each component would be expected to explain the same percentage of the total variance namely, 100 divided by the number of original variables (the value of this is 16.7 in our case as we have data for six states).[16] Another way to put this is to say that the total variance of the system (and thus the sum of the latent roots or eigenvalues) will always be equal to the number of original variables[17] (6 in our case) and so if there were no cross-correlations each component could be expected to have a latent root or eigenvalue of 1. It is possible to test whether the value arrived at in our study differs in any statistically significant way from the value we would observe if all of the original variables (state separation rates) were completely uncorrelated. In particular, we can test whether or not the eigenvalue of 1.731 differs to a statistically significant extent from 1 - Griffith and Amrhein (1997, p 168) report the test procedure.[18] Applying the test it is found that the eigenvalue of 1.731 is significantly different from 1 at the 1% level.

As an aid to interpretation, Table 2 shows the matrix of correlation coefficients (i.e. the factor loadings) implied by the coefficients which make up the eigenvectors reported in Table 1. For the sample size we are working with (99 observations on each variable) a correlation coefficient must be greater than 0.198 to be regarded as significantly different from zero at the 5% level and greater than 0.258 to be regarded as significantly different from zero at the 1% level.[19] All of the correlation coefficients linking the state separation rates with Component 1 are well above 0.258.[20]

[16] The first component accounts for 28.9 percent of the total variance in the original data set. If quarterly data is used the first component accounts for 34.8 percent of the total variance.
[17] The reader should note that we are working with standardised variables
[18] The test statistic is $z = (1-\lambda)\Big/\left(\lambda\left(\sqrt{2/n}\right)\right)$ where λ is the eigenvalue and n is the sample size.
[19] The test statistic is $t = \left(r\sqrt{n-2}\right)\Big/\left(\sqrt{1-r^2}\right)$ where n is the sample size and r is the sample correlation coefficient.
[20] This is also the case if quarterly data is used.

[TABLES 2 & 3 NEAR HERE]

To assess how much of the movement over time in each state's separation rate can be accounted for by the common cycle (the first principal component) it is necessary to compute the squares of the correlation coefficients given in Table 2. These are given in Table 3. As mentioned above it is in the nature of principal components analysis (using standardised variables) that the sum of the squared correlations for each column will equal to the amount of the variance explained by the associated principal component (we can see this by comparing the column sums in Table 3 with the eigenvalues reported at the foot of Table 1). In addition, the relative size of each element as we scan across the squared correlations in each row of Table 3 tells us about the relative contribution of each of the components towards explaining the variation in the separation rate for that state. Scanning across the rows of Table 3 we see that in no state does the common factor account for more than ½ of the variation in the separation rate in that state and for three states (Queensland, Western Australia and Tasmania) it accounts for less than 1/5 of the state variation in the separation rate.

It seems reasonable therefore to conclude that there is a common cyclical component to each of the state's separation rates but it appears to account for only a small part of the total variation we observe in each state's separation rate over time. In particular, there are large idiosyncratic variations, especially in the case of Queensland, Western Australia and Tasmania.

5. THE POSSIBLE ROLE OF INDUSTRY STRUCTURE

Looking at Table 2 we see that the highest loadings on the common cycle component (the first component) are for New South Wales, Victoria and South Australia (these are the three states where employment in manufacturing industry makes up a relatively high share of total employment) while the lowest loadings are for Tasmania, Western Australia and Queensland. It is of interest to ask if there is any relationship between the results of the principal components analysis and measures of similarity in industry structure across the states.

Given the focus of this paper the most useful calculations to make involve the pair-wise comparisons of structure across the regions. A common measure of similarity or dissimilarity is the coefficient of regional specialisation:[21]

$$CRS_{AB} = 1/2\left(\sum_i \left|\left(X_{iA}/X_A\right) - \left(X_{iB}/X_B\right)\right|\right)$$

[21] For the history of the CRS and related measures see Thirlwall and Harris (1967).

where the amount of a particular activity in region A is X_{iA}, the amount of the same activity in region B is X_{iB},, the sum of all activity in region A is X_A, and the sum of all activity in region B is X_B.

