EMPLOYMENT VOLATILITY AND THE GREAT MODERATION: EVIDENCE FROM THE AUSTRALIAN STATES AND TERRITORIES

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ABSTRACT: Macroeconomic policy discussion in Australia presumes that there was once and for all reduction in the volatility of aggregate output and employment in the late 80s or early-mid 90s and that all states and territories were party to this 'Great Moderation'. In this paper we examine Australian data on national and state & territory employment, focusing in particular on whether there have been common national and state & territory changes in the volatility of employment growth. We find that there was no change in volatility for SA, WA and the ACT while there was a change in volatility, associated with 'the great moderation' in the early-mid 1990s for NSW, VIC, QLD, TAS and the NT. The different experiences of the states and territories signals the need for more, and more evidence-led, discussion in Australia of the regional aspects of macroeconomic stabilisation policy.

KEY WORDS: Macroeconomic policy, employment.

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1. INTRODUCTION

There is a large body of evidence to suggest that many economies, including the Australian economy, experienced a reduction in the volatility of aggregate output and employment in the 1980s or 1990s. In relation to Australia, previous work shows that there was a once and for all sustained reduction in output and/or employment volatility in the mid-1980s or the early 1990s (see for example Simon (2001), Smith & Summers (2002), Cecchetti et al (2005), Cotis & Coppel (2005), Taylor et al (2005) and Shepherd & Dixon (2008)). Indeed, the evidence for the reduction in volatility across many countries in that time period is so pervasive that the term ‘Great Moderation’ has been universally adopted since its introduction by Ben Bernanke in his address at the meetings of the Eastern Economic Association, Washington, DC, in February (2004). With the onset of the Global Financial Crisis in 2008, this period of macroeconomic stability in the USA may have come to an end, or it may be that conditions of stability will resume when the recovery eventually occurs. 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 October 2009 and has been falling since then (previous recessions had seen unemployment rates more than double and reach levels 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.

The nature and causes of the Great Moderation are matters of considerable interest, not least because of the implications for the analysis of macroeconomic performance and policy. However, although there is by now an enormous literature on the Great Moderation in many countries - 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[1], and 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, the only studies that have been published on this topic 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

[1] 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 & DeFina (1998, 2004), Dixon & Shepherd (2001), Owyang et al (2005, 2009), and Wilkerson (2009).

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. On the basis of these two studies it would seem there is good reason to wonder if it is appropriate to describe the moderation (at least for the USA) as "great".

In this paper we examine the employment performance of the Australian economy over the last thirty-two years, focusing in particular on whether there have been common national and regional changes in the structure and volatility of employment movements.[2] We have three objectives. First, by providing a study for a country other than the USA, we aim to add to existing knowledge concerning regional behavior. Secondly, while we follow previous authors in using employment growth rates as the basis for our analysis of regional volatility, a distinctive feature of our contribution is that we explicitly consider whether observed changes in volatility are best explained as changes in the volatility of the shocks affecting the system or changes in the cyclical response to those shocks. Thirdly, since our sample period includes the period of the Global Financial Crisis, we may be able to say, at least for Australia, if this episode overturns the notion that the economy is still in an era of low(er) volatility.

2. METHODOLOGY

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 it would not be wise to simply copy their methodology, as their approach 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

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[2] 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 USA also use employment as the basis for their assessment of volatility. However it should be noted that Shepherd & Dixon (2008) found that output volatility and employment volatility were closely related at the national level for Australia.

such as Kim & Nelson (1999), McConnell & Quiros (2000), Stock & Watson (2002), Ahmed *et al.* (2004), Sensier & van Dijk, (2004), and Summers (2005) examined the question by using autoregressive models to distinguish between changes in noise volatility and changes in the economy's cyclical response to shocks. 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 (the noise component) affecting the system, rather than a change in the dynamic structure (the cyclical response) of the economy.[3] 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-path of (the logarithm of) employment (L_t) is driven by trend (τ_t), cycle (c_t) and noise (μ_t) components:

$$L_t = \tau_t + c_t + \mu_t \tag{1}$$

Following the literature in this area, we will assume that the trend component can be approximated 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 assumptions imply that the observed L_t can be represented as:

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

(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 ΔL_t series:

$$\Delta L_t = \mu + \beta_1 \Delta L_{t-1} + ...\beta_{k-1} \Delta L_{t-k-1} + e_t \tag{3}$$

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

If estimation of (3) reveals an autoregressive (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 (ie the residuals). Assuming that 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.

