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ABSTRACT

In this paper we examine Australian data on national and regional employment numbers, focusing in particular on whether there have been common national and regional changes in the volatility of employment. A subsidiary objective is to assess whether the results derived from traditional growth rate models are sustained when alternative filtering methods are used. In particular, we compare the results of the growth rate models with those obtained from Hodrick-Prescott models. Using frequency filtering methods in conjunction with autoregressive modeling, we show that there is considerable diversity in the regional pattern of change and that it would be wrong to suppose that results derived from the aggregate employment series are generally applicable across the regions. The results suggest that the so-called great moderation may have been less extensive than aggregate macro studies suggest.

Key Words: Regional employment, State business cycle, Structural change, Volatility

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1. Introduction

Assessments of macroeconomic performance typically concentrate on the behavior of aggregate variables, such as GDP, aggregate employment or unemployment, and the national inflation rate. Although this focus on the overall behavior of the economy is of course perfectly legitimate, it must be stressed that national performance measures may conceal marked differences at the regional or local level.[1] Also, the information obtained from an examination of regional features provides useful (additional) insight into the nature of social and economic adjustment processes. In this paper we examine whether changes in volatility identified for national (employment) data are reflected across the regions of the economy, or whether the degree of regional diversity is such that conclusions about national performance are not applicable at the regional level.

The background to our analysis is that evidence from previous macro-studies suggests that many economies experienced a move to greater stability at some point in the 1980s or 1990s, measured by a reduction in the volatility of aggregate output and employment. Indeed, so widespread is the evidence for this, that the term 'Great Moderation' has been universally adopted since its introduction by Bernanke in his address at the meetings of the Eastern Economic Association, Washington, DC February 20, 2004.[2] Although there is by now an enormous literature on the great moderation - see Davis and Kahn (2008) for a survey - there has unfortunately been little work on changes in volatility of the same or related macroeconomic time series at the regional level,[3] and

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[1] The data set used in this paper if for the eight states of Australia. Australia's population is heavily concentrated in urban areas indeed, 2/3 of the population lived in the (eight) state capital cities. For this reason there is considerable overlap between regional and urban studies in Australia.

[2] The Global Financial Crisis was quite moderate in its effects in Australia. The national unemployment rate rose from 4.1 in April 2008 to 5.8 in June 2009 where it remained until August 2009 and has been falling since then (previous recessions had seen unemployment in excess of 10%). As a result, for Australia at least, it still makes sense to talk of a sustained moderation having occurred at some date in the past.

[3] This is odd as there is now an extensive literature on the diversity of state business cycles, diversity in the timing of contractions and recoveries and in both the duration and depth of recessions – see for example, Carlino and DeFina (1998, 2004), Dixon and Shepherd (2001), Owyang et al (2005, 2009), and Wilkerson (2009).

without such evidence there is arguably a question mark about just how extensive (and thus how 'great') the moderation actually was. So far as we are aware, only two studies have been published on this topic and both of those are for the USA. Carlino (2007) examines quarterly data for employment growth rates in the USA over the period 1956-2002. Relying on the assumption that changes in volatility occurred at the same time (1983/84) in all of the states, he focuses on interstate differences in volatility before and after that date and finds that "while all states shared in the decline, employment growth volatility declined much more dramatically in some states than in others" (Carlino, 2007, p 13). Owyang et al (2008) allow for differences not only in the magnitude, but also in the timing of changes in volatility across states. Based on an analysis of monthly data for employment growth rates in the USA over the period 1956-2004, they find "significant variation in both the timing and magnitude of the state's volatility reductions" (Owyang et al, 2008, p 579) and are unable to find evidence of a structural break (ie a change in volatility) for one-quarter of the states. There is thus good reason to wonder if it is appropriate to describe the moderation (at least for the USA) as "great".

In this paper we compare the national and regional employment performance of the Australian economy over the last thirty years, focusing in particular on whether there have been common national and regional changes in the structure and volatility of employment movements.[4] We have three aims. First, by providing a study for a country other than the USA, we aim to add to existing knowledge concerning regional behaviour. Secondly, while (initially) we follow previous authors in using (raw) employment growth rates as the basis for our analysis of volatility, we also show that it is important to separate out the cycle and noise components of the growth rate series, to determine whether observed changes in volatility are due to changes in the cyclical process and/or changes in noise volatility (we also provide statistical tests for identified changes in volatility). Thirdly, in the penultimate section of the paper we take a different approach to assessing volatility changes than is found in either Carlino (2007) or Owyang et al (2008), who base their analysis entirely on growth rates. In particular, we use a preliminary high-pass filter to remove the trend component of the series and then apply

[4] 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. For similar reasons, the studies for the US also use employment as the basis for their assessment of volatility.

autoregressive modeling to separate the de-trended series into cycle and noise components. In that section of the paper we attempt to do two things: (i) to show how the Hodrick-Prescottt (HP) filter can usefully be applied in this context, and (ii) to assess whether the results for the analysis of volatility changes based on the use of a 'filter' are the same as the results based on the use of the 'growth rate' method.

2. Statistical considerations

The studies published by Carlino (2007) and Owyang et al (2008) provide useful insight into the structure of regional employment fluctuations and highlight the need to consider regional as well as aggregate fluctuations. However, a limitation of their work is that it is based only on an examination of the 'raw' growth rates and does not therefore provide evidence about whether observed volatility changes reflect changes in the shocks (noise) affecting the system or changes in the cyclical response to those shocks. In studies of the changing variability of (national) output growth, authors such as Kim and Nelson (1999), McConnell and Quiros (2000), Stock and Watson (2002), Ahmed, Levin and Wilson (2004), Sensier and van Dijk, (2004), and Summers (2005) examined this question by using autoregressive models to distinguish between changes in noise volatility and changes in the economy's cyclical response. In most cases, the source of the increased stability for the US economy is seen to arise from a reduction in the variance of the shocks affecting the system (ie a reduction in noise), rather than a change in the dynamic structure (ie the cyclical response) of the economy.[5] Following this lead, we will consider whether any changes in volatility in our (Australian) regional data set should be regarded as arising from changes in noise volatility or changes in the nature of the cyclical process itself.

Our analysis is based on the assumption that the time-paths of employment are generated by stochastic processes that can be represented as the sum of trend (τ) and cyclical (c) components, with additional noise (e) or other irregular components:

$$y_t = \tau_t + c_t + e_t \qquad (1)$$

[5] Simon (2001) and Taylor et al (2005) found similar results for Australian output growth.

The objective is to identify the cycle and noise components for the national and regional employment series and then determine whether there are changes in the structures of the cycles and/or the noise processes. The problem is that the various components of (1) are not directly observable and we have data only on the joint outcome y_t. It follows that statistical restrictions or restrictions derived from economic theory have to be placed on the data-generating processes in order to obtain estimates of the unobserved components.

2.1 Random walk trends

It is often assumed, partly because of the evidence from unit root tests, that the trend component of macroeconomic time series can be approximated as a random walk with drift, and that the cyclical and noise components can be represented respectively as stationary autoregressive (AR) and white noise processes. These assumptions imply that the observed y_t can be represented as:

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

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 is regarded as a statistical representation of the cyclical component (Engle and Kozicki, 1993) and the noise component is the unexplained variation in the model. Assuming that (3) is applied to the first differences of the logarithms of the data, the nature and strength of the cyclical process is explained by the size and structure of the AR parameters in the growth rate of the variable, with the model order chosen either on the basis of parameter significance tests or model selection criteria, such as the Schwartz-Bayesian criterion. Structural changes in the model can then be identified by testing for volatility changes in the noise component and changes in the cycle-generating AR parameters. In the case of the cyclical component, a more (or less) moderate cycle would be indicated by a lower (or higher) set of AR parameters.