If the value of the *CRS* is 0 it indicates that the pattern of activities in region A is the same as that for region B and so there is no (relative) specialisation. The other extreme would be where region A specialises in only one activity and region B has no involvement in that activity in which case the *CRS* will have a value of 1. In addition, the *CRS* has a very simple and intuitively appealing interpretation. Its value is equal to the proportion of the regional activity (eg the proportion of state employment) which would have to be 'reallocated' or 'move' in order for the two regions to have the same pattern of activity.

The CRS, which has a long history in the literature in regional studies and economic geography, is a related to a measure introduced by Paul Krugman.[22] The Krugman index is calculated as:

$$KI_{AB} = \sum_i \left| \left(X_{iA} / X_A \right) - \left(X_{iB} / X_B \right) \right|$$

Obviously there is no point computing both the CRS and the Krugman index. Given its history and the ease with which the CRS may be interpreted I will work with it.

In Table 4 I report on calculations of 'pair-wise' coefficient of regional specialisation which compare each state's industrial structure against each other state. The Coefficients of Regional Specialisation are for employment by industry and state for 2005.[23]

[TABLE 4 NEAR HERE]

If we look for the lowest numbers for each state in Table 4 (the reader will recall that numbers closer to zero indicate greater similarity) we see that Victoria and New South Wales are most alike in their industrial structure and that South Australia is more like Victoria than any other state. Queensland and Western Australia are more like each other than they are like any other state (mining is concentrated in QLD and WA) while Tasmania, although it is more like South Australia than any other state, shows the greatest dissimilarity of all the states.

These patterns are rather like those found in the loadings on the first component (as given in the first column of Table 2). The highest loadings were for New South Wales, Victoria and South Australia (with loadings of 0.62, .69 and .66 respectively) there was then a gap with the

[22] See Krugman (1991, p 75f) and Krugman (1993, p 250f). Notice that Krugman does not 'halve the sum' unlike the *CRS* measure. Other than that it is identical.

[23] The data is taken from the Australian Bureau of Statistics Labour Force Statistics in DX Database Tables LQE1-209 and 909 and refers to the number of employed persons by ANZIC industry (the data is at the 3-digit level where all employees are classified as belonging to one or other of 53 industries).

next highest loading being for Tasmania (with a loading of 0.41) and then another gap with the lowest loadings being for Queensland and Western Australia (both with loadings of 0.36). It would seem then that there may be a connection between cyclical behaviour and industrial structure. However, given that we have such a small number of regions to work with, this conclusion while it is suggestive and consistent with prior expectations, should be regarded as tentative, at best. Clearly, much more work could be done attempting to provide a deeper interpretation of each of the components and to explain why each one includes some states and not others. This task goes well beyond the scope of this paper which has a more limited aim, namely the identification of a ‘national’ common cycle.

6. CONCLUDING REMARKS

This paper has looked at the behaviour of separation rates over time in the six states of Australia. It was concluded that there is a common cyclical component to each of the state’s separation rates but that it accounts for only a small part of the total variation we observe in the data set. In addition there are large idiosyncratic variations, especially in the case of Queensland, Western Australia and Tasmania. A number of researchers including Dixon and Shepherd (2001), Groenewold & Hagger (2003) and Smyth (2003) have found that there are considerable differences in the time series properties of the level of unemployment across Australian states. The results reported in this paper are not only consistent with those findings but also suggest that the explanation lies in the different time series behaviour of the rate at which workers flow from employment to unemployment and that this in turn may be connected to industry structure. These findings strengthen the case for regional policy in Australia.

REFERENCES

Afifi, A. and Clark, V. (1996) *Computer-aided Multivariate Analysis*. Third edition, Chapman and Hall: London.

Balakrishnan R. and Michelacci C. (2001) Unemployment dynamics across OECD countries. *European Economic Review,* 45, pp. 135-65.

Barro, R. (1997) *Macroeconomics.* Fifth edition, MIT Press: Cambridge, Mass.

Borland, J. (1996) Labour market flows data for Australia. *Australian Economic Review,* 29, pp. 225-35.

Burgess, S. and Turon, H. (2005) Unemployment dynamics in Britain. *Economic Journal*, 115, pp. 423-48.

