Department of Economics

Working Paper Series

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December 2009

Research Paper Number 1088

ISSN: 0819-2642
ISBN: 978 0 7340 4441 9

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Regional Dimensions of the Australian Business Cycle

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Abstract

This paper deals with the identification of, and explanations for, co-movement in regional business cycles using data for Australian states and territories (regions). We show that both raw growth rates and the deviations from a Hodrick-Prescott trend reflect noise in the series as well as any cycle but that it is possible to manipulate the deviations from a Hodrick-Prescott trend in a simple way so as to reveal its cyclical component. We measure the extent of co-movements in employment fluctuations amongst the regions. We find that cross-region correlations in employment cycles can be explained by regional industry structure and size while the noise component of regional fluctuations appears instead to be related to physical geography.

Key Words

Regional Employment, Business Cycles, Autoregressive Modelling, Co-Movement.

JEL Clasification Codes

R11 C22 E32

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INTRODUCTION

The empirical analysis of the business cycle has traditionally been concerned with an examination of the cyclical relationship between macroeconomic time series at the national level, with a particular emphasis on the behavior of real output and its components, and other key macro variables such as the real wage, unemployment and inflation. Alongside these traditional contributions, with the increasing availability of regional data, there is also a developing literature which examines the regional dimensions of macroeconomic behaviour and whether identified national features, including cyclical features, are reflected across the regions of the economy. The information obtained from an examination of regional features can provide useful (additional) insight into the nature of macroeconomic adjustment processes and the likely regional impact of macroeconomic policies.

Within the literature, there are several studies which examine aspects of regional economic fluctuations, especially in relation to employment and unemployment dynamics. Recent examples of work in this area in this journal include: MARTIN (1997), MARTIN and TYLER (2000), DIXON, SHEPHERD and THOMSON (2001), SHEPHERD and DIXON (2002), GROENEWOLD and HAGGER (2003), PONS-NOVELL and TIRADO-FABREGAT (2006), ROBSON (2006), ANDRESEN (2009).

There is now a developing literature on the co-movement of regional series and the relationship between regional co-movements and similarity (or dis-similarity) of industrial structure, amongst other things. Examples include FRANKEL and ROSE (1998), CLARK and WINCOOP (2001), KALEMI-OZCAN et al (2001), BARRIOS and DE LUCIO (2003), BARRIOS et al (2003), BEINE and COULOMBE (2003), IMBS (2004), GRIMES (2005), BELKE and HEINE (2006), WEBER (2006), NORMAN and WALKER (2007), MONTOYA and DE HAAN (2008), PONCET and BARTHELEMY (2008), ANDRESEN (2009). Although contributions such as those cited have advanced our understanding of regional issues, the analysis of regional co-movements is an area in which there is need for further research. Most of the studies undertaken to date refer to Europe or North America, the procedures for the identification of the business cycle can often be queried (more on this later), and also, as we shall see, there seems to be little agreement in the literature as to the importance of regional industry structure as a determinant of regional performance and especially the association between similarity of industry structure and synchronicity of cycles.

In this paper we examine regional employment evolutions (to borrow an evocative phrase from MARTIN and TYLER (2000)) in Australia over the last thirty years, focusing in particular on cyclical fluctuations in employment. Our primary objective is to determine the nature of employment cycles in the states and territories of the Australian Commonwealth, whether the cycles follow a similar pattern, and how divergences or similarities in the cycles can be explained. Previous work on Australia by DIXON and SHEPHERD (2001) focused on the behaviour of regional unemployment with a view to determining whether the time paths of state and territory unemployment rates share common trend and cyclical features. Using cointegration and common features test procedures, they found that there are no common trends in unemployment across the states and that common cyclical features can be identified only across the larger states, and not for the smaller states and territories. In assessing these results, it should be noted that the behaviour of the unemployment rate depends on many factors other than the level of economic activity, such things at the level of social security benefits, the opportunity for further education, the skill composition of the unemployed, etc, and so it can be argued that a clearer picture of state activity is obtained by focusing on employment rather than the unemployment rate. Ideally, one would wish also to examine regional output movements but, given the limited availability of regional output data in Australia, employment is currently the best macroeconomic indicator available.

Apart from the focus on employment, a distinctive feature of our analysis is that we examine the trend and cyclical properties of the data with the aid of statistical procedures that allow different specifications of the trend-generating process. Many studies base their analysis on cross-correlations of the raw growth rates of the time series – examples include FRANKEL and ROSE (1998), FATAS A. (1997), CLARK and WINCOOP (2001), KALEMI-OZCAN et al (2001), WEBER (2006) – while others, including DIXON and SHEPHERD (2001), are based on the assumption that trends in the data are characterized as random walks and that cyclical features can be represented as autoregressive processes in the growth rates of the series. However, this assumption is valid only if the trends in the series are properly represented as random walks. From the large literature on unit root testing, we know that the power of statistical tests to distinguish between different trend-generating processes is low and there is therefore considerable uncertainty about whether trends in macroeconomic time series should be characterized as random walks.[1] In this paper we consider the behaviour of regional employment levels using the random walk trend assumption, but we also allow for the possibility of other trend-generating processes. This allows us to assess whether the results are sensitive to different assumptions about the nature of the employment trends and to ensure that we are correctly identifying cyclical features rather than some composite of cycle and noise.

STATISTICAL CONSIDERATIONS

Our primary objective is to assess whether employment movements across the Australian states and territories follow a similar pattern. The states and territories (referred to hereafter simply as states – and indeed we will use the terms 'regions' and 'states' interchangeably) are: News South Wales (NSW), Victoria (VIC), Queensland (QLD), South Australia (SA), Western Australia (WA), Tasmania (TAS), Northern Territories (NT) and the Australian Commonwealth Territory (ACT). The data used in this study is the number of civilian employees, measured on a (seasonally adjusted) quarterly basis over the period 1978Q2-2008Q4.

[FIGURE 1 NEAR HERE]

Figure 1 shows the path of aggregate employment for Australia, measured by the standardized logarithm of the series (the logarithm of the series, corrected to zero mean and unit variance). The distinctive features of this plot are the pronounced upward trend in employment and the two major recessions, one in the early 1980s and the other in the early 1990s. Figure 2 shows the employment paths for each of the 8 states. To facilitate a visual comparison between the states, these plots also show the standardized logarithms

[1] See for example: COCHRANE (1988), PERRON (1990, 1997), LUMSDAINE and PAPELL (1997), BAI and PERRON (1998), LEYBOURNE, MILLS and NEWBOLD (1998), ABADIR and TALMAIN (2002).

of the series. Clear evidence is present of trends in all of the series and there are degrees of cyclicality present in the data, some of which appear to mirror the behaviour of the aggregate series. However, it isn't possible to say anything definite about the trend or cyclical patterns in the data from a visual inspection alone and formal statistical tests are needed to determine the nature of the series components and whether the observed fluctuations are similar or dissimilar across the regions. Before we turn to this formal testing, it is helpful to consider the methodology that underlies the statistical modeling of the series.