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 a 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 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 the Π 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 process and the model for estimation purposes is the multivariate representation of equation (3), which is simply equation (4) minus the levels term, i.e.:

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

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 also provide additional information about the nature of any cyclical interaction between the series.

2.2 Alternative trend representations

A potential problem with models such as equations (3) and (4) is that the identification of the cycle as an autoregressive process in the growth rate of the series 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). Although it is common to assume that macroeconomic trends can be regarded as random walks, the literature on unit root tests indicates that the power of such tests to distinguish between random walk trends and anything other than linear trends is low, and it is quite plausible to model the trend processes with alternative non-linear trends, such as segmented linear trends, fractionally integrated processes, or mixed trend processes.[6] In addition, a worrying feature of models based on the analysis of growth rates is that they typically yield the result that the business cycle is a very minor component of the series, with the bulk of the variation contained within the noise component. In view of this and especially given the uncertainty surrounding the trend-generating process, it seems desirable to examine the data with the aid of a trend-cycle identification procedure (specifically, a filter) that does not require the imposition of a unit root in the data-generating process. This allows us to assess whether conclusions about volatility (and especially the dates assigned to any breaks in volatility) are robust with respect to alternative trend-cycle extraction procedures.

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 advance in order to make an operational choice from the various alternatives. The approach we adopt 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

[6] See for example: Cochrane (1988), Perron (1990, 1997), Lumsdaine and Papell (1997), Bai and Perron (1998), Leybourne et al (1998), and Abadir and Talmain (2002).

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 (i.e. the detrended) series, to identify 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. 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 Hodrick and Prescott (1997) filter has long been used as a detrending method in the empirical business cycle literature.[7,8] However, since the Hodrick-Prescott filter acts a high-pass filter, it generates a detrended series that contains both cycle and noise components. 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 of any HP filtered series is desirable. One of our contributions is to show how this can be achieved quite easily.

In the empirical analysis which follows, we present results derived from both the growth rate series and the HP filtered series.[9] The cyclical and noise components of the each series are identified with the aid of AR modeling and we then apply statistical tests to determine the whether any changes in the cyclical structure or noise volatility of the employment series can be identified.[10] This approach provides important insights about

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[7] See, for example, Blackburn and Ravn (1992), Hess and Shin (1997), and Artis and Zhang (1997).

[8] Alternatives to the Hodrick-Prescott filter include the Butterworth high-pass and band-pass filters and the moving-average band-pass filter popularized by Baxter & King (1999). The Butterworth filter is discussed by Gomez (2001), Harvey and Trimbur (2003) and Iacobucci and Noullez (2005).

[9] As an additional check on this procedure, we also used a Butterworth high-pass filter to derive the detrended series and examined the similarity between the Butterworth-detrended series and the HP detrended series. The two series were very similar in form and the correlation between them was very strong at 0.96. This confirms what a number of authors have suggested (eg Harvey and Trimbur, 2003), that the Hodrick-Prescott filter acts as something similar to a Butterworth high-pass filter.

[10] An alternative to this procedure would be to identify the cycle and trend components with a combination of band-pass and high-pass filters (with frequency ranges set to isolate business cycle and noise

the nature of regional fluctuations and allows us to assess whether the conclusions about breaks in volatility derived from an examination of the growth rate series are robust with respect to alternative trend-cycle-noise identification procedures.

3. Growth rate models

Our objective is to assess whether there have been any significant changes in the cyclical structure and volatility of employment movements across the Australian states and territories, and whether identified changes reflect the pattern observed for the national employment series. The states and territories (referred to hereafter simply as 'states' or 'regions') of Australia (AUS) are: New South Wales (NSW), Victoria (VIC), Queensland (QLD), South Australia (SA), Western Australia (WA), Tasmania (TAS), the Northern Territory (NT) and the Australian Capital 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 - 2008Q3. A plot of the Australian aggregate employment series (measured as the standardized logarithm) is shown in Figure 1.

[FIGURE 1 NEAR HERE]

Figure 2 shows the time series for the first difference in the logarithms of the AUS employment series (in other words, the growth rate of employment in each period).

[FIGURES 2 AND 3 NEAR HERE]

Figure 3 below shows the time series for the number employed in each of the 8 states. To facilitate a visual comparison between them, these plots also show the standardized logarithms of the series. The key features of these plots are the pronounced upward trend in employment and the two major recessions, one in the early 1980s and the other in the early 1990s. There are varying degrees of cyclicality and volatility present in the state series, some of which appear to mirror the behaviour of the aggregate series. However, it

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components). We choose the HP method, coupled with autoregressive modeling, partly to facilitate easy replication of our results, and also because it allows us to apply standard tests for structural change in the AR model. Note, however, that it possible to test for structural change in the cycle identified by band-pass filtering with methods similar to those which we use later to identify changes in the volatility of the noise component. As a matter if interest, and as a further check on the robustness of our results, we did examine structural changes in the aggregate employment series using band-pass and high-pass filters, and the results were similar to those obtained by the HP autoregressive model. Beine and Coulombe (2003) and Grimes (2005) also find that the Baxter-King and HP filters yield similar results.

isn't possible to say anything definite about the 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 series exhibit common structural changes, including changes in volatility.

Preliminary data testing, based on the ADF test, indicates that the regional employment series can all be characterized as I(1) variables. Although in the previous section of the paper 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 cycle and noise components depends on whether the series share a common trend, and so 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 eight series and if they were driven by a single common trend we would expect to identify seven cointegrating vectors. Based on an evaluation of the trace and maximum eigenvalue test statistics, the Johansen test suggests that there is only one cointegrating vector and seven stochastic trends. This result indicates that the employment rates 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.[11] This implies that we can proceed on the assumption that there are no common stochastic trends in the data and that it may be possible to identify key features of the dynamics of the series by an examination of the growth rate series of each of the individual states.

Figure 4 shows the employment growth rates for each of the states. Clearly there are differences in the timing and severity of recession episodes and some apparent changes in volatility. At the same time, for some regions (eg WA), it is not immediately

[11] 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.

obvious that there has been any permanent change in volatility at any time during our sample period.

[FIGURE 4 NEAR HERE]

3.1 Breaks in the volatility of the growth rates of employment

We begin by following Carlino (2007) and others who seek to date the onset of moderation for any region by inspecting the (rolling) volatility of the 'raw' data for the rate of growth of employment.[12] One reason why we do this is to see if dates for any change in volatility based on inspection of the growth rate series are the same as those arrived at when the employment series is de-trended by the use of a 'filter' (more on this in section 4 of the paper). The variances of employment growth were calculated over a rolling window of 20 quarters. A plot of the rolling variance of national employment growth is given in Figure 5 below. The turning points in the rolling variances should give an indication of potential break points.

[FIGURE 5 NEAR HERE]

The plot for the national series points to a sustained reduction in volatility sometime after 1993.[13] To determine whether any break should be considered statistically significant, we compared the variances for the sample sub-periods using the Levene (1960) test for variance equality. As an additional test, we also examined the variance ratios of the sub-periods, $Var(\Delta y_{t1})/ Var(\Delta y_{t2})$, where the subscripts 1 and 2 refer to the first and second sample periods and undertook a set of simulation experiments to determine the degree of random variation one would expect to observe in time series of the kind we are examining. Monte Carlo experiments based on 10,000 replications suggest that for a white noise process, with sample lengths and breaks of the kind examined in this paper, we would expect to see random differences in the variance ratio in a range from about 0.45 to 1.65 at the conventional 5% significance level (these are the critical values

[12] By 'raw' we mean "before separating out the cycle and noise components of the growth rates".
[13] Simon (2001), Cotis & Coppel (2005) and Shepherd & Dixon (2008) – amongst others – date the reduction in volatility in various national aggregates for Australia to be in the early 1990s.

suggested by the 95% distribution of the calculated variance ratios).[14] In the case of national employment growth, with the sample split at 1992Q4/1993Q1, Levene's test suggests that the variance of national employment growth is significantly lower (at a probability level of 0.001) from 1993 onwards, compared with the pre-1993 period.