Carvalho, V. and Harvey, A. (2005) Growth, cycles and convergence in US regional time series. *International Journal of Forecasting* 21, pp. 667-86.

Dixon, R. (2001) Australian labour force data: How representative is the population represented by the matched sample? *Economic and Labour Relations Review,* 12, pp. 303-330.

Dixon, R. and Mahmood, M. (2006) Hans Singer's model of the severity of recessions. *Cambridge Journal of Economics* 30, pp. 835-46.

Dixon, R. and Shepherd, D. (2001) Trends and cycles in Australian state and Territory unemployment rates. *Economic Record,* 77, pp. 252-69.

Dixon R., Freebairn J. and Lim G. (2003) Why are recessions as deep as they are? *Australian Journal of Labour Economics,* 6, pp. 37-64.

Dunteman, G. (1989) *Principal Components Analysis*. Sage publications: Newbury Park.

Foster, W. (1981) Gross flows in the Australian labour market: A first look. *Australian Economic Review* 23, pp. 57-64.

Griffith, D. and Amrhein, C. (1997) *Multivariate Statistical Analysis for Geographers.* Prentice Hall: Upper Saddle River, N.J.

Groenewold, N. and Hagger, A. (2003) Natural-rate estimates for the Australian states: an SVAR approach. *Regional Studies,* 37, pp. 251-63.

Krugman, P. (1991) *Geography and Trade*. MIT Press: Cambridge, Mass.

Krugman, P. (1991) Lessons of Massachusetts for EMU. In F. Torres and F. Giavazzi (eds) *Adjustment and Growth in the European Monetary Union*. Cambridge University Press: Cambridge.

Leeves, G (1997) Labour market gross flows and transition rates 1980-1992. *Economic and Labour Relations Review,* 8, pp. 110-27.

Mankiw, N. (1997) *Macroeconomics.* Third edition, Worth Publishers: New York.

Smyth, R. (2003) Unemployment hysteresis in Australian states and territories: Evidence from panel data unit root tests. *Australian Economic Review,* 36, pp. 181-92.

Taylor, P. (1977) *Quantitative Methods in Geography: An Introduction to Spatial Analysis*. Houghton Mifflin, Boston.

Thirlwall, A. and Harris, C. (1967) Measuring the localisation of industry. *Manchester School*, 35, pp. 55-68.

Western J., Stimson R., Baum S. and Van Gellecum Y. (2005) Measuring community strength and social capital. *Regional Studies*, 39, pp. 1095–109.

APPENDIX: THE ABS LABOUR FORCE SURVEY AND GROSS FLOWS (MATCHED RECORDS) DATA

The empirical work in this paper is based on information obtained from those persons included in the Labour Force Survey conducted by the Australian Bureau of Statistics and whose responses (records) can be matched across successive months.[24] The Labour Force Survey (LFS) is a component of the Monthly Population Survey which is based on a multi-stage area sample of private dwellings (currently about 30,000 houses, flats, etc.) and a (much) smaller number of non-private dwellings (hotels, motels, etc.). (Non-private dwellings make up about 3% of the total LFS sample.) Households selected for the LFS are interviewed each month of eight months, with one-eighth of the sample being replaced each month. In the interviews an attempt is made (inter alia) to establish whether each person is in or out of labour force and, if in, whether employed or unemployed. To derive labour force estimates for the 'population', expansion factors (weights) are applied to the sample responses. Weighting ensures that LFS estimates conform to the benchmark distribution of the population by age, gender and geographic area. Whilst the estimates for 'stocks' (such as the number unemployed, the number in the labour force etc) are adjusted for any under-enumeration and non-response, the Gross Flows estimates are not.