[FIGURE 2 NEAR HERE]

Trend, Cycle and Noise Representations

A common procedure when examining the time-path of a variable such as employment is to assume that the series is generated by a stochastic process that can be represented as the sum of trend (τ) and cyclical (c) components, with additional noise (e) or other irregular components:

$$y_t = \tau_t + c_t + e_t \tag{1}$$

The problem is that the components of (1) are not directly observable and hence statistical restrictions or restrictions derived from economic theory have to be placed on the data-generating process in order to obtain the required estimates. It is often assumed, partly because of the evidence from unit root tests, that the trend component of many macroeconomic time series can be represented as a random walk with drift, and that the cyclical and noise components can be represented respectively as stationary autoregressive and white noise processes. These components are of course unobserved and we have observations only on the joint outcome, described by the path of y_t, which follows an I(1) process if the trend is represented as a random walk:

$$y_t = \mu + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + ...\alpha_k y_{t-k} + e_t \quad \text{with } \alpha_1 = 1 \text{ and } \sum_{i=2}^{k} \alpha_i < 1 \tag{2}$$

In this case, the trend is removed by first-differencing and the cyclical component can be identified by fitting an autoregressive model to the first difference Δy_t series:

$$\Delta y_t = \mu + \beta_1 \Delta y_{t-1} + ...\beta_{k-1} \Delta y_{t-k-1} + e_t \qquad (3)$$

In the event that estimation of (3) reveals an AR process, this can itself be regarded as a statistical representation of the cyclical component (ENGLE and KOZICKI, 1993) while the noise component is the unexplained variation in the model. If the model is applied to the first differences of the logarithms of the data, the cycle is effectively identified as a cycle in the growth rate of the variable and the nature and strength of the cyclical process is explained by the size and structure of the AR parameters, with the model order chosen either on the basis of parameter significance tests or model selection criteria, such as the Schwartz-Bayesian criterion.

In the multivariate context we are considering, $\boldsymbol{y}_t$ represents the vector of state employment levels and a proper understanding of the trend and cyclical components requires some consideration of the cointegration properties of the data, as well as the autoregressive process. An important preliminary matter to consider is whether the trends in the data are common, because if they are it implies that there is a long-run equilibrium relationship between the variables. At the same time, if the series are cointegrated, it implies that the cyclical dynamics of the series are explained partly by an error correction component (which represents the adjustment of the series to their common equilibrium trend) as well as the autoregressive feature (which generates the cycle around the equilibrium path).

The typical procedure for identifying the presence of common trends in the data is to estimate a vector error-correction (VEC) model of the form:

$$\Delta \mathbf{y}_t = \boldsymbol{\mu} + \Pi \mathbf{y}_{t-1} + \Theta_1 \Delta \mathbf{y}_{t-1} + \ldots + \Theta_k \Delta \mathbf{y}_{t-k} + \boldsymbol{e}_t \qquad (4)$$

where $\mathbf{y}$ is the vector of state employment levels, Π is the parameter matrix associated with the (trend) levels of the series and the Θ matrices contain the AR parameters. In this model, the series in $\mathbf{y}$ are regarded as non-stationary and cointegration is indicated only if there is a linear combination of the series which is stationary. Following JOHANSEN (1988), the test for cointegration revolves around an examination of the Π matrix, with the presence or absence of cointegration indicated by the rank of that matrix. If a cointegrating relationship is identified, it implies that the series share a common long-run path and that cyclical fluctuations are generated by the autoregressive features of the model and the adjustment to the common trend implied by the cointegrating relationship. In contrast, if there are no common trend features, the cyclicality of the series is fully explained by the stationary autoregressive features and the model for estimation purposes is simply the multivariate representation of equation (3), which is simply equation (4) minus the levels term:

$$\Delta \mathbf{y}_t = \boldsymbol{\mu} + \Theta_1 \Delta \mathbf{y}_{t-1} + \ldots + \Theta_k \Delta \mathbf{y}_{t-k} + \boldsymbol{e}_t \qquad (5)$$

Apart from the fact that the multivariate model allows us to address the question of whether the series share common trends, in comparison with the univariate model, it does in principle provide additional information about the nature of any cyclical interaction between the series.

A potential problem with models such as those represented by equations (2) and (4) is that the identification of the cycle as an autoregressive process in the growth rate is valid only if the trend can adequately be represented as a random walk, so that the cyclicality in each series is fully contained within the growth rate (and the equilibrium error-correction component if the series are cointegrated). The justification for the assumption that the stochastic trend can be represented as a random walk comes in part from the findings of unit root tests, which suggest that unit roots are present in many macroeconomic time series. However, as we noted earlier, the power of unit root tests to distinguish between random walk trends and anything other than linear trends is low and it is quite plausible to model the trend process with alternative non-linear trends, such as segmented linear trends, fractionally integrated processes, or mixed trend processes.

The essential problem is that for non-stationary variables of the kind encountered in macroeconomics, there is a vast range of possible trend-cycle-noise decompositions and an appropriate framework or appropriate criteria have to be specified in order to make an operational choice from the various alternatives. The approach we adopt in this paper is to use the insights offered by spectral analysis and frequency filtering procedures to derive stationary (filtered) series, which are then used in a standard autoregressive modeling framework to identify cycle and noise components. This approach allows for the possibility that the time paths of the series may in principle be generated by fluctuations that can arise at any frequency across the spectrum, from trend components near the zero frequency to noise components at the high frequency end of the spectrum.

The problem then becomes one of determining the appropriate frequency-range over which the power of the series should be extracted. In this paper a high-pass filter is used to extract the trend and further analysis is then applied to the stationary filtered (detrended) series, to determine the nature of the cycle and noise components. In order to determine the position of the filter wall in the initial detrending procedure, we apply the notion, common in macroeconomics, that business cycles have a duration of somewhere between about 1-2 years and 8-10 years.[2] This means that any variation at a frequency lower than say the 10-year cycle-frequency is regarded as trend variation and any variation at a frequency higher than the 2 year cycle is regarded as noise variation.