Turning to the state volatilities, Table 1 below shows the break dates and variance ratios for each state and territory, based on the rolling variances of the raw employment growth rates, and the Levene test probabilities.[15]

[TABLE 1 NEAR HERE]

Using the 5% significance level, it would appear that there has been no statistically significant volatility break in SA or WA over the period. There does appear to have a been a break (fall) in growth rate volatility in each of the other states, although these breaks have not all occurred at the same time, but have rather been spread out over a 5-6 year period.[16] Leaving aside SA and WA for the moment, this does at first sight lend some support to the notion of a general moderation in employment growth volatility in Australia, albeit occurring with a significant degree of time dispersion across the regions. However, as noted in section 2 above, each of the series contains an aggregation of 'cycle' and 'noise' components and, without further analysis, it isn't possible to determine whether identified breaks reflect changes in the volatility of the system noise or changes in the cyclical structure of the system itself, which determines the cyclical response to any given pattern of noise. In the next sub-section we extract the cycle (and noise) component of the growth rate series and consider whether the conclusions arrived at above are applicable to the regional cycle and noise components.

3.2 Autoregressive models

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 estimating univariate AR models for each state, with the equivalent national model shown for purposes of comparison.

[14] The value for the ratio of the variances under the null is unity (not zero).

[15] These have been arrived at using the same procedure described immediately above for the national series.

[16] As Owyang et al (2008, p 582) noted, these results (that there are significant differences in state volatilities) rule out the hypothesis that the moderation at the national level is the result of state fluctuations "becoming less synchronous while state-level volatility remained the same".

Employment Growth: 1978Q2 – 2008Q3

AUS: $\Delta l_t = 0.0019 + 0.604\ \Delta l_{t-1}$ $\qquad R^2 = 0.37$
$\qquad\quad (0.003) \quad (0.000)$

NSW: $\Delta l_t = 0.0024 + 0.383\ \Delta l_{t-1}$ $\qquad R^2 = 0.14$
$\qquad\quad (0.001) \quad (0.000)$

VIC: $\Delta l_t = 0.0020 + 0.475\ \Delta l_{t-1}$ $\qquad R^2 = 0.23$
$\qquad\quad (0.002) \quad (0.000)$

QLD: $\Delta l_t = 0.0053 + 0.307\ \Delta l_{t-1}$ $\qquad R^2 = 0.09$
$\qquad\quad (0.000) \quad (0.001)$

SA: $\Delta l_t = 0.0021 + 0.262\ \Delta l_{t-1}$ $\qquad R^2 = 0.07$
$\qquad\quad (0.004) \quad (0.004)$

WA: $\Delta l_t = 0.0046 + 0.309\ \Delta l_{t-1}$ $\qquad R^2 = 0.09$
$\qquad\quad (0.000) \quad (0.001)$

TAS: $\Delta l_t = 0.0019 + 0.361\ \Delta l_{t-1}$ $\qquad R^2 = 0.13$
$\qquad\quad (0.040) \quad (0.000)$

NT: $\Delta l_t = 0.0064 + 0.113\ \Delta l_{t-1}$ $\qquad R^2 = 0.01$
$\qquad\quad (0.026) \quad (0.216)$

ACT: $\Delta l_t = 0.004 + 0.235\ \Delta l_{t-1}$ $\qquad R^2 = 0.05$
$\qquad\quad (0.001) \quad (0.009)$

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 and the associated probability values. Parameter significance tests and the 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. For this state, 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 NT 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 VIC, which has the highest R^2 of all the states, 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. This means that even for those states where a cyclical process is identified, it is very weak and the bulk of the variation in the growth rate series for all of the states is accounted for by the noise term (more on this shortly).

3.3 Volatility and stability analysis

In this section we consider whether there have been any significant changes in the nature of the cyclical process or changes in the noise affecting the system. We approached the analysis of this problem in a series of steps. Concentrating first on the cyclical process itself, we applied a Wald test for structural change (parameter stability) to the previously estimated AR models, to identify any significant breakpoints, utilizing the conventional 5% significance criterion.[17] Where breakpoints were indicated, we re-estimated the models over the implied sub-samples and identified the nature of any changes in the autoregressive process. Having identified and discussed the cyclical component of the (growth rate) series, we then turned to an examination of the noise components of all the models by calculating the rolling volatilities of the noise series, to identify turning points that might indicate potential break points in the noise structure.

The parameter stability tests indicated that there is a single significant breakpoint at 1991Q3/1991Q4 in the autoregressive (ie 'cyclical') process for the national Australian employment growth series.[18] The tests for the individual states indicate single significant breakpoints in NSW (at 2000Q3/2000Q4), VIC (at 1992Q2/1992Q3), and WA (at 1992Q1/1992Q2). For all of the other states, the breakpoint tests indicate no significant changes in the autoregressive cyclical process. The identified breakpoint in the national series is matched (roughly) in the regional series only in VIC and WA, while in NSW the break is identified as occurring much later, in 2000.

The full sample and sub-period estimates for AUS, NSW, VIC and WA are shown below. To facilitate the interpretation, the probability levels of the estimates are shown in brackets below the parameter estimates.

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[17] The usual Chow test for parameter stability is unreliable in the present context, because it assumes a constant variance across the estimation sub-periods, whereas there are strong indications of volatility changes across the states. The Wald test is a Chi-squared test which allows for differences in variance between sub-periods.

[18] The date of the breakpoint in the national employment series is roughly the same as the date identified by Shepherd and Dixon (2008) using monte carlo simulation methods and the break detection algorithm of Andersson (1985). The similarity of the break dates generated by these different methods suggests that the result is fairly robust.

AUS:

1978Q2 - 2008Q3: $\square l_t = 0.002 + 0.60\ \square l_{t-1}$ $\qquad R^2 = 0.37$
(0.003) (0.000)

1978Q2 – 1991Q3: $\square l_t = 0.001 + 0.73\ \square l_{t-1}$ $\qquad R^2 = 0.51$
(0.151) (0.000)

1991Q4 - 2008Q3: $\square l_t = 0.003 + 0.36\ \square l_{t-1}$ $\qquad R^2 = 0.15$
(0.000) (0.011)

The results for Australia indicate that there is a strong cyclical process at work in the first period, and the model has a higher degree of explanatory power than the full sample estimate. In the second period, a much weaker cyclical process is identified and the explanatory power of the model is very low.