Data on gross flows between months is based on the matched sample - that is, persons surveyed in a given month whose responses in that month can be matched with responses in the previous month. The matched sample differs from the total sample for three reasons: the exclusion of respondents in non-private dwellings, sample rotation and 'non-response'. For the LFS, private dwellings (such as houses and flats) and non-private dwellings (such as hotels and motels, boarding houses and short-term caravan parks, hospitals and homes, educational colleges and aboriginal settlements) are separately identified and sampled. The transient nature of many of the occupancies and the procedures used to select persons in non-private dwellings preclude the possibility of matching any of them who may be included in successive surveys. Indeed, no attempt is made to match these responses. However in relation to private dwellings, even though there is sample rotation,[25] a high proportion of the dwellings selected in one

---

[24] Extensive discussion of the source of the data and the method used by the ABS to translate sample data into 'population equivalents' may be found in Dixon (2001) and in the references cited therein. Much of what follows is taken from that article or from the ABS publication *Labour Statistics: Concepts, Sources and Methods,* ABS Catalogue Number 6102.0.55.001, Ch 19.

[25] As it is not reasonable to retain the same respondents in the survey for a long period of time, a proportion of the private dwellings in the sample are replaced each month. This procedure is known as sample rotation. Since the monthly LFS commenced in 1978, dwellings have been retained in the survey for eight consecutive months so that about one-eighth of the sample has been replaced each month.

survey remains in the sample for the following survey and the response rate in the survey is quite high. This means that it is possible to match the characteristics of most of the persons in those dwellings from one month to the next, to record any changes that occur, and hence to produce estimates of flows between the different categories of the population and labour force. Overall, those whose records can be matched represent about 80% of all people in the survey and these records represent around 93% of the population.[26] Although this is less than 100%, key indices such as the unemployment rate and the participation rate calculated for the matched sample are highly correlated both over time and across states with the same indices for the whole population.

[26] This is because the members of the 'missing' rotation group (1/8 of the total sample) will have characteristics pretty much identical to those who have remained in the survey across successive months. If we expand the 80% to allow for this we have a figure of around 93% of the total sample. This is less than 100% due to non-response and the fact that some members of the population reside in non-private dwellings. See Dixon (2001) for further discussion.

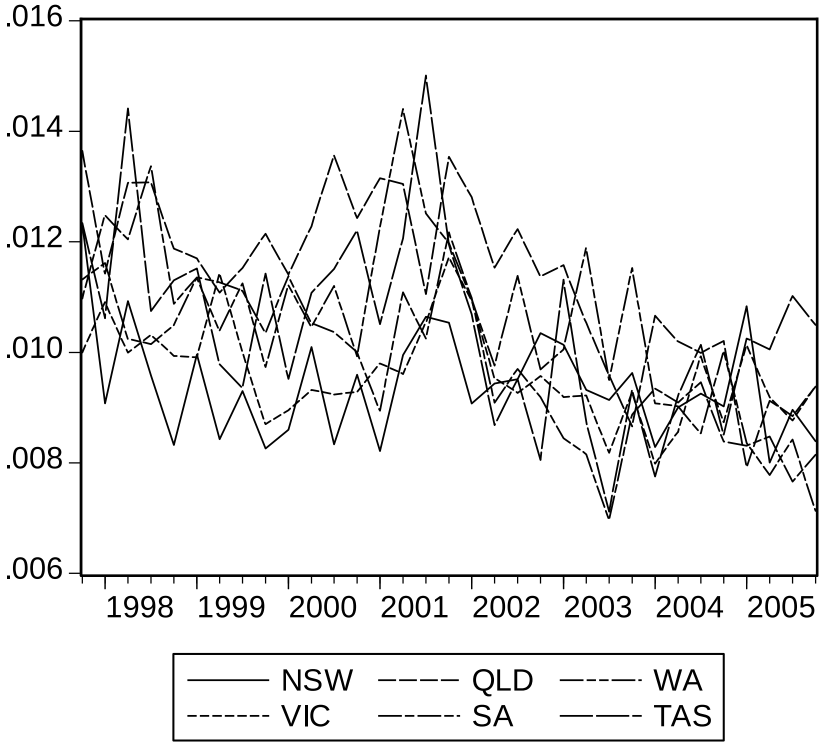

Figure 1. Seasonally adjusted separation rates by state: 1997:4-2005:4.