The two sets of methods that have become increasingly popular in the frequency-identification of cycle and noise components are the Butterworth high-pass and band-pass filters[3] and the moving-average band-pass filter popularized by BAXTER and KING (1999).[4] In contrast, the HODRICK and PRESCOTT (1997) filter has long been used as a detrending method in the empirical business cycle literature. In many applications, the Hodrick-Prescott filter is applied to the selected series and correlation analysis is then applied directly to the detrended series, on the assumption that any observed correlations reflect cyclical co-movement. See ARTIS and ZHANG (1997, 1999), HESS and SHIN (1997), FRANKEL and ROSE (1998), KALEMI-OZCAN et al (2001), BARRIOS and DE LUCIO (2003), BARRIOS et al (2003), BELKE and HEINE (2006), MONTOYA and DE HAAN (2008) and PONCET and BARTHELEMY (2008) for recent examples of research on regional business cycle co-movements using this approach . However, since the Hodrick-Prescott filter acts a high-pass filter, it generates a detrended series that contains both cycle and noise components, and it is possible that any observed correlations may reflect noise correlations between the series rather than cyclical correlations proper. This suggests that care should be taken in interpreting the results of the Hodrick-Prescott filter and that a formal modeling of the noise and cyclical components is desirable. As will be seen, we conclude that researchers interested in regional business cycles may be seriously misled if

[2] A useful discussion of the duration of business cycle phases can be found in HARBERLER (1936).
[3] The Butterworth filter is discussed by GOMEZ (2001), HARVEY and TRIMBUR (2003) and IACOBUCCI and NOULLEZ (2005). SHEPHERD and DIXON (2008) show that for macroeconomic time series the results are likely to be similar.
[4] BEINE and COULOMBE (2003) and GRIMES (2005) find that the Baxter-King and H-P filters yield similar results.

they rely on correlations based on a Hodrick-Prescott detrended series which includes noise as well as the cycle

Our approach is to use the Hodrick-Prescott filter first to detrend the employment series and then to estimate the cycle and noise components within an autoregressive model framework. We follow this approach, rather than use the Butterworth or Baxter-King high-pass and band-pass procedures, mainly to facilitate replication and extension of our results by others.[5] In the empirical analysis that follows, we present results derived from the Hodrick-Prescott series, but the cyclical and noise components of the detrended series are identified with the aid of AR Modeling and we then examine these components with a view to determining the univariate and multivariate data patterns. As will be seen, this yields important insights about the nature of regional employment co-movements and also allows us to assess whether the conclusions derived from an examination of the 'gross' detrended series (which includes noise as well as the cycles) also apply when we look at correlations between the cycles in the detrended series (which excludes the noise component).

GROWTH RATE MODELS

Preliminary data testing, based on the ADF test, suggests that the regional employment series can be characterized as I(1) variables. Although we have suggested that alternative trend representations are potentially admissible, we proceed initially on the assumption that the trends can be regarded as random walks and that AR, VAR and VEC models can legitimately be applied to the growth rates of the series. The appropriate model for the estimation of the cyclical relationships depends on whether the series share a common trend, and the first thing to consider is whether there are any cointegrating relationships between the series.

We tested for cointegration using the procedure suggested by JOHANSEN (1988). In this context, we have 8 series and if they were driven by a single common trend we would expect to identify 7 cointegrating vectors. Based on an evaluation of the trace and

[5] At the same time, as a check on the results, we did apply the high-pass and band-pass procedures, and subsequent comparative analysis indicated that there are no significant differences between the results from the Hodrick-Prescott-AR model and those derived from the Butterworth filters.

maximum eigenvalue test statistics, the Johansen test suggests that for our data set there is only one cointegrating vector and seven stochastic trends. This result indicates that the state employment series do not share a common trend and that there is unlikely to be any cointegrating relationships between subsets of the variables. To investigate this matter further, we applied the Johansen procedure to bivariate subsets of the series and the test statistics again failed to identify any cointegrating relationships in the bivariate models. These results strongly support those of DIXON and SHEPHERD (2001) who also failed to identify any common stochastic trends in the state and territory unemployment rates. They imply that we can proceed on the assumption that there are no common stochastic trends in the data and that the cyclical features of the data can be identified from an examination of the series growth rates.

Plots of the employment growth rates (measured by the first difference of the logarithm of the series) are shown in Figure 3.

[FIGURE 3 NEAR HERE]

A visual inspection of the series points to the possible presence of autoregressive cyclical features. It would also seem that the volatility of employment appears to be greater for TAS, NT and ACT than for the other states. The contemporaneous correlation pattern of the series is shown in Table 1.

[TABLE 1 NEAR HERE]

The correlation matrix (of employment growth rates) suggests that the closest co-movement across the series is between the two largest states, NSW and VIC, followed by a weaker but significant relationship with the three other largest states, QLD, SA and WA. For the three remaining smaller states TAS, NT and ACT, there appear to be insignificant or very marginal correlations both within that group and between that group and the larger states.

Autoregressive Models

The correlation patterns provide only a general guide to the state growth rate patterns. In the present context, it is important to bear in mind that the correlation information is also limited because it represents the outcome of the correlation between series which contain both noise and cycle components, so we don't actually know whether the correlations represent noise or cyclical associations. Equally, the standard deviations don't tell us whether the volatility pattern is generated by cyclical or noise volatility, or both. Following the approach outlined earlier, in this section we estimate a series of autoregressive models, with the cycle identified by the AR process and the residual variation identified as the system noise. We begin by examining univariate AR models for each state, with the equivalent national model shown for purposes of comparison.

Employment Growth: 1978:Q2 – 2008:3

AUS: $\Delta l_t = 0.0019 + 0.604\ \Delta l_{t-1}$ $\quad R^2 = 0.37$

NSW: $\Delta l_t = 0.0024 + 0.383\ \Delta l_{t-1}$ $\quad R^2 = 0.14$

VIC: $\Delta l_t = 0.0020 + 0.475\ \Delta l_{t-1}$ $\quad R^2 = 0.23$

QLD: $\Delta l_t = 0.0053 + 0.307\ \Delta l_{t-1}$ $\quad R^2 = 0.09$

SA: $\Delta l_t = 0.0021 + 0.262\ \Delta l_{t-1}$ $\quad R^2 = 0.07$

WA: $\Delta l_t = 0.0046 + 0.309\ \Delta l_{t-1}$ $\quad R^2 = 0.09$

TAS: $\Delta l_t = 0.0019 + 0.361\ \Delta l_{t-1}$ $\quad R^2 = 0.13$

NT: $\Delta l_t = 0.0064 + 0.113\ \Delta l_{t-1}$ $\quad R^2 = 0.01$

ACT: $\Delta l_t = 0.004 + 0.235\ \Delta l_{t-1}$ $\quad R^2 = 0.05$

All of the estimated equations passed the usual tests for serial correlation and normality and in the interests of economy we report only the parameter estimates. Parameter significance tests and Schwarz-Bayesian model selection criterion both indicate that an AR(1) model structure is appropriate for each state and the estimated AR parameters are statistically significant at the conventional 5% level, with the exception of NT. In the case of NT, the AR parameter is insignificantly different from zero at the 5%

significance level, and the model R^2 is extremely low, which together imply that we can't reject the possibility that employment growth in that state follows a white noise process around a constant mean growth rate. As far as the other states are concerned, while a significant AR cyclical process is identified in each case, the degrees of explanatory power are generally low and even in NSW, which has the highest R^2, the AR component accounts for only 23% of the variability of the series, which means that the noise component is dominant, accounting for over 75% of the variance of the series. In the other states, the degree of explanatory power is even lower. It should also be noted that the explanatory power of the model is much greater for the national AUS equation than it is for any of the individual state models and the autoregressive structure appears to be more pronounced for the aggregate series.