NSW:

1978Q2 – 2008Q3 $\square l_t = 0.002 + 0.38\ \square l_{t-1}$ $\qquad R^2 = 0.14$
(0.0005) (0.000)

1978Q2 – 2000Q3: $\square l_t = 0.002 + 0.45\ \square l_{t-1}$ $\qquad R^2 = 0.20$
(0.05) (0.000)

2000Q4 - 2008Q3: $\square l_t = 0.003 - 0.08\ \square l_{t-1}$ $\qquad R^2 = 0.01$
(0.03) (0.68)

VIC:

1978Q2 – 2008Q3: $\square l_t = 0.002 + 0.47\ \square l_{t-1}$ $\qquad R^2 = 0.23$
(0.002) (0.000)

1978Q2 - 1992Q2: $\square l_t = 0.001 + 0.59\ \square l_{t-1}$ $\qquad R^2 = 0.34$
(0.217) (0.000)

1992Q3 - 2008Q3: $\square l_t = 0.004 + 0.11\ \square l_{t-1}$ $\qquad R^2 = 0.01$
(0.000) (0.38)

WA:

1978Q2 – 2008Q3: $\square l_t = 0.004 + 0.31\ \square l_{t-1}$ $\qquad R^2 = 0.10$
(0.000) (0.000)

1977Q2 - 1992Q1: $\square l_t = 0.003 + 0.49\ \square l_{t-1}$ $\qquad R^2 = 0.24$
(0.009) (0.000)

1993Q3 - 2008Q3: $\square l_t = 0.005 + 0.17\ \square l_{t-1}$ $\qquad R^2 = 0.03$
(0.000) (0.169)

There are two things to note about these results. First, while the earlier inspection of the 'raw' growth rate data point to a general reduction in volatility across all or most states, over a period of 5 or 6 years, the AR model results indicate that has been a reduction in the volatility of *the cyclical process* in only three (ie less than one-half) of the eight regions. Secondly, the time pattern of the changes in the cycle process, where they occurred, is different, being spread across eight years. Having said this, we should emphasise that the low explanatory power of the AR model models suggests that the bulk of any volatility change in the raw growth employment rates must be explained by variation in the noise component rather than the cyclical process itself.

We now consider whether there is any evidence to suggest that there may have been changes in the volatility of the noise processes across the states. As mentioned earlier, our approach is to examine the rolling volatilities of the estimated noise components (the residuals) from the AR models, to see if there any significant turning points, which might indicate possible volatility changes. Figure 6 shows the rolling volatility of the noise series from the estimated AUS national model, calculated over a moving window of 20 quarters.

[FIGURE 6 NEAR HERE]

This plot is highly suggestive of a decline in noise volatility at 1995Q1/1995Q2 and, using this breakpoint, the variance ratio (of the first period to the second) is 2.06, suggesting that the noise variance of the post-1995 period is roughly half that of the pre-1995 period. Levene's test and the simulation results noted earlier indicate that this variance reduction is statistically significant at the 5% level.

The conclusion for the national employment series is that the economy experienced a significant reduction in the shocks affecting employment growth from 1995 onwards, which is about 2 years later than the break indicated by the raw growth rate series. This is probably explained by the fact that the raw growth rate series includes not only the impact of the noise component, which exhibits a break in 1995, but also the impact of the cyclical component, which exhibits a change to a more moderate cycle around 1993. What we now need to consider is whether this conclusion in relation to noise volatility is generally applicable across the states.

Using the same procedures as for the AUS analysis, we identified likely turning points from plots of the rolling variances of the noise components (that is, the residuals from of the individual state AR models). We then tested for variance breaks with the Levene test and by calculating the variance ratios *Var(1)/Var(2)* of the identified sample periods. The break dates and the variance ratios for each state are shown in Table 2 below.

[TABLE 2 NEAR HERE]

Again, using the 5% significance level, it would appear that there has been no (statistically significant) break in noise volatility for SA or WA over the period but there does appear to have a been a break (a fall) in noise volatility in each of the other states, although these breaks have been spread over a period of 5-6 years.

4. Hodrick-Prescott business cycle models

In this section we examine changes in the volatility in employment based on frequency filtering applied to the (log) levels of the employment series rather than based on their first differences (ie the growth rates). The analysis presented below draws on the methodology outlined in Section 2 above. One of our aims is to see if this approach yields the same results for changes in volatility as we obtained from an analysis of the growth rates.

A basic problem with the use of the first differencing procedure to identify cyclical features is that it effectively acts as an inefficient filtering procedure, which emphasizes the higher frequency ranges of the spectrum. These higher frequency ranges are usually associated with the noise component of the model, rather than the cycle, and so one of the consequences of using the first difference filter is that it may generate a detrended series which is dominated by noise rather than cyclical variation. This provides part of the explanation of why growth rate models of the cycle tend to have a relatively low explanatory power. This point is illustrated in Figure 7, which compares the results for AUS employment movements of applying the Hodrick-Prescott Filter and the raw growth rate of the series (reprinted from Figure 2 above). The upper plot of Figure 7 shows the first difference of the logarithm of the series, which is equivalent to a growth rate series. The lower plot shows the detrended series derived from the Hodrick-Prescott filter, with the smoothing parameter set at the 1600 level recommended by Hodrick and Prescott for quarterly data. A comparison of these two plots highlights a key feature of the first difference procedure, which is that it generates a detrended series which greatly reduces the magnitude of the cyclical component in relation to the noise component. This is reflected in the relative variances of the series, as the variance for the Hodrick-Prescott series is over 5 times as high as for the first difference series. The contemporaneous correlation between the growth rate series and the Hodrick-Prescott output is also low, at 0.17. However, a visual inspection of the plots indicates that the two series do both identify the major employment recessions of the 1980s and 1990s.

[FIGURE 7 NEAR HERE]

Given the potential pitfalls in using the growth rates (ie the first difference in the logs) to identify cyclical features, we would argue that it is important to consider alternative procedures, which preserve a greater element of the cyclical variation of the series. In this section we complete our analysis of structural change and volatility by examining the cycle and noise properties of the national and regional employment series after detrending with the Hodrick-Prescott (HP) filter. We follow the same procedures used for the growth rate models. We commence by testing for changes in volatility in the 'raw' detrended series for each state. The cycle and noise components of each detrended series are then identified with an autoregressive model and we then test for changes in the stability and volatility of each component in turn.

A plot of the filtered aggregate (national) series was shown in the lower panel of Figure 7. Equivalent plots of the filtered series for the states are shown in Figure 8. A comparison with Figure 4 reveals the dominance of noise in the growth rate series and the clear presence of cycles as well as noise in the filtered series.

[FIGURE 8 NEAR HERE]

Again, to determine whether a break should be considered statistically significant, we compared the variances of the rolling volatilities for the sample sub-periods using the Levene (1960) test for variance equality. In the case of national employment deviations from trend, with the sample split at 1993Q4/1994Q1, Levene's test suggests that the variance of national employment growth is significantly lower (at a probability level of 0.001) from 1994 onwards, compared with the pre-1994 period.

Turning to the state volatilities, Table 3 below shows the break dates and variance ratios for each state and territory, based on the rolling variances of the state employment deviations from the HP trend, and the Levene test probabilities.

[TABLE 3 NEAR HERE]

The pattern of breaks indicates a fairly clear move to reduced volatility around 1993/1994 for six of the states and around 1989 for the other two. However, since the detrended series includes both cycle and noise, we can't tell from this series whether the variance reductions reflect reduced noise (smaller shocks) or a more dampened cyclical response to any noise. 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 then test for changes in the stability of the cycle and the volatility of the noise.

4.1 Autoregressive modeling of the filtered series

We begin by reporting estimates of the AR models of the detrended series for each of the states. The raw series (the inputs to the filter) are the logarithms of the employment levels and, as with the growth rate models, we identify the cycle component as the explained variation in the AR(1) model.[19] No constant terms are reported, since the mean is removed in the filtering procedure and the filtered series describe deviations around the zero mean.