This framework follows an impulse-propagation approach to the analysis of the business cycle, due originally to Frisch (1933), which supposes that shocks affecting the economy (or the regions) are the impulse factors that generate cyclical fluctuations, via a propagation process that transforms the shocks into a cyclical feature. In macro-theoretic terms, the propagation processes might include factors such as imperfect wage and price flexibility, adjustment costs, induced changes in investment via the accelerator, and the like, which cause the shocks to exhibit cyclical persistence. Expressed in terms of the autoregressive model, the values of the noise term e_t are the shocks that give rise to the cyclical feature and the form of the cycle is determined by the structure of the AR process.

In the multivariate context we are considering, L_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 model structure outlined above assumes that the path of employment is best explained with a linear time-invariant system, with constant parameters, and that changes in the volatility of employment growth are explained by changes in the volatility of the noise process. However, an alternative (or additional) possibility is that volatility changes may arise from changes in the structure of the cyclical process, represented in the autoregressive model structure as changes in the size or structure of the AR parameters. Given that there may be changes in either the cyclical component or the noise component (or both) it is important to try to separate the two effects or we may otherwise reach misleading conclusions about the sources of volatility changes in the composite ΔL_t series. For example, in the autoregressive model, an unusually large downturn (or upturn) in employment growth might be explained by a large negative (or positive) shock or by a rise in the magnitude of the AR parameter that acts to transmit the noise to the cycle.

The typical procedure for identifying parameter changes in the model is to include one or more dummy variables in equation (3) and then investigate the likely number and timing of breaks. This is illustrated in equation (4), which shows, for the purposes of exposition, a simple first-order model with a common single break in the mean and autoregressive parameters of the model at time *k*:

$$\Delta L_t = \mu + \mu d + \beta_1 \Delta L_{t-1} + \beta_1 d \, \Delta L_{t-1} + e_t \qquad (4)$$

Where *d* is a dummy variable that takes the value $d = 0$ for $t < k$ and $d = 1$ for $t \geq k$.

In practice, the model may incorporate more than one structural break, with possibly different break times for the mean and autoregressive parameters, and the statistical challenge is to determine an appropriate method to identify both the likely number and timing of the breaks, particularly when there may also be changes in the equation variance[4]. The procedure we use to test for volatility changes is discussed in section 4.

3. AUTOREGRESSIVE MODELS OF THE CYCLICAL PROCESS

In this section we examine the behaviour of employment growth with the aid of autoregressive models that are used to identify the cycle and noise components of the series. Our objectives are to assess: whether there have been any apparent changes in the volatility of employment growth across the Australian states and territories; whether identified changes for the states reflect the pattern observed for the national employment series; and whether any identified volatility changes are

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[4] There is now a large and still developing literature devoted to this topic. See, for example, Perron (1990, 1997), Andrews (1993), Inclan & Tiao (1994), Lumsdaine & Papell (1997), Bai & Perron (1998), Elliot & Muller (2006) and Qu & Perron (2007).

caused by changes in the shocks (the noise process) that initiates the cycle or changes in the nature of the cyclical response to a given set of shocks.[5] The data used in this study is the number of civilian employees, measured on a (seasonally adjusted) quarterly basis over the period 1978Q2 - 2010Q3. A plot of the time-path of Australian national employment growth, measured by the first difference of the logarithm of the employment series, is shown in Figure 1. The key features of the plot are that it appears to exhibit a cyclical process, it identifies the two major recessions of the period, in the early 1980s and the early 1990s, and it is suggestive of a reduction in the volatility of employment growth in the early-mid 1990s.