Based on the AR model estimates of the cycle and noise components, we calculated the correlations between the cyclical components of each of the states and the noise components. The correlation matrices are shown in Tables 2 and 3.

[TABLES 2 AND 3 NEAR HERE]

The cyclical correlations are broadly similar to the series correlations shown earlier in table 1, which suggests that the significant cross correlations in the growth rate series identified for NSW and VIC in particular, and less strongly QLD, SA and WA, can be regarded as reflecting cycle correlations, rather than just similar noise (although there is a significant noise correlation for NSW and VIC). Nevertheless, it is important to note that the correlations are generally weak and this reflects in part the low explanatory power of the AR models. The question is whether these low correlations, and the low explanatory powers of the models, should be interpreted as indicators of weak cross-state cyclical interactions, or whether they reflect the inadequacy of the first difference procedure as a means of identifying business cycle features. We come back to this matter later.

A drawback of the univariate modeling approach is that it does not allow for possible interactions between the state employment movements, and it is arguably more efficient to estimate a multivariate model. Following this line of reasoning, we estimated a vector autoregressive (VAR) model of the series, to determine whether additional insight is obtained from such a systems approach. The model order selection criteria suggested that a single lag is sufficient to capture the system dynamics and we estimated a VAR(1) model incorporating all of the states. This model yielded little additional insight about the cyclical interactions between the states, beyond what can be discerned from the correlation matrix of Tables 1 and 3, and the results are not reported. The R^2 values of the individual equations of the VAR model are shown in table 4, alongside those of the AR models.

[TABLE 4 NEAR HERE]

The results indicate that the only states for which the VAR model provides any significant additional explanatory power are VIC and possibly NSW, SA and WA. Note, however, that the additional explanatory power is not great (an extra 10% or so of explained variation) and these are the states that we have already identified, via the correlation matrix, as having the closest association.

We turn now to the application of the Hodrick-Prescott filter. This is potentially a more powerful tool to identify cyclical features in data.

HODRICK-PRESCOTT BUSINESS CYCLE MODELS

In this section we examine the properties of the national and regional employment series after detrending with the Hodrick-Prescott (HP) filter. We first examine the detrended series and then separate out the cycle and noise components of each series. The cycle and noise components of the detrended series are identified with an autoregressive model and we then use those series to examine the degree of regional co-movement. Plots of the filtered (i.e. detrended) series for the states are shown in Figure 4.

[FIGURE 4 NEAR HERE]

It is quite clear from Figure 4 that there are strong cyclical features present in all the series and the preliminary task is to estimate the autoregressive models, to pin down the power of the series contained within these cycles, relative to the noise component, and the examine how the cycle and noise components are related across the states.

[TABLE 5 NEAR HERE]

Table 5 gives the (contemporaneous) correlation matrix of the Hodrick-Prescott filtered components for each pair of regions. While this table seems to indicate the presence of both common and idiosyncratic elements across regions, there are a number of reasons to question the usefulness of this data as evidence of the presence or absence of business cycle common features. Some of the values are odd, given what we know about the economic history of Australia. For example it is odd to find that NSW and VIC are so poorly correlated given that they have very similar industrial, economic, social and spatial structures. It is also unusual to see a negative correlation between business cycles in two regions in the same country. More important, however, is the fact that this 'gross' detrended series potentially includes noise as well as the cycle – see equation (1) above – and it is possible that the noise component is obscuring the truth about any co-movement in regional business cycles. As mentioned previously, our approach in this paper is to estimate the cycle and noise components of the de-trended series within an autoregressive model framework.

Autoregressive Modeling of the Filtered Series

We begin by reporting estimates of the univariate AR models of the detrended (i.e. filtered) series for each of the states. The raw series (the inputs to the filter) are the (detrended) logarithms of the employment levels and the model orders were selected with reference to 5% parameter significance tests. No constant terms are reported, since the mean is effectively removed in the filtering procedure, and so the filtered series describe deviations around the zero mean.

Detrended Employment: 1978:Q2 – 2008:3

AUS: $l_t = 1.31\, l_{t-1} - 0.21\, l_{t-2} - 0.23\, l_{t-3}$ $\qquad R^2 = 0.91$

$$\text{NSW: } l_t = 1.22\, l_{t-1} - 0.37\, l_{t-2} \qquad R^2 = 0.81$$

$$\text{VIC: } l_t = 1.28\, l_{t-1} - 0.40\, l_{t-2} \qquad R^2 = 0.23$$

$$\text{QLD: } l_t = 1.14\, l_{t-1} - 0.33\, l_{t-2} \qquad R^2 = 0.76$$

$$\text{SA: } l_t = 1.00\, l_{t-1} - 0.07\, l_{t-2} - 0.17\, l_{t-3} \qquad R^2 = 0.72$$

$$\text{WA: } l_t = 1.11\, l_{t-1} - 0.26\, l_{t-2} \qquad R^2 = 0.79$$

$$\text{TAS: } l_t = 1.16\, l_{t-1} - 0.41\, l_{t-2} \qquad R^2 = 0.73$$

$$\text{NT: } l_t = 0.89\, l_{t-1} - 0.26\, l_{t-2} \qquad R^2 = 0.54$$

$$\text{ACT: } l_t = 0.98\, l_{t-1} - 0.35\, l_{t-2} \qquad R^2 = 0.59$$

The AR models for the detrended series show highly pronounced cyclical features, represented by the relatively high AR parameters and the relatively high R^2 values. The degree of co-movement between these estimated cycles is reported in the correlation matrix of Table 6, which shows the contemporaneous correlation of the cyclical components.

[TABLE 6 NEAR HERE]

The H-P cyclical correlations indicate a robust and consistent cyclical pattern, with relatively strong and positive cyclical correlations across NSW, VIC, QLD, SA,WA and TAS, which is suggestive of a common cycle across these states. In contrast, the cyclical correlations with ACT and NT are weak and would appear to support the conclusion that those two states follow idiosyncratic patterns.