Detrended Employment: 1978Q2 – 2008Q3

AUS: $l_t = 0.93\, l_{t-1}$ (0.000) $R^2 = 0.86$

NSW: $l_t = 0.88\, l_{t-1}$ (0.000) $R^2 = 0.79$

VIC: $l_t = 0.91\, l_{t-1}$ (0.000) $R^2 = 0.82$

QLD: $l_t = 0.85\, l_{t-1}$ $R^2 = 0.73$

[19] We chose to estimate the models as AR(1) models to facilitate comparison with the growth rate models. We also estimated AR(2) or AR(3) models where significance tests indicated a possibly higher model order, but the results were essentially the same as for the AR(1) models.

$$(0.000)$$

SA: $l_t = 0.83\, l_{t-1}$ $\quad R^2 = 0.69$
(0.000)

WA: $l_t = 0.88\, l_{t-1}$ $\quad R^2 = 0.78$
(0.000)

TAS: $l_t = 0.81\, l_{t-1}$ $\quad R^2 = 0.67$
(0.000)

NT: $l_t = 0.71\, l_{t-1}$ $\quad R^2 = 0.50$
(0.000)

ACT: $l_t = 0.72\, l_{t-1}$ $\quad R^2 = 0.53$
(0.000)

In comparison with the growth rate models, the AR models for the detrended series show highly pronounced cyclical features, represented by the relatively high AR parameters and R^2 values.

4.2 Stability and volatility analysis of the filtered series

The autoregressive growth rate models discussed in section 3.3 identified a moderation in (cyclical) volatility in AUS, NSW, VIC, and WA, with breaks dated respectively at 1991Q3/1991Q4, 2000Q3/2000Q4, 1992Q2/1992Q3, and 1992Q1/1992Q, and a general reduction in noise volatility for most states either in the late 1980s (for TAS, NT, ACT) or early-mid 1990s (for NSW, VIC, QLD) and no change in volatility for SA and WA. We now consider whether similar structural changes can be identified in the autoregressive processes of the HP-AR models and then see whether there is any evidence to suggest changes in the noise structure of the system. We begin by applying the Wald stability test to the autoregressive models.

The parameter stability tests indicate a significant breakpoint in the AUS model in 1993Q4/1994Q1. Single break dates in the autoregressive process are also indicated for NSW, VIC, and WA (at 1993Q3/1993Q4, 1993Q3/1993Q4 and 1995Q2/1995Q3 respectively) but no significant breaks are identified for any of the other states. The breaks identified by the HP-AR model for NSW, VIC and WA are all at a similar date (the mid 90s) and are closer to the national break date than were the cyclical components of the growth rate model. As with the growth rate model, no structural breaks are identified for QLD, SA, TAS, NT and ACT. The full sample and sub-period estimates for AUS, NSW, VIC and WA are shown below.

AUS:

1978Q2 - 2008Q3: $l_t = \underset{(0.000)}{0.93}\ l_{t-1}$ $R^2 = 0.86$

1978Q2 - 1993Q4: $l_t = \underset{(0.000)}{0.95}\ l_{t-1}$ $R^2 = 0.89$

1994Q1 - 2008Q3: $l_t = \underset{(0.000)}{0.78}\ l_{t-1}$ $R^2 = 0.69$

NSW:

1978Q2 – 2008Q3: $l_t = \underset{(0.000)}{0.88}\ l_{t-1}$ $R^2 = 0.79$

1978Q2 – 1993Q3 $l_t = \underset{(0.000)}{0.93}\ l_{t-1}$ $R^2 = 0.82$

1993Q3 - 2008Q3: $l_t = \underset{(0.000)}{0.73}\ l_{t-1}$ $R^2 = 0.66$

VIC:

1978Q2 – 2008Q3: $l_t = \underset{(0.000)}{0.91}\ l_{t-1}$ $R^2 = 0.82$

1978Q2 – 1993Q3: $l_t = \underset{(0.000)}{0.94}\ l_{t-1}$ $R^2 = 0.85$

1993Q4 - 2008Q3: $l_t = \underset{(0.000)}{0.74}\ l_{t-1}$ $R^2 = 0.68$

WA:

1978Q2 – 2008Q3 $l_t = \underset{(0.000)}{0.88}\ l_{t-1}$ $R^2 = 0.78$

1978Q2 – 1995Q2: $l_t = \underset{(0.000)}{0.93}\ l_{t-1}$ $R^2 = 0.84$

1995Q3 - 2008Q3: $l_t = \underset{(0.000)}{0.65}\ l_{t-1}$ $R^2 = 0.51$

The results for AUS and for the individual states suggest considerable differences between the HP and growth rate models in the dates to be assigned to changes in the cyclical process. Both models identify a moderation in the cyclical component of the series in NSW, VIC and WA, but there are significant differences in the timing of the breaks, with the HP model suggesting break dates in 1993 for NSW and VIC, and 1995 for WA. This compares with break dates suggested by the growth rate model of 1992 for VIC and WA, and 2000 for NSW. The HP model thus appears to identify a more consistent time-pattern of break points for those states which did exhibit significant cyclical adjustments, with adjustments occurring between 1993 and 1995. In contrast, the growth rate model suggests a more disparate adjustment pattern, with breaks stretching between 1993 and 2001. However, both sets of models agree that there was no moderation in the cyclical component in any of the other 5 states.

Quite apart from the differences between the models in the timing of the identified breaks, it is important to recognize that they also carry very different implications for any assessment of the extent and magnitude of any moderation in employment variability. In the case of the growth rate models, the very low explanatory power of the AR models indicates a minor role for the cyclical process in generating employment fluctuations and that any significant moderation in total employment variability must have been caused by a reduction in noise volatility. For the HP models, however, the R^2 values suggest that for most states over 2/3 of the total variation in the series is explained by the cyclical process rather than the noise, which allows a potentially much more significant role for the cyclical process in explaining changes in employment volatility. The results for the HP-AR model suggest that a significant moderation in the cyclical process can be identified in only three of the eight states, which means that no general moderation across the states can be identified for the most significant component of employment variability. For the three states for which structural changes in the cycle can be identified, the results suggests that the moderation in the cycle was very significant, with reductions in the explanatory power of the cycle, judged by the R^2 values, for NSW, VIC and WA. More generally, the HP models indicate that there is little evidence of a *general* moderation, at least as far as the cyclical component of the detrended series is concerned.

The final matter we consider is whether any significant reduction in noise volatilities can be identified in the national series and across the states. For the national series the most likely break date suggested by the HP model is 1995Q1/1995Q2. Using this breakpoint, the variance ratio (of the first period to the second) is 1.70. Levene's test indicates that this variance reduction is statistically significant at the 5% level.

The most likely break dates for each individual state are shown in Table 4 below, based on an assessment of the rolling variances of the noise residuals from the HP-AR models. The table shows that the reduction in noise volatility in NSW occurs in 1995Q4/1996Q1, which is a little later than the 1995Q1/1995Q2 timing of the national break. In VIC and QLD significant reductions in noise volatility occur in 1993Q4/1994Q1 and 1992Q1/1992Q2, which are both earlier than the national break date. For WA and SA, no significant noise reductions are identified and for the remaining three states (TAS, NT and ACT) there are significant breaks in noise volatility identified in 1989, which is a full 6 years earlier than the identified timing of the national break.

[TABLE 4 NEAR HERE]

An interesting feature to note about this tabulation is that for many of the states the dates of the HP noise breakpoints are very similar to those derived from the growth rate model, as too are the variance ratios, which in turn reinforces our earlier remarks that the conclusions from the growth rate models are largely a reflection of what is happening over time to the noise in the system.

5. Summary and conclusions

In this paper we have used autoregressive modeling techniques to identify the cycle and noise components of employment fluctuations in Australia, focusing on both the national economy and employment movements in each of the states. Our objective has been to determine whether changes in the cyclical structure and volatility of employment movements in the Australian macro-economy are also reflected in changes in the cyclical structure and volatility of employment movements across the states and territories. A subsidiary objective was to assess whether the results derived from traditional growth rate models are sustained when alternative filtering methods are used. In particular, we compare the results of the growth rate models with those obtained from Hodrick-Prescott autoregressive models.