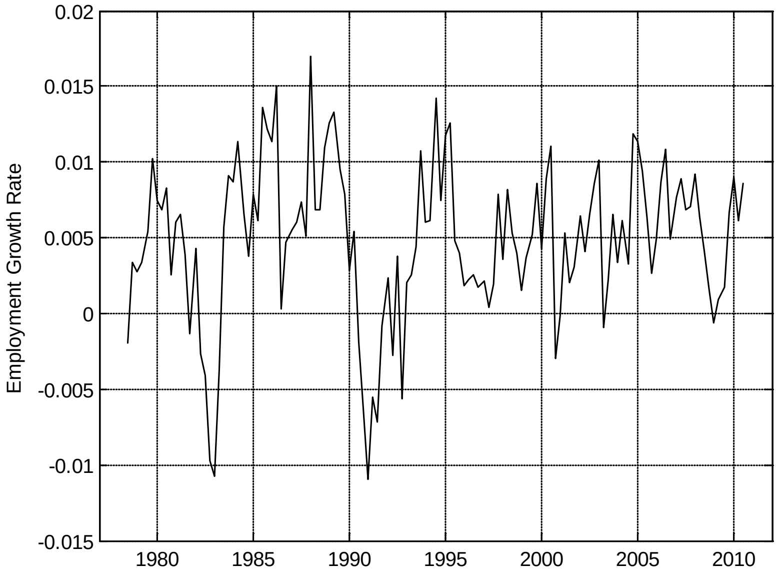

Figure 1. The Growth Rate of Australian Aggregate Employment. Source: the Authors

[5] In what follows we use the term "states" to refer to the "states and territories".