Of particular interest, given the use made by other researchers of the de-trended series which include both cyclical and noise components[6] is to enquire into the relationship between the correlations for the cycle given in Table 6 and the correlations for the series which include both cycle and noise, which were given in Table 5. The pairings indicated in italics in Table 6 are significantly different from the values given in

[6] See for example ARTIS and ZHANG (1997, 1999), HESS and SHIN (1997), FRANKEL and ROSE (1998), KALEMI-OZCAN et al (2001), BARRIOS and DE LUCIO (2003), BARRIOS et al (2003), BELKE and HEINE (2006), MONTOYA and DE HAAN (2008) and PONCET and BARTHELEMY (2008).

Table 5 at the 5% level.[7] That is, 13 out of 28, or almost half of the pairings, show a significantly different degree of co-movement depending upon whether we look at correlations between the 'gross' detrended series (which include noise as well as the cycle – these are given in Table 5) or we look at correlations between the cycles in the detrended series (which exclude the noise component – these are given in Table 6). We conclude that researchers interested in regional *business cycles* may be seriously misled if they rely on correlations based on the detrended series, because they include both noise and cyclical variation (more on this shortly).

Turning to the noise correlations – shown in Table 7 – we can see that they are much lower than the cyclical correlations, indicating perhaps that the states have experienced rather different shocks over the period.

[TABLE 7 NEAR HERE]

We turn now to consider the relationship between these various co-movements and the commonality of industry structure amongst other things.

EXPLAINING THE CYCLICAL CO-MOVEMENTS

Many authors have looked at the co-movement of regional series and wondered if common cycles can be explained by similarity of industry composition, the distance between regions in geographic space, whether or not they share a common border (or if there is national border), and their size. Examples include CLARK and WINCOOP (2001), KALEMI-OZCAN et al (2001), BARRIOS and DE LUCIO (2003), BARRIOS et al (2003), BEINE and COULOMBE (2003), IMBS (2004), GRIMES (2005), BELKE and HEINE (2006), WEBER (2006), NORMAN and WALKER (2007), MONTOYA and DE HAAN (2008), PONCET and BARTHELEMY (2008) and ANDRESEN (2009). Almost all of this research has been concerned either with comparisons between regions in Canada and the USA, European regions and regions in the USA or with comparisons between regions in Europe before and after EMU. While most authors find a role for such factors as the size of regions, "the

[7] These conclusions are based on the application of Fisher's z-transformation test for testing the equality of (independent) correlation coefficients.

existing evidence seems to suggest a rather limited role for a regions' industry structure in explaining its employment growth [ie co-movements in employment or output growth]" (BELKE and HEINE, 2006, p 91).[8]

Earlier we noted that many of these studies were attempting to explain cross-correlations of the deviations from a HP trend, but we have also seen that these deviations include (region specific) noise and the correlations (based on simple deviations from the HP trend) may not be closely related to the set of correlations based on the true cyclical component of the series. As an example of how misleading the results based on correlating deviations from the HP trend can be, we present two plots below. The first (Figure 5) shows the size of the correlation coefficient between two regions based on deviations from the HP trend (the correlations given in Table 5 above) plotted against the Krugman index of dissimilarity in industrial structure (a common measure of comparative industry structure which will be discussed in more detail below). Clearly there is only a weak relationship between the two variables, indeed the correlation coefficient is -0.342. Figure 6 shows the size of the correlation coefficient between two regions based on *the cyclical component* of deviations from the HP trend (these correlations are given in Table 6 above) plotted against the Krugman index of dissimilarity in industrial structure. Clearly, in this case there is a strong relationship between the two variables, and indeed the correlation coefficient of -0.889 indicates that there is a strong tendency for greater dissimilarity (similarity) to be associated with less (more) highly correlated cycles in employment. Comparing these results, it is easily seen that we may obtain misleading results if we do not ensure that we are in fact correlating cyclical components of the series rather than noise.[9]

[FIGURES 5 and 6 NEAR HERE]

[8] One of the original and still one of the key papers in this area, CLARK and WINCOOP (2001), find no statistically significant relationship between co-movement and measures if similarity of industry structure (p 72). A previous study looking at GSP and hours worked for the six states of Australia over the period 1986- 2005 found "no evidence that differences in [co-movement across] states … are related to differences in industrial structure, suggesting that alternative approaches which give greater weight to industrial structure are unlikely to provide much additional information" (NORMAN and WALKER, 2007, p 365).

[9] Of course even leaving this aside, it is still desirable if we wish to study business cycle co-movements to purge the HP filtered data of its noise component.

We turn now to see if we can explain the co-movements of the regional business cycle (given in Table 6) and regional noise (given in Table 7). In addition to industrial structure, researchers have typically included the distance between regions in geographic space, whether or not they share a common border, and their size in explanatory regressions. In this study we will include as explanatory variables, the following:

Krugman index of dissimilarity in industrial structure: This is a measure which is commonly used in the literature.[10] Suppose have data for (say) employment in *i* industries[11] and we want to compare two regions, region A and region B, then the Krugman index would be calculated as:

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

where employment in a particular industry in region A is X_{iA}, employment in the same industry in region B is X_{iB},, total employment in all industries in region A is X_A, and total employment in all industries in region B is X_B. It is in the nature of the Krugman index that it will always lie between the values of 0 (indicating that the two distributions are the same) and 2 (where the two distributions have nothing in common). Because the index is higher the more dissimilar the two distributions, the index is sometimes said to be an "Index of Dissimilarity".

'Adjacency': This is a dummy variable which takes on a value of 1 if the two regions share a border and 0 if they do not.[12] As an alternative to adjacency we also use a variable, *Distance:* This is measured as the natural log of the geographic distance between capital cities in kilometers. In the case of TAS we have summed the distance between TAS to VIC and the distance between VIC and the other region.

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[10] See KRUGMAN (1991, p 75f and 1993, p 250f). The Krugman measure is related to a measure with a long history in regional studies called the 'Coefficient of Regional Specialisation' (see ISARD (1960), p 270ff) and DIXON and THIRLWALL (1975, p 16f)). CLARK and WINCOOP (2001), BARRIOS et al (2003), BARRIOS and DE LUCIO (2003), IMBS (2004), BELKE and HEINE (2006) and PONCET and BARTHELEMY (2008) provide examples of the use of this variable in the context of studying regional co-movements.