Table 5 provides a summary of our results for significant break dates in volatility, organized according to whether the results are obtained from a study of the growth rates, as with previous authors, or by the application of a filter – in our case the Hodrick-Prescott filter. For each model we present break dates based solely on examination of the series before it is decomposed into its cycle and noise and components and then after.

[TABLE 5 NEAR HERE]

Our results suggest that the use of the first difference filter (growth rate models) to identify cyclical features yields some insight, but the results are dominated by the noise component of the model. In contrast, the Hodrick-Prescott high-pass filter emphasizes the cyclical features of interest and, used in conjunction with autoregressive modeling, it generates results which are richer and more consistent than the growth rate models provide. Indeed, we would recommend: (a) that future research into these issues be based on a filtered series and not data for growth rates and (b) that AR modeling be applied to separate out the source of the volatility (cycle cf noise).

The results suggest that there have been significant changes in the cyclical stability and volatility of employment fluctuations in Australia. However, it also suggests that there is considerable diversity in the regional pattern of adjustment and that it would be wrong to suppose that results derived from the aggregate employment series are generally applicable across the regions. In particular, the results indicate that, while a move to a weaker cyclical structure in employment can be identified for Australian aggregate employment, similar changes appear to have occurred only in NSW, VIC and WA. In the other five states, no similar changes are identified – emphasizing that the Australian economy should not be thought of as a homogenous entity.

Although the results point to significant regional differences in the extent of structural changes in employment cycles, they also suggest that most of the Australian states experienced a reduction in noise volatility, from the late 1980s in some states and the early-mid 1990s in others. This reduction in noise volatility mirrors results reported for (output growth) noise volatility in several countries, including the United States, and in the Australian case is consistent with the timing of the move to a more predictable monetary policy based on inflation targeting – a move which a number of commentators believe explains reductions in aggregate employment and output volatility in Australia.[20]

[20] See Shepherd and Dixon (2008) and the references cited therein.

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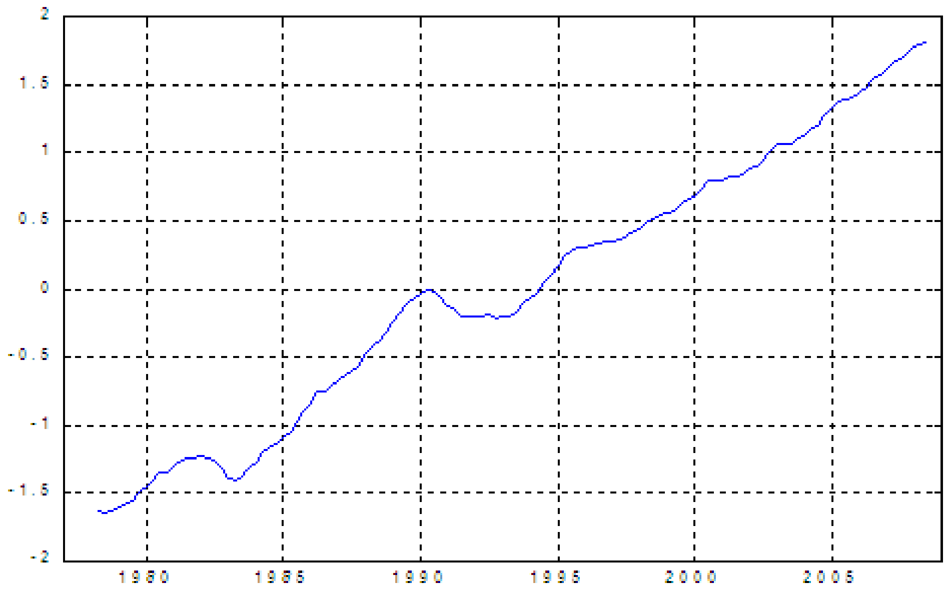

Fig. 1. Australian aggregate employment (standardized logarithms)

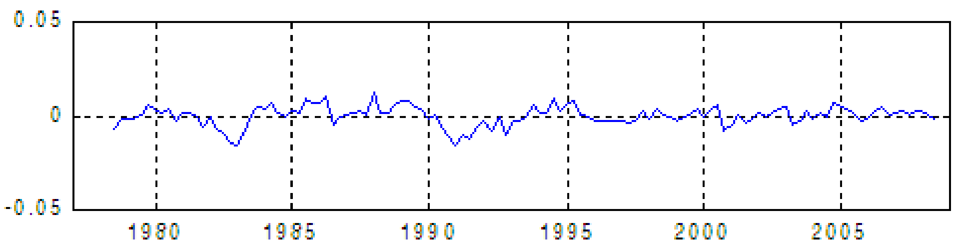

Fig. 2. The growth rate of Australian aggregate employment

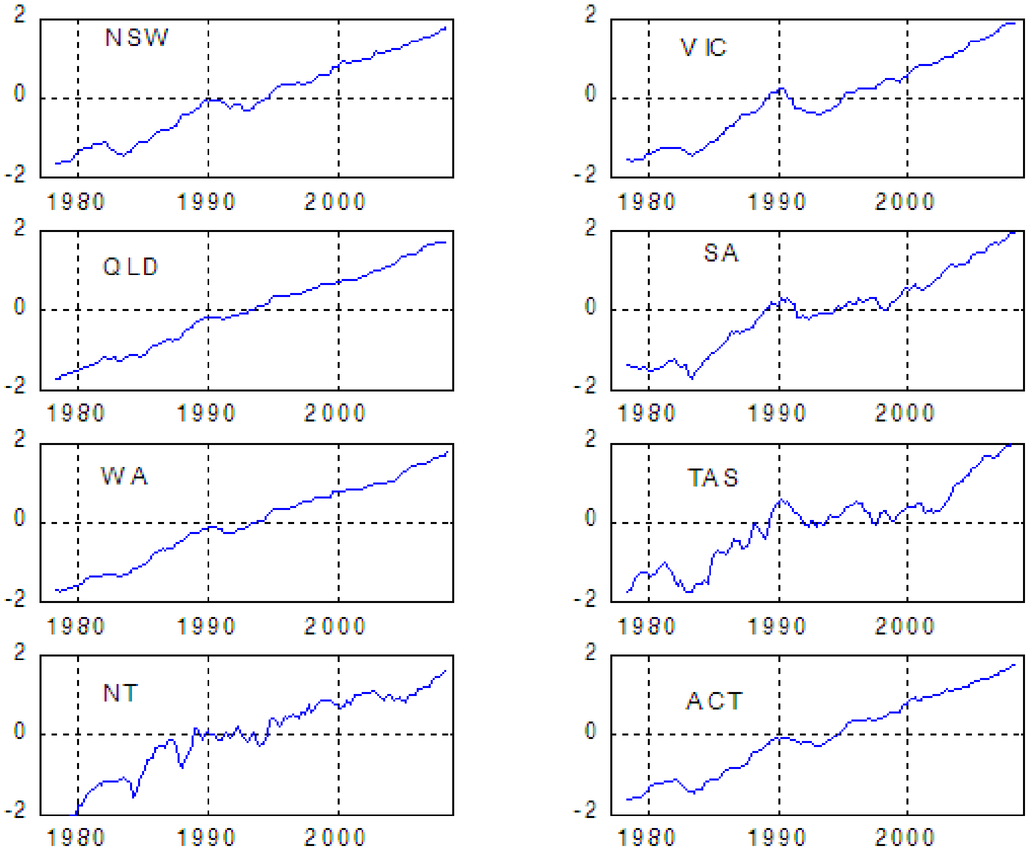

Fig. 3. State employment (standardized logarithms)