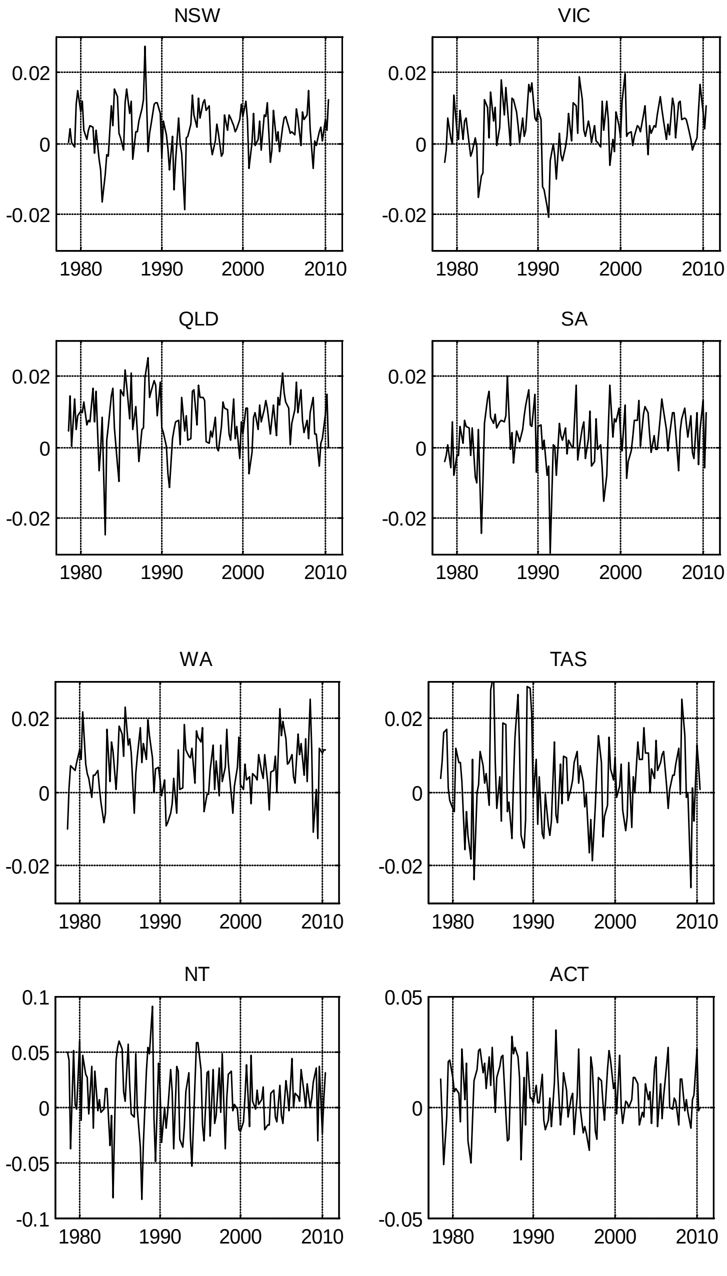

Figure 2. State Employment Growth Rates**.** Source: the Authors.

Figure 2 shows the employment growth rates of each state, again measured by the first difference of the logarithm of the series. For the individual states, there appear to be varying degrees of cyclicality (and volatility) and the larger states appear, to some extent, to mirror the behaviour of the aggregate series. The volatility of employment growth appears to be generally higher for the smaller states (TAS, ACT and particularly NT) and for some states (particularly WA) it is not immediately obvious that there has been any permanent change in volatility at any time during the sample period. However, it 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.[6]

Our approach is to estimate a series of autoregressive models, with the cycle identified by the autoregressive process and the residual variation identified as the system noise. Preliminary data testing, based on the Augmented Dickey–Fuller (ADF) test, indicates that the levels of the regional employment series can all be characterized as I(1) variables, which implies that the trends can be regarded as random walks and that autoregressive (AR), vector autoregressive (VAR) and vector error correction (VEC) models can legitimately be applied to the growth rates of the series. The appropriate model for estimation of the cycle and noise components depends in part on whether the series share a common trend, and so the first thing to consider is whether there are any co-integrating relationships between the series. We tested for co-integration 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 co-integrating vectors. Based on an evaluation of the trace and maximum eigenvalue test statistics, the Johansen test suggests that there is only one co-integrating 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 co-integrating relationships between subsets of the variables. To investigate this matter further, we applied the Johansen (1988) procedure to bivariate subsets of the series and the test statistics again failed to identify any co-integrating

[6] The computations reported in the paper were all undertaken in MATLAB 7.

relationships in the bivariate models.[7] This implies that we can proceed on the assumption that there are no common stochastic trends in the data and that the dynamics of the series can be identified from an examination of the employment growth rates alone, with no additional equilibrium-correction term.

We begin by estimating univariate autoregressive models of employment growth for each state, with the equivalent national model shown for purposes of comparison. The growth rate of employment (ΔL_t) is measured as the first differences of the logarithms of the employment series.

Employment growth: 1978Q2 – 2010Q3

AUS: $\Delta L_t = 0.0020 + 0.608\, \Delta L_{t-1}$ $R^2 = 0.37$

NSW: $\Delta L_t = 0.0026 + 0.377\, \Delta L_{t-1}$ $R^2 = 0.14$

VIC: $\Delta L_t = 0.0022 + 0.484\, \Delta L_{t-1}$ $R^2 = 0.23$

QLD: $\Delta L_t = 0.0052 + 0.311\, \Delta L_{t-1}$ $R^2 = 0.10$

SA: $\Delta L_t = 0.0023 + 0.262\, \Delta L_{t-1}$ $R^2 = 0.05$

WA: $\Delta L_t = 0.0047 + 0.298\, \Delta L_{t-1}$ $R^2 = 0.09$

TAS: $\Delta L_t = 0.0019 + 0.334\, \Delta L_{t-1}$ $R^2 = 0.11$

NT: $\Delta L_t = 0.0071 + 0.081\, \Delta L_{t-1}$ $R^2 = 0.01$

ACT: $\Delta L_t = 0.0045 + 0.222\, \Delta L_{t-1}$ $R^2 = 0.05$

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. The Schwarz-Bayesian model selection criterion and parameter significance tests both indicate that an AR(1) model structure is appropriate for each state and the estimated AR parameters are all statistically significant at the conventional 5% level, with the exception of

[7] 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.