[11] Data for employment by industry is available for 53 industries covering all sectors in the economy. We use the average value of KI for each pair of regions over our sample period. This gives essentially the same results as we obtain if we use the values of the KI for the middle year of our sample period (1993)

[12] TAS (a large island to the south of VIC) is separated from VIC by Bass Strait which is around 250 km wide. Since there is considerable sea and air traffic between TAS and VIC (and much less direct sea or air traffic between TAS and other states) we have recorded TAS as being adjacent to (having border) with VIC but not being adjacent to any other state. In terms of climate etc TAS is more like VIC than any other state.

Size: This is measured as the sum of the natural log of the populations of the two regions in the middle year of our sample period.[13]

Table 8 below shows the results obtained by regressing the correlations of cycles and noise given in Tables 6 and 7 on these three explanatory variables (as is the case with other studies, we use Distance and Adjacency as alternatives). Since the dependent variable is itself a sample estimate, WHITE's (1980) correction for heteroskedasticity has been applied in each case. The figures in parentheses are p-values, and we use the 5% value as the boundary for acceptance or rejection.

[TABLE 8 NEAR HERE]

We find that cross-region correlations based on the cyclical component of the deviations from the HP trend (given in Table 6) can be explained by industry structure and by size (see the second and third columns of Table 8). Specifically, we find that regional business cycles will be less (more) highly correlated the more dissimilar (similar) their industrial structure[14] and the larger are their size (state populations in our case).[15] Interestingly, we find no role for adjacency (in other words, we find no evidence of an internal border effect) or geographic distance effects in explaining cyclical co-movement (this is not uncommon in the regional literature).

Since our statistical procedure has allowed us to identify separately the cycle and noise components of state employment fluctuations, we are able to consider possible explanations for noise correlations across the regions – so far as we are aware this has not been done before. In contrast to our findings in relation to regional cycles, we find that the cross-region correlations based on the noise component of the deviations from the HP trend (Table 7 above) cannot be explained by any of our explanatory variables (see the third and fourth columns of Table 8), although (at the 5½ % level) there is a possible

[13] CLARK and WINCOOP (2001), BARRIOS and DE LUCIO (2003) and IMBS (2004) provide examples of the use of this variable in the context of studying regional co-movements. It clearly has its origin in the gravity model of trade and other regional interactions.
[14] DIXON and SHEPHERD (2000) found that Australian states and territories with similar industrial structures also have similar unemployment rates.
[15] This latter result may reflect similarity of central place activities and not just greater trade between the regions.

relationship between noise co-movements and adjacency; in other words, there does appear to be a 'border effect' in relation to the noise component of regional employment fluctuations. This finding seems to us to make sense given that 'adjacency' is a proxy for similar climate and geology and thus is likely to indicate similar (random) shocks effecting (say) agriculture and (mineral) exports. In other words, the noise component of state employment fluctuations may be related to physical geography.

SUMMARY AND CONCLUSION

In this paper we use have used frequency filtering and autoregressive modeling techniques to identify the cycle and noise components of Australian regional employment fluctuations. Our objectives have been to determine the nature of employment cycles in the states and territories of the Australian Commonwealth, whether the cycles follow a similar pattern, and how divergences or similarities in the cycles can be explained. Our analysis suggests that the use of the first difference filter (growth rate models) to identify cyclical features yields useful insights, but the results are dominated by the noise component of the model and the strength of the relationships between regional cycles are difficult to identify and appear to be weak. A high-pass filter, such as the Hodrick-Prescott filter, allows identification of the cyclical features of interest and generates results which are richer and more robust than the growth rate models provide. However, we have emphasized that detrending with a high-pass filter produces a series which includes both cycle and noise components and that further modeling to separate the cycle and noise components is needed to avoid misleading conclusions about the nature and strength of cycle and noise relationships.

Our results suggest that similar cyclical features are present in a core group of states in Australia, including NSW, VIC, QLD in particular, but also SA and WA. In contrast, the smaller states, NT and ACT, exhibit a high degree of idiosyncratic behaviour. In the case of TAS, the growth rate model suggests idiosyncratic behaviour, but the HP results place this state within the core group, but less strongly so than in the other states.

As has become common in the literature on this topic, we considered a variety of factors that might explain the observed degree of cyclical co-movement, including state size, proximity and similarity (or dissimilarity) of industrial structures. We find that cross-region correlations in employment cycles can be explained by industry structure and by state size, and that state business cycles will be more (less) highly correlated as the industrial structures of the states are more (less) alike. Since our statistical procedure has allowed us to separately identify the cycle and noise components of state employment fluctuations we are able to consider possible explanations for noise correlations across the regions – so far as we are aware this has not been done before. The noise component of state employment fluctuations does not seem to be related to industry structure and by state size, but appears instead to be related to physical geography.

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Table 1. Correlation Matrix of State Employment Growth Rates

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
NSW	1.00							
VIC	0.52	1.00						
QLD	0.35	0.38	1.00					
SA	0.34	0.35	0.39	1.00				
WA	0.28	0.41	0.42	0.32	1.00			
TAS	0.19	0.24	0.19	0.11	0.22	1.00		
NT	-0.04	0.05	0.12	-0.04	0.07	-0.14	1.00	
ACT	0.19	0.06	0.04	0.21	0.06	0.15	-0.17	1.00

Correlation 5% significance level = 0.18

Table 2. Correlation Matrix of Employment Growth Rate Cyclical Components

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
NSW	1.00							
VIC	0.53	1.00						
QLD	0.39	0.40	1.00					
SA	0.33	0.36	0.41	1.00				
WA	0.36	0.44	0.44	0.32	1.00			
TAS	0.22	0.24	0.19	0.10	0.21	1.00		
NT	-0.04	0.06	0.11	-0.05	0.10	-0.18	1.00	
ACT	0.24	0.08	-0.008	0.18	0.15	0.18	-0.21	1.00

Table 3. Correlation Matrix of Employment Growth Rate Noise Components

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
NSW	1.00							
VIC	0.36	1.00						
QLD	0.36	0.20	1.00					
SA	0.24	0.16	0.36	1.00				
WA	0.24	0.19	0.34	0.22	1.00			
TAS	0.08	0.12	0.09	0.00	0.14	1.00		
NT	-0.01	-0.03	0.07	-0.12	0.06	-0.21	1.00	
ACT	0.15	0.01	-0.04	0.09	0.07	0.11	-0.16	1.00

Table 4. R^2 Values for AR(1) and VAR(1) Models

State	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
R^2 AR(1)	0.14	0.23	0.09	0.07	0.09	0.13	0.01	0.05
R^2 VAR(1)	0.23	0.35	0.13	0.20	0.18	0.16	0.02	0.08