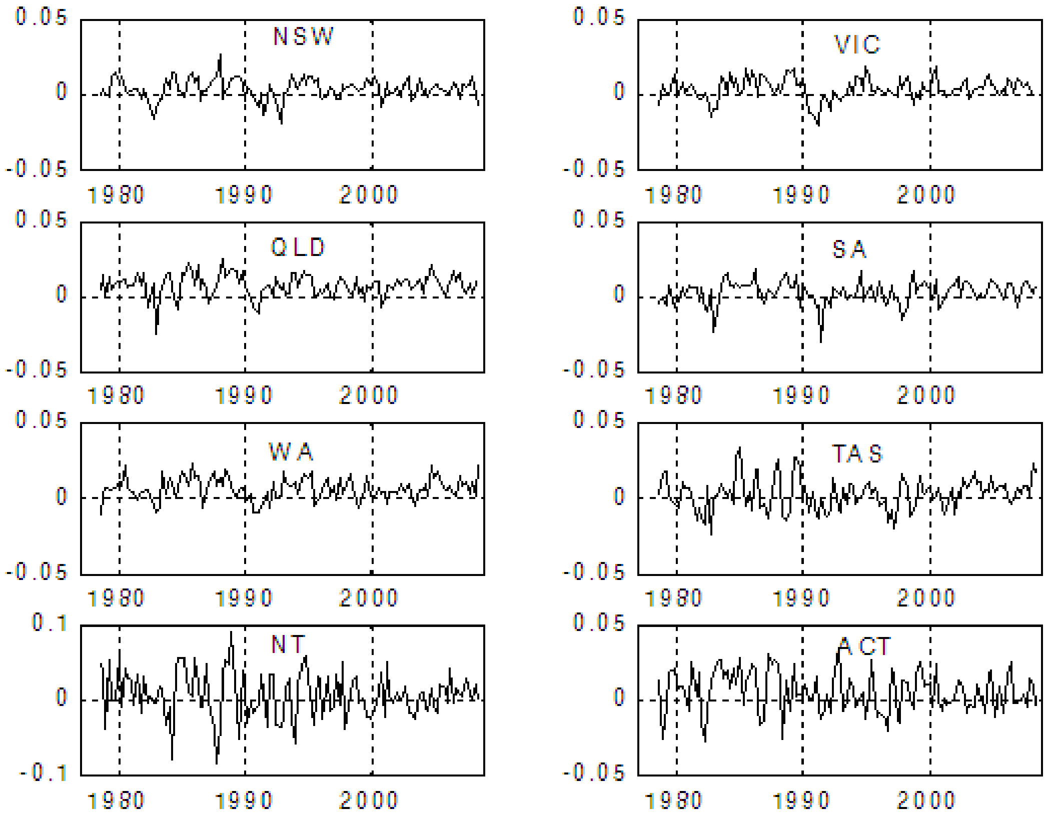

Fig. 4. The growth rate of employment in each state

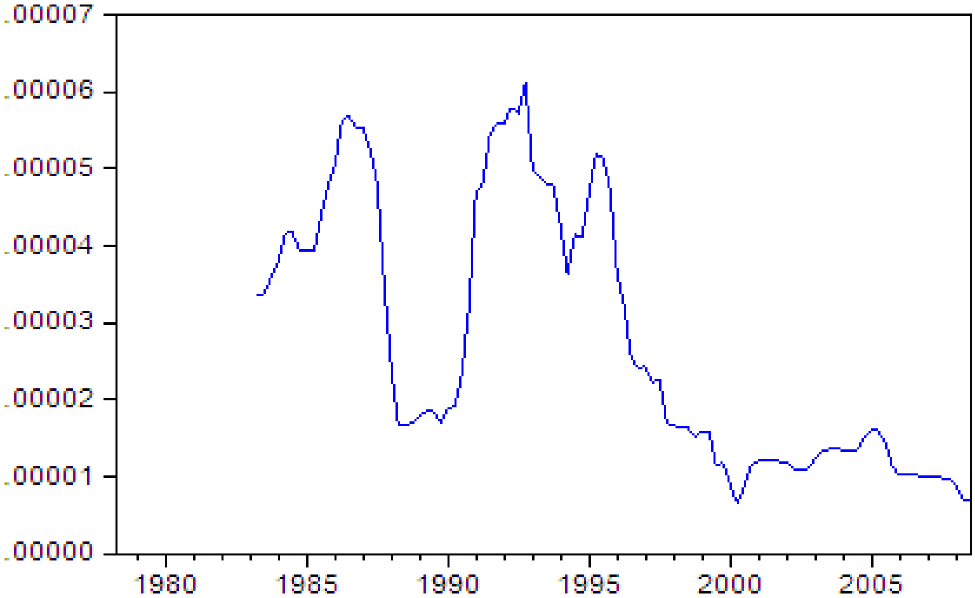

Fig. 5. Rolling variances of the AUS employment growth rate

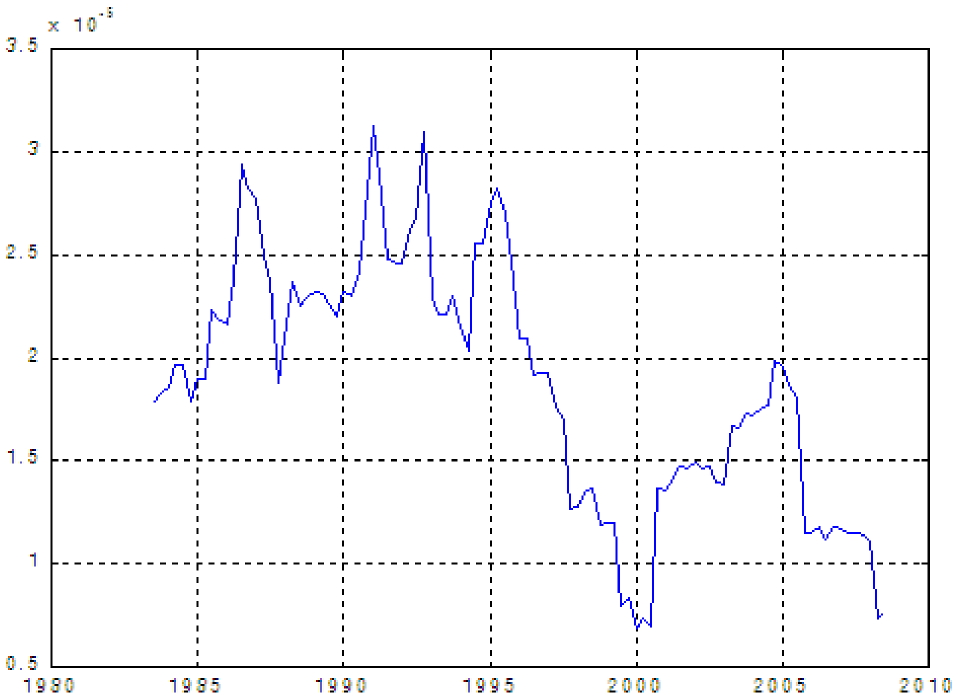

Fig. 6. The rolling volatility of the AUS noise component

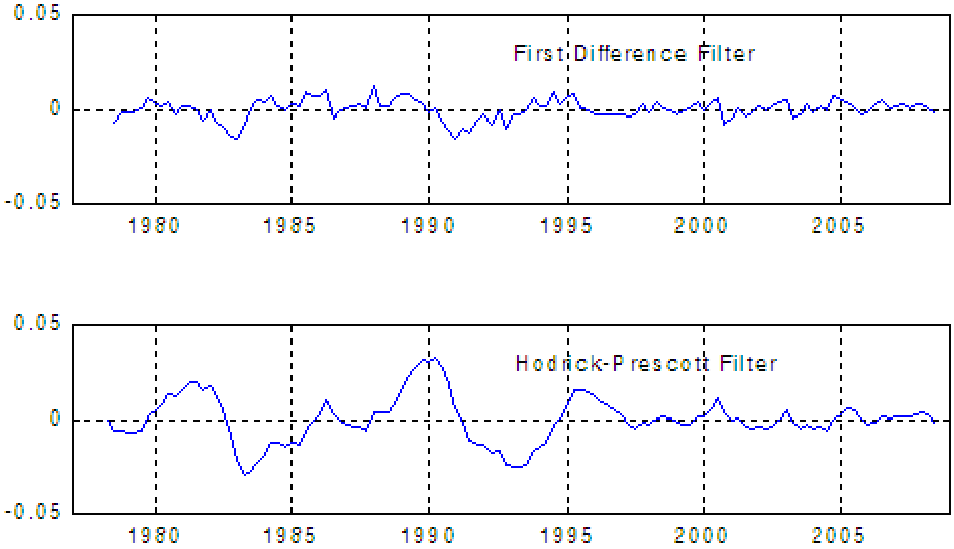

Fig. 7. Time series comparison for AUS data of the growth rate of employment (upper panel) and the detrended series from the Hodrick-Prescott filter (lower panel)

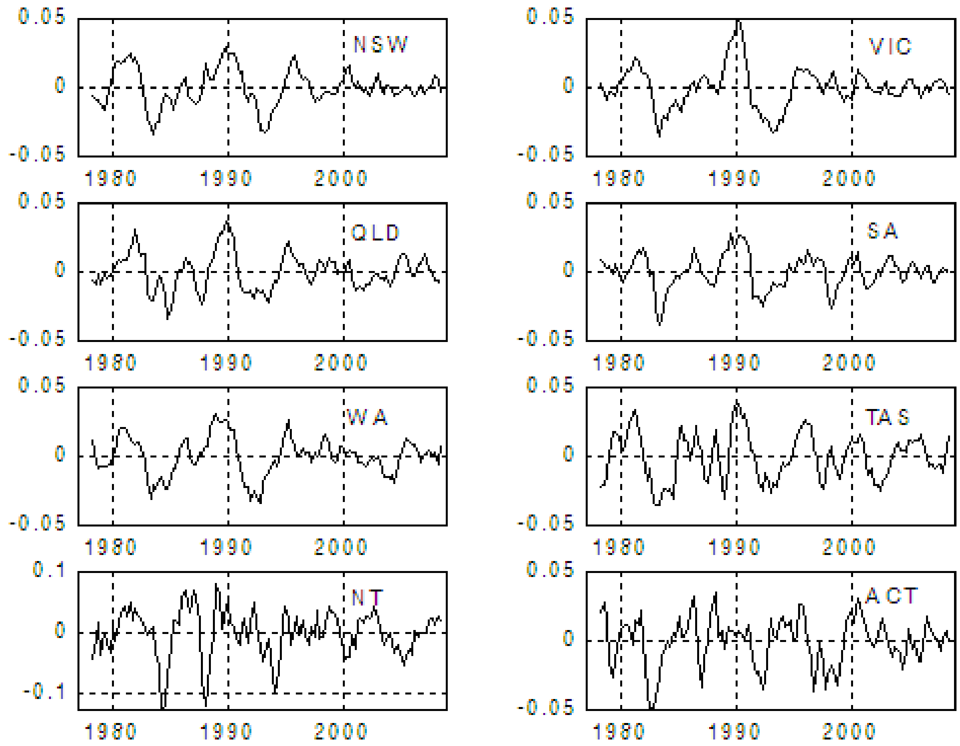

Fig. 8. Detrended series from the Hodrick-Prescott filter for each state

Table 1

Break dates and variance ratio tests applied to the 'raw' state growth rates

State	Break date(s)	Variance ratio	Levene test probability
NSW	1992Q4/1993Q1	2.77	0.003
VIC	1993Q4/1994Q1	2.94	0.000
QLD	1991Q1/1991Q2	2.96	0.002
SA	1992Q4/1993Q1	1.64	0.093
WA	1995Q3/1995Q4	1.59	0.065
TAS	1992Q3/1992Q4	2.45	0.001
NT	1989Q1/1989Q2	2.13	0.005
ACT	1989Q2/1989Q3	1.85	0.007

Table 2

Break dates and variance ratio tests applied to the 'noise component' of the state growth rates

State	Break date(s)	Variance ratio	Levene test probability
NSW	1993Q1/1993Q2	2.12	0.019
VIC	1995Q1/1995Q2	1.81	0.041
QLD	1991Q1/1991Q2	2.52	0.003
SA	1993Q1/1993Q2	1.42	0.240
WA	1995Q1/1995Q2	1.11	0.950
TAS	1989Q1/1989Q2	2.32	0.046
NT	1989Q1/1989Q2	2.14	0.050
ACT	1989Q1/1989Q2	1.82	0.029

Table 3

Break dates and variance ratio tests applied to the HP detrended series

State	Break date(s)	Variance ratio	Levene test probability