NT. For this state, the AR parameter is not significantly different from zero at the 5% probability 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 much 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. In this context, note that the higher R^2 (and higher AR parameter) for the aggregate AUS equation, in comparison with the individual states, presumably reflects the co-variance between the employment growth rates of the individual states.

Although our primary concern is to identify whether the regions have experienced similar changes in cyclical stability and volatility, it is helpful to consider first whether the states exhibit any broad co-movement in the underlying employment growth rate series or the state noise components identified from the AR(1) models. If particular states appear more closely related than others, it is interesting to know whether they also exhibit similarity in any identified changes in cyclical structure or noise volatility.

Table 1a. Correlation Matrix of State Employment Growth Rates. Source: the Authors

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
NSW	1.00							
VIC	0.51	1.00						
QLD	0.34	0.36	1.00					
SA	0.35	0.36	0.37	1.00				
WA	0.29	0.40	0.42	0.34	1.00			
TAS	0.20	0.24	0.23	0.10	0.22	1.00		
NT	-0.05	0.06	0.11	-0.03	0.09	-0.17	1.00	
ACT	0.20	0.08	0.07	0.23	0.09	0.18	-0.20	1.00

Table 1b. Correlation Matrix of Employment Growth Rate AR Cyclical Components. Source: the Authors.

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
NSW	1.00							
VIC	0.51	1.00						
QLD	0.35	0.37	1.00					
SA	0.34	0.36	0.38	1.00				
WA	0.28	0.40	0.43	0.34	1.00			
TAS	0.20	0.24	0.23	0.10	0.22	1.00		
NT	-0.06	0.05	0.12	-0.03	0.08	-0.17	1.00	
ACT	0.20	0.08	0.07	0.23	0.09	0.18	-0.19	1.00

Table 1c. Correlation Matrix of Employment Growth Rate AR Noise Components. Source: the Authors.

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
NSW	1.00							
VIC	0.34	1.00						
QLD	0.27	0.16	1.00					
SA	0.26	0.17	0.31	1.00				
WA	0.15	0.18	0.29	0.26	1.00			
TAS	0.08	0.13	0.17	0.00	0.12	1.00		
NT	-0.08	0.05	0.12	-0.03	0.11	-0.18	1.00	
ACT	0.13	-0.01	0.09	0.20	0.05	0.16	-0.19	1.00

Table 1 shows the (pair-wise) correlation matrix of the state employment growth rates (Table *1a*) and the equivalent correlation matrices for the cycle and noise components of the AR(1) models (Tables *1b* and *1c*), where the cyclical component is measured as the output implied by the estimated AR process and the noise component is the model residual. The growth rate correlations (shown in Table *1a*) suggest 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. In itself this is not surprising given that NSW and VIC are quite large and TAS, NT and ACT are quite small relative to the other states.

The majority of the correlations for the cyclical components are significantly different from zero, with relatively strong correlations identified for NSW and VIC in particular and to a lesser extent for QLD, SA and WA, while the cyclical components for TAS, NT and ACT appear to be largely unrelated to the cycle in other states. A comparison of Tables *1a* and *1b* suggests that the identified correlations in the growth rates are largely a reflection of the correlations between the cyclical components and none of the cyclical correlations given in *1b* are significantly different[8] at the 5% level from the growth rate correlations shown in *1a*. In the case of the noise component, there are weak correlations across the larger states, but no significant correlations within the group of smaller states or between the smaller and larger states. The relationship between the noise correlation pattern and the cycle correlation pattern is what one might expect in a modeling framework in which the noise component contains the shocks that initiate cyclicality in the series. In other words, the weak noise correlations are ultimately transformed into stronger cyclical correlations and we would expect the identified pattern in those cyclical correlations to reflect in part the cross-state pattern of the noise components that initiate the cycles.