Table 5. Correlation Matrix of Hodrick-Prescott Filtered Component

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
NSW	1.00							
VIC	0.31	1.00						
QLD	0.67	0.07	1.00					
SA	0.69	0.35	0.62	1.00				
WA	0.62	0.31	0.45	0.54	1.00			
TAS	0.69	0.29	0.77	0.61	0.48	1.00		
NT	0.83	0.17	0.75	0.69	0.59	0.76	1.00	
ACT	0.26	-0.21	0.36	0.23	0.09	0.29	0.36	1.00

Table 6. Correlation Matrix of Hodrick-Prescott Filtered Cyclical Components

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
NSW	1.00							
VIC	*0.79*	1.00						
QLD	0.62	*0.70*	1.00					
SA	0.64	*0.64*	0.59	1.00				
WA	0.66	*0.73*	*0.73*	0.57	1.00			
TAS	0.54	0.53	*0.39*	0.45	0.43	1.00		
NT	*0.19*	0.30	*0.31*	*0.18*	*0.26*	*0.09*	1.00	
ACT	0.27	*0.13*	*0.05*	0.28	0.21	0.28	0.20	1.00

Correlation 5% significance level = 0.18

Table 7. Correlation Matrix of Hodrick-Prescott Filtered Noise Components

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
NSW	1.00							
VIC	0.36	1.00						
QLD	0.32	0.19	1.00					
SA	0.27	0.17	0.36	1.00				
WA	0.13	0.17	0.29	0.21	1.00			
TAS	0.11	0.16	0.12	0.03	0.15	1.00		
NT	-0.04	-0.03	0.18	-0.03	0.04	-0.09	1.00	
ACT	0.16	0.05	0.11	-0.05	0.09	0.19	0.15	1.00

Correlation 5% significance level = 0.18

Table 8. Results of regressions for cycle and noise correlations on various explanatory variables

Explanatory variable	Correlations in Table 6 (Cycles)		Correlations in Table 7 (Noise)	
Constant	0.7333 (0.001)	0.7026 (0.000)	0.4954 (0.0584)	0.1804 (0.007)
Krugman Index	-0.8293 (0.000)	-0.8214 (0.000)	-0.3388 (0.057)	-0.2216 (0.106)
Size	0.0532 (0.000)	0.0551 (0.001)	0.0195 (0.282)	0.0274 (0.115)
Distance	0.0040 (0.851		-0.0324 (0.255)	
Adjacency		-0.0080 (0.756)		0.0624 (0.054)
R^2	0.873	0.872	0.512	0.544
No. of obs.	28	28	28	28

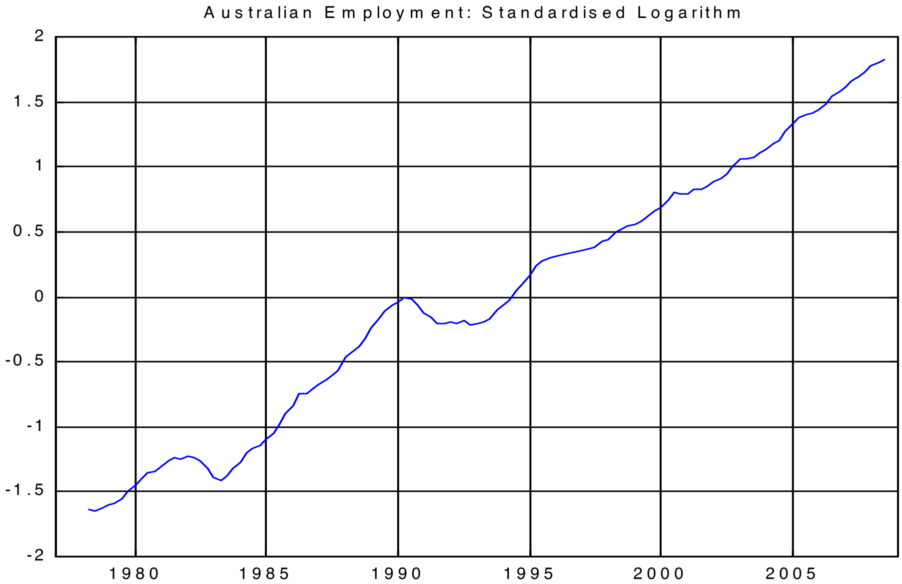

Fig 1. Australian Employment Level (Standardized logarithm)

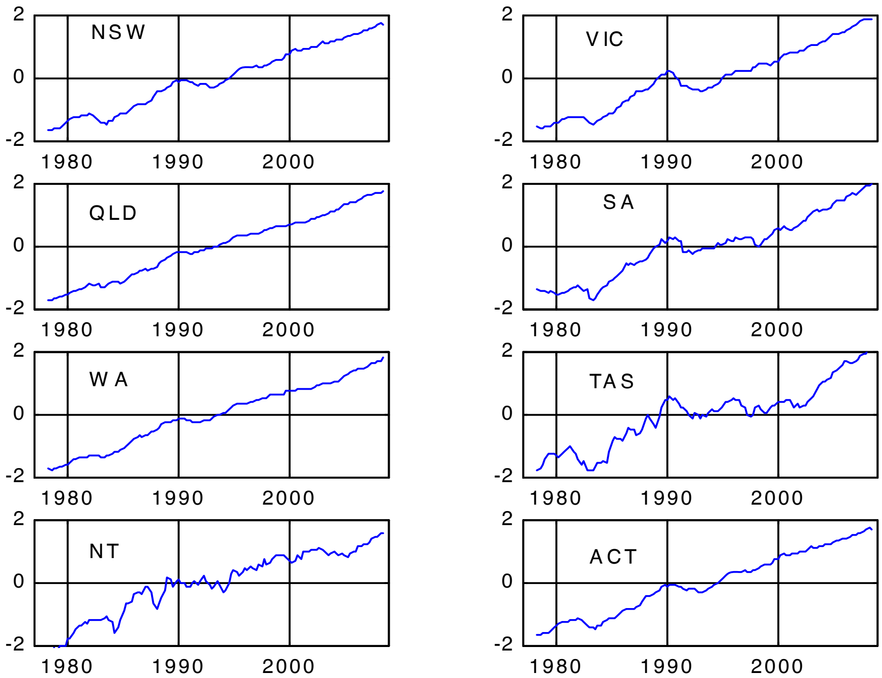

Fig 2. State Employment Levels (Standardized Logarithms)