NSW	1994Q1/1994Q2	5.64	0.000
VIC	1994Q1/1994Q2	8.03	0.000
QLD	1994Q1/1994Q2	4.03	0.000
SA	1994Q1/1994Q2	2.93	0.001
WA	1993Q3/1993Q4	4.13	0.000
TAS	1993Q3/1993Q4	2.66	0.001
NT	1989Q1/1989Q2	3.04	0.001
ACT	1989Q1/1989Q2	1.77	0.001

Table 4

Break dates and variance ratio tests applied to the 'noise component' of the HP detrended series

State	Break date(s)	Variance ratio	Levene test probability
NSW	1995Q4/1996Q1	2.22	0.005
VIC	1993Q4/1994Q1	2.31	0.004
QLD	1992Q1/1992Q2	2.40	0.004
SA	1994Q1/1994Q2	1.22	0.763
WA	1995Q2/1995Q3	1.32	0.453
TAS	1989Q1/1989Q2	2.08	0.004
NT	1989Q1/1989Q2	2.39	0.028
ACT	1989Q1/1989Q2	1.82	0.012

Table 5

Break dates

	Growth Rate Series			HP Detrended Series		
State	Raw (C + N)	Cycle	Noise	Raw (C + N)	Cycle	Noise
AUS	**1992Q4/1993Q1**	**1991Q3/1991Q4**	**1995Q1/1995Q2**	**1993Q4/1994Q1**	**1993Q4/1994Q1**	**1995Q1/1995Q2**
NSW	1992Q4/1993Q1	2000Q3/2000Q4	1993Q1/1993Q2	1994Q1/1994Q2	1993Q3/1993Q4	1995Q4/1996Q1
VIC	1993Q4/1994Q1	1992Q2/1992Q3	1995Q1/1995Q2	1994Q1/1994Q2	1993Q3/1993Q4	1993Q4/1994Q1
QLD	1991Q1/1991Q2	no break	1991Q1/1991Q2	1994Q1/1994Q2	no break	1992Q1/1992Q2
SA	no break	no break	no break	1994Q1/1994Q2	no break	no break
WA	no break	1992Q1/1992Q2	no break	1993Q3/1993Q4	1995Q2/1995Q3	no break
TAS	1992Q3/1992Q4	no break	1989Q1/1989Q2	1993Q3/1993Q4	no break	1989Q1/1989Q2
NT	1989Q1/1989Q2	no break	1989Q1/1989Q2	1989Q1/1989Q2	no break	1989Q1/1989Q2
ACT	1989Q2/1989Q3	no break	1989Q1/1989Q2	1989Q1/1989Q2	no break	1989Q1/1989Q2