A drawback of our univariate modelling approach is that it does not allow for possible interactions between the state employment growth 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 growth rate series, to determine whether additional insight is obtained from such a systems approach. In comparison with the AR models, for which one-period lags are suggested, the Schwarz-Bayesian criterion actually suggests that the VAR model should incorporate no lags (a zero order model), which means that the growth rates are best modelled as white noise processes around a constant mean growth rate. The reason for this result is that the additional explanatory power of the first-order system is not sufficient to outweigh the penalty imposed by the additional number of parameters. Although

[8] This conclusion is based on the application of Fisher's z-transformation test for testing the equality of (independent) correlation coefficients. Using Fisher's test for the equality of the (population) correlation coefficients we fail to reject the null that the two corresponding (population) correlation coefficients are not significantly different at the 5% (and indeed at the 10% level) for any of the pairs in Tables *1a* and *1b*.

the Schwarz criterion suggests that a first-order model is an over-parameterization of the system, we nevertheless 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 Table 1 and so the results are not reported. The R^2 values of the individual equations of the VAR were also not much higher than those derived from the univariate AR models. The results indicate that the only states for which the VAR model provides any significant additional explanatory power are VIC, SA and WA, but the additional power is not great (an extra 10% or so of explained variation) and these are states that we have already identified, via the correlation matrix, as having a close association. For the other states, the additional explanatory power is trivial, which confirms the earlier comment that the increased explanatory power of the VAR is not sufficient to offset the penalty the Schwarz model selection imposes on the additional VAR parameters.

4. THE VOLATILITY OF EMPLOYMENT GROWTH

The autoregressive model estimates provide the information we can use to assess whether employment growth exhibits any changes in volatility over the sample period and, if present, whether they are explained by changes in the structure of the cyclical adjustment process or changes in the underlying noise process. Earlier we suggested that a visual inspection of the growth rate series points to a possible reduction in volatility for the AUS series and for some of the individual states, particularly NSW and VIC. In order to assess whether these possible changes are statistically significant, we need to employ a test for structural change in the variance of the AR model noise process. Our approach is to examine the variance of the residual noise process derived from the AR(1) estimate of equation (3) for each state and for the national series, using the test for changes in variance suggested by Inclan and Tiao (1994). The procedure utilizes a test statistic derived from the behavior of the normalized (and centered) cumulative sum of squares of the residual noise series.

Starting with the residual noise series e_t from the estimated model, where e_t is of length T, which in the present context is 128, the first step in the test procedure is to calculate the following series:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \qquad\qquad k = 1, \ldots, T$$

Where C_k is the cumulative sum of the squared residuals and C_T is the final sum of the squared residuals:

$$C_k = \sum_{t=1}^{k} e_t^2 \quad \text{and} \quad C_T = \sum e_t^2$$

For the case of a single change in variance, Inclan and Tiao (1994) suggest that the most likely date of a change in volatility (if any change occurred) can be can be identified by searching for the point at which the modular value of D_k is maximized. The significance of the identified break is then determined with reference to the following test statistic:

$$TS(D_k) = \sqrt{T/2}\; D_k^* \qquad\qquad D_k^* = \max_k |D_k|$$

Inclan and Tiao (1994) demonstrate that, under variance homogeneity, $\sqrt{T/2}\; D_k$ has an expected value equal to zero. With the aid of Monte Carlo replications, the authors calculate asymptotic and small sample critical values, and the null of no change in the series variance is rejected (at the chosen significance level) only if $TS(D_k)$ exceeds the relevant critical value. For our purposes, with a noise series of length T = 128, the 5% and 1% critical values are approximately 1.28 and 1.53 respectively[9].