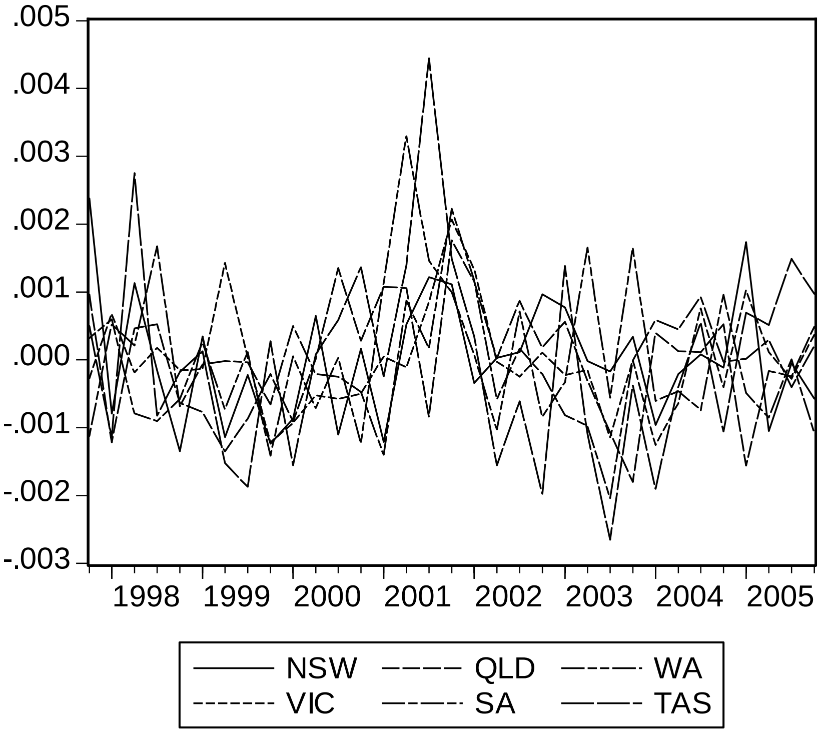

Figure 2. De-trended separation rates by state: 1997:4-2005:4.

Table 1. Principal components of the state separation rates

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
Eigenvectors:						
NSW	0.475	0.192	-0.285	-0.360	-0.707	0.164
VIC	0.528	-0.390	-0.029	-0.098	0.139	-0.734
QLD	0.272	0.238	0.750	0.455	-0.305	-0.079
SA	0.500	-0.435	0.186	-0.051	0.319	0.650
WA	0.274	0.133	-0.565	0.761	0.075	0.062
TAS	0.313	0.740	0.028	-0.270	0.529	-0.034
Eigenvalue	1.731	1.028	0.983	0.919	0.713	0.626
Variance Prop.	0.289	0.171	0.164	0.153	0.119	0.104
Cumulative Prop.	0.289	0.460	0.624	0.777	0.896	1.000

Table 2. Correlations of each variable with the Principal components (Loadings)

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
NSW	0.624	0.195	-0.283	-0.345	-0.597	0.130
VIC	0.695	-0.396	-0.029	-0.093	0.117	-0.581
QLD	0.357	0.241	0.744	0.436	-0.258	-0.063
SA	0.658	-0.441	0.184	-0.048	0.269	0.514
WA	0.360	0.135	-0.561	0.729	0.064	0.049
TAS	0.411	0.750	0.028	-0.259	0.446	-0.027

Table 3. Squares of correlation coefficients given in Table 2

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Sum
NSW	0.390	0.038	0.080	0.119	0.357	0.017	1.000
VIC	0.482	0.157	0.001	0.009	0.014	0.338	1.000
QLD	0.128	0.058	0.554	0.191	0.067	0.004	1.000
SA	0.432	0.194	0.034	0.002	0.072	0.265	1.000
WA	0.130	0.018	0.314	0.532	0.004	0.002	1.000
TAS	0.169	0.563	0.001	0.067	0.199	0.001	1.000
Sum	1.731	1.028	0.983	0.919	0.713	0.626	6.000

Table 4. Coefficients of Regional Specialisation

	NSW	VIC	QLD	SA	WA	TAS
NSW	0.000					
VIC	0.065	0.000				
QLD	0.089	0.105	0.000			
SA	0.110	0.086	0.100	0.000		
WA	0.106	0.108	0.081	0.095	0.000	
TAS	0.144	0.133	0.122	0.106	0.136	0.000