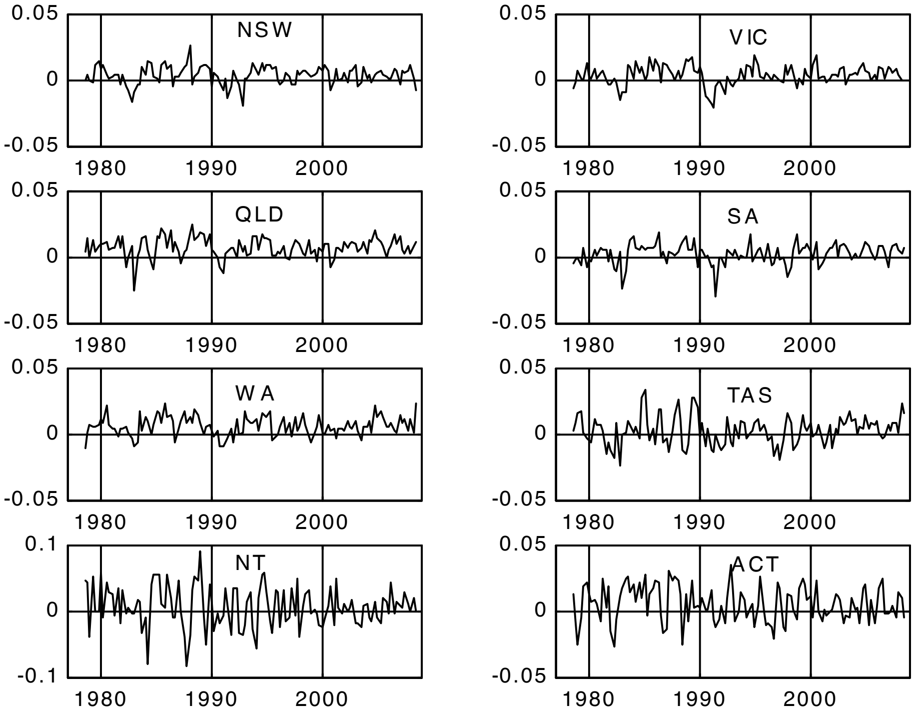

Fig 3. Employment Growth Rates by State

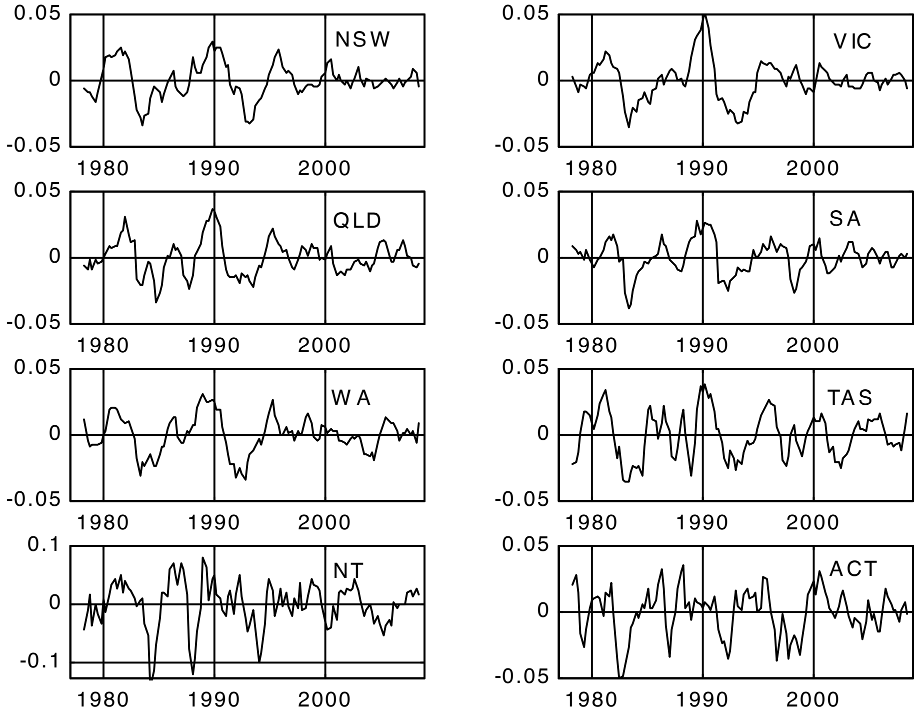

Fig 4. Hodrick-Prescott Filtered Component

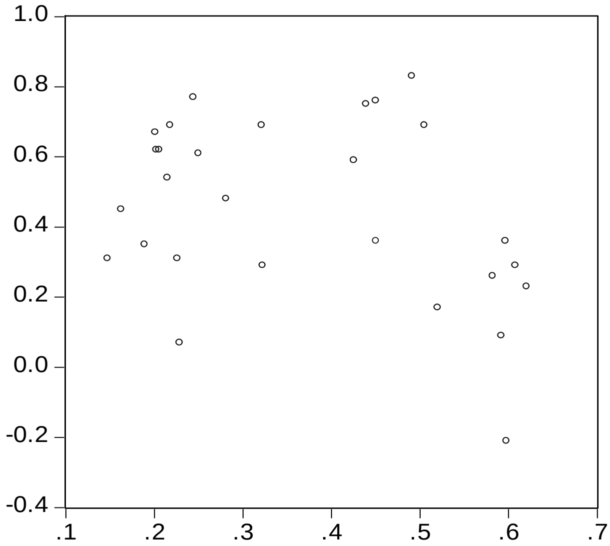

Fig 5. Correlations given in Table 5 (vertical axis) plotted against Krugman's index of the dissimilarity in industrial structure of the two regions (horizontal axis)

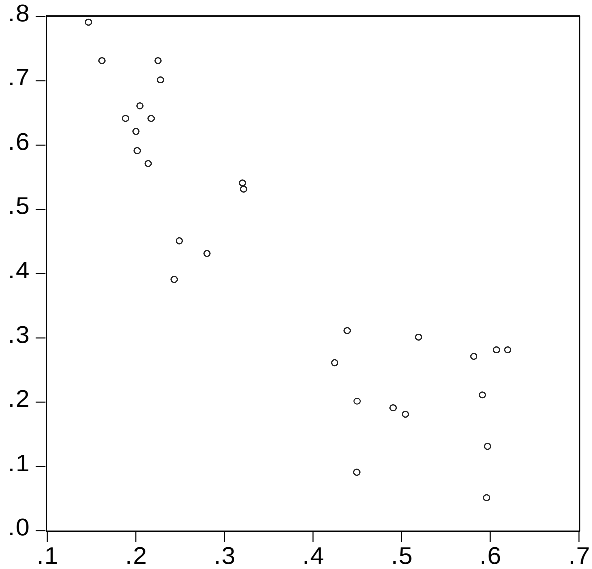

Fig 6. Correlations given in Table 6 (vertical axis) plotted against Krugman's index of the dissimilarity in industrial structure of the two regions (horizontal axis)