The results of applying the variance change test to the noise series of AUS and the individual states are reported in Table 2. Where a break is identified, the Table shows the most likely date and the variance ratios of the implied sub-periods, $Var(e_{t1})/Var(e_{t2})$, where the subscripts 1 and

[9] These are the values implied by the table of critical values reported in Inclan and Tiao (1994). We also examined the case of multiple change points, but the test for a single break in the series is sufficient for our purposes, particularly in view of the limited sample.

2 refer to the pre-break and post-break sample periods. As an additional test of the significance of the variance changes, we 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 1.55 at the conventional 5% significance level (these are the critical values suggested by the 95% distribution of the calculated variance ratios).[10]

The results suggest that a significant reduction in noise volatility can be identified for AUS, dated at 1995Q3.[11] For the individual states, noise volatility reductions are identified for the three largest states (NSW, VIC and QLD) and for two of the smaller states (TAS and NT). Notice, in passing, that these results (lower volatility for some regions) hold even though our data set includes the period of the Global Financial Crisis. For the remaining states (SA, WA and ACT) no significant volatility change is identified.

The break dates for VIC and NT roughly match the AUS date, while the break is identified as occurring 2 years earlier for NSW, and 4 years earlier for QLD and TAS. Note also that the conclusions concerning the significance of the noise volatility changes are confirmed by both the change-point test and the magnitudes of the variance ratios. For NSW, VIC and TAS, the noise variance of the post-break period is about half the size of the pre-break period, which our simulations suggest is a significant difference. For QLD and NT, the variance change appears to be larger.

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[10] The value for the ratio of the variances under the null in this case is unity rather than zero.

[11] Shepherd & Dixon (2009) conjecture that this fall in volatility follows on from, and may well reflect, the adoption of (flexible) inflation targeting in Australia.

Table 2. Break Dates and Variance Ratios for AR Model Noise. Source: the Authors

State	Break Date	$TS(D_k)$	$Var(e_{t1})/Var(e_{t2})$
AUS	1995Q3	1.28	1.97
NSW	1993Q1	1.61	1.93
VIC	1995Q1	1.39	1.88
QLD	1991Q2	1.87	2.55
SA	*No Break*	1.15	*na*
WA	*No Break*	0.92	*na*
TAS	1991Q3	1.41	1.99
NT	1995Q1	1.79	3.01
ACT	*No Break*	1.25	*na*

The break dates shown in Table 2 are the most likely change points, equivalent to point estimates, but there is of course a degree of uncertainty connected with the precise dates and it would be helpful to have some idea of the range of possible dates over which the change might have occurred, equivalent to a 95% confidence interval. In an attempt to shed some light on this matter, we used the variance change statistic to identify the earliest and latest dates at which a significant break is identified, using the 5% significance level. Although this procedure is slightly ad hoc, it does give an indication of the range of uncertainty surrounding the change-point estimates, and whether the differences between the states should be regarded as statistically significant. For AUS the identified break date is the only significant change point, at 1995Q3, so there is no uncertainty range. For the individual states, the ranges are: NSW (93Q1-96Q3), VIC (95Q1-95Q2), QLD (85Q2-96Q3), TAS (89Q3-94Q1, NT (89Q2-2002Q1). The ranges of dates for NSW and VIC are relatively narrow, and they suggest that the move to lower volatility did happen at some time over the early-mid 1990s, as the point estimates suggest. For the other states, the range of uncertainty is much wider, particularly for QLD and NT, but it should be noted that in all cases they over-lap the NSW and VIC dates, which means that we can't rule out the possibility of a general change to lower volatility across those states (the states where a significant change is identified) in the early-mid 1990s. Having said this, it should be noted again that no significant change in volatility is identified throughout the period for SA, WA and ACT, which suggests that they did not experience any common break that might have occurred across the other states.

The results reported in Table 2 are based on the assumption that the "true" parameters of the AR model remain constant over time and that equation (3) provides a reasonable estimate of the noise process. Before we accept the conclusions from this model, however, we need to consider whether there is any evidence to suggest that the parameters of the model may have changed over the sample period. This allows us to assess whether the identified volatility reduction is partly or wholly explained by a dampening of the cyclical adjustment process (equivalent to reduction in the magnitude of the AR parameter) rather than the reduction in noise volatility identified by the constant-parameter model. We examined this question by applying a Wald test for structural change in the mean and autoregressive parameters,[12] utilizing equation (4), which allows for step-changes in the equation parameters. We applied the test to the national series, and to all of the states for which volatility changes are identified, using both the break dates of Table 1 and all of the dates within the calculated uncertainty ranges. In all cases, the Wald test failed to reject the null of no structural change at the 5% significance level and the dummy variables in equation (4) were insignificantly different to zero. This implies that the previous conclusions regarding the source of the volatility reduction are robust with respect to possible changes in the AR model structure.

In summary, we have identified a significant reduction in the volatility of employment growth in the national series (AUS) and 5 of the 8 states of the Australian Commonwealth (NSW, VIC, QLD, TAS, NT), but there is no identified reduction in volatility in the 3 remaining states (SA, WA

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[12] The usual Chow test for structural change is unreliable in the present context because it assumes that the variances of the sub-samples are the same. The Wald test is a test for parameter constancy that allows for unequal variances across the sample periods.

and ACT). For the states where a reduction in volatility is identified, our results suggest that it occurred in the early 1990s and the source was a reduction in the volatility of the shocks affecting those states rather than a change in the structure of the cyclical adjustment process.

5. SUMMARY AND CONCLUSIONS

In this section we summarize our findings and provide some tentative interpretation of what might explain these findings.

- We identify a reduction in the volatility of aggregate employment growth in Australia in the early-mid 1990s.
- The majority of the correlations for the cyclical components are significantly different from zero, with relatively strong correlations identified for NSW and VIC in particular and to a lesser extent for QLD, SA and WA, while the cyclical components for TAS, NT and ACT appear to be largely unrelated to the cycle in other states.[13]
- In the case of the noise component, there are weak correlations across the larger states, but no significant correlations within the group of smaller states or between the smaller and larger states.
- Analysis of the individual states indicates that there was a reduction in employment growth volatility in 5 of the 8 states (NSW, VIC, QLD, TAS, NT) and this result (lower volatility for some regions) is obtained even though our data set includes the period of the Global Financial Crisis.
- There appears to have been no reduction in volatility in any of the other 3 states (SA, WA, ACT).
- Our finding that there is significant variation in both the timing and magnitude of volatility reductions across the state and territories of

[13] In Dixon and Shepherd (2009), we focused on likely explanations for similarities or dissimilarities in state and territory business cycles in Australia. We considered there 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. Consistent with the growing body of literature on the intra and inter-national co-movement of output and/or employment, we found that cross-state correlations in employment cycles can be explained by the size of the regions and industry structure, such that regional business cycles will be more (less) highly correlated as the industrial structures of the states are more (less) alike.

Australia is consistent with the findings of researchers for the United States (Carlino (2007) and Owyang et al (2008)).

- Although there is some variation in the point estimates of the break dates for those individual states who experienced a reduction in volatility, we can’t reject the possibility that they experienced a common break in the early-mid 1990s.
- Our analysis points to the conclusion that the reduction in volatility is explained by a reduction in the volatility of the noise shocks affecting the regions rather than a change in the autoregressive process that generates the cycles.
- While Macroeconomic economic policy discussion in Australia presumes that all states and territories were party to this Great Moderation, the different experiences of the states and territories signals the need for more, and for more ‘evidence-led’, discussion in Australia of the regional aspects of macroeconomic stabilisation policy.

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