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To Pool or to Aggregate? Tests with a Dynamic Panel Macroeconometric Model of Australian State Labour Markets

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ABSTRACT

We construct a dynamic error correction model of the Australian labour market using a macroeconomic panel across seven states from 1972:3 to 1999:1. Long run equilibrium estimates support a real wage-productivity gap and an unemployment gap. The dynamic short-run estimates support expectations-augmented Phillips curves for wages and prices, and Keynesian demand-led employment growth. We compare three procedures – pooled, aggregate and mean group estimates. Considerable heterogeneity existed across states in the pooled procedure, and state-level variables had a significant impact in the aggregate procedure. Out-of-sample aggregate forecasting for the pooled, aggregate and mean group procedures indicate that the pooled one performs best.

JEL CLASSIFICATION: E24, E31, C30
KEYWORDS: Panel cointegration, panel macroeconometric modelling, Australian state labour markets, aggregation

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CONTENTS

1. Introduction

The national labour market is an integral of its disaggregated components in various dimensions, such as by the type of economic activity, demographic characteristics or by internal political geography. In this paper we study the last dimension by examining dynamic multi-equation panel models of data from the States and Territories and their respective capital cities in Australia.[1] The national, or aggregate, labour market experience has been well documented and extensively analysed (for recent examples on the Australian economy, see Debelle and Vickery (1998b), Gruen, Pagan and Thompson (1999), and Beechey et al (2000)). In the massive macroeconometric literature, there is an untested presumption that the use of national aggregate data is always appropriate. Accordingly there has been very little empirical macroeconomic analysis at a disaggregated level. However it is reasonable to ask whether macroeconometric analysis is sufficiently undertaken using nationally aggregated data, or whether one gains by using pooled procedures on panels of state-level data, or indeed whether one should treat states as separate, independent macroeconomic entities. There are at least three good reasons for thinking that there are gains to be had from an empirical dynamic panel study of state-disaggregated labour markets.

The first reason is that it is likely that geography matters for the economic activities of a country, particularly for one that is physically large and diverse. Countries like Australia, the USA, UK, Mexico and Canada are likely to be sufficiently diverse geographically to justify studying state-disaggregated models. One may expect less gain for countries like the Netherlands, Ireland or perhaps New Zealand. In the last twenty years, the importance of geography for explaining international trade has been well documented. Equally, one might expect geography to matter for intranational economic activities in a physically large and diverse country. With sufficient data now available at the state level (at least in Australia) for macroeconometric modelling of wages, prices, employment and the labour force, it is important to determine the key characteristics and interrelationships of that data. There is a growing literature that studies interstate economic relations (which we discuss below), but we are aware of no previous research that jointly models real wages, employment and the labour force across states within a country. Given the diversity of the economic geography in a country, we need to establish whether the maintained model should account for possible parameter heterogeneity and the imperfect correlation of shocks across states.

A second and related reason is that there is growing evidence that state level variables persistently deviate from long run national trends for much longer than one might have expected. With national macro-modelling, there is an implicit assumption of an insignificant loss of information from using data that takes sums or weighted averages of its components. Underlying this assumption is the belief that internal labour, goods and financial markets are highly integrated, very efficient and with very low barriers to trade. Thus, deviations from national trends ought to be corrected rapidly. It turns out that this is not always true. Debelle and Vickery (1998a) construct a panel macro model for Australia, focussing on unemployment across states, and test whether interstate mobility is an important part of the adjustment mechanism following state-specific shocks. They find that permanent (or at least very persistent) differences between states remain. Most migration occurs within 4 years, which is a significant amount of time. Dixon and Shepherd (2001) reject tests for common trends for unemployment rates across Australian states, but find common cycles, thus leading to the conclusion that regional unemployment policies are needed. With regard to state-wide consumer price indices, panel unit root tests of intranational purchasing power parity do tend to reject the hypothesis of no cointegration, but the implied persistence of deviations after shocks remains substantial.[2] These examples suggest that segmentation is widespread across various inter-state markets which therefore should not be assumed homogenous,

[1] For ease of expression, henceforth we shall refer to 'states' only.

[2] In the case of Australia, Chaudhuri and Sheen (2001) find persistence measured as a half-life of 7 to 8 quarters for panel unit root tests of city CPIs. Cechetti, Mark and Sonora (2000) find much slower convergence of CPIs for US cities, with a half-life of about 8 years.

particularly in the short run, and further that there may be information gains from working with disaggregated dynamic panels.

A third reason for studying state panels is a technical one - they may resolve the notoriously low power problem of stationarity tests when using aggregate data over short time spans. One solution to the problem is to lengthen the historical span of the data, but this raises the risk of needing to introduce structural breaks to the model. In addition, aggregate national macroeconometric models are notorious for their very complex and *ad hoc* lag structures, and this problem would probably worsen if longer time spans were introduced. An alternative strategy is to try to gain information by drawing on data from the component cross-sections of national macro variables – the pooling or averaging across the components may achieve significant noise reduction. By taking this approach, we hope to extract information from the cross-section dimension, thus raising the power of the stationarity tests.

To study our panel of labour market variables for the states of Australia over 107 quarters from 1972:3-1999:1, we set up a general error correction model derived from a theoretical framework for dynamic macroeconomics. The resultant VAR model includes all lagged endogenous variables in each equation, as well as some driving exogenous variables. We examine two long run hypotheses: the relationship between wages and productivity (which suggests a negative relationship between the real wage and employment), and the 'wage curve' hypothesis of Blanchflower and Oswald (1994) (with a negative relationship between unemployment and wages). The short run hypotheses include new Keynesian employment dynamics with Phillips curves for wages and prices.

With our dynamic modelling, we raise the important question: "Does state heterogeneity matter?" The answer to this question is important given that most macroeconomic modelling is done using national aggregates presuming little cost to that aggregation. We tested for state heterogeneity in two ways. First, we estimated our dynamic panel model assuming all parameters are constant across states. The estimates from this pooled procedure are consistent in a dynamic model only if we have state homogeneity (see Pesaran and Smith (1995)), and so the existence of state heterogeneity would generate a serious problem. Thus we tested whether each parameter (one at a time) is the same across states. We find that we can reject the equality across states for many parameters in our model, which means that pooled estimates for these are biased measures of the average effects of the relevant variables. Second, we aggregated our state data, and then estimated an identical dynamic structural model with this aggregate data, testing then to see if the component state variables have any impact. Again, Pesaran and Smith (1995) have shown that the parameter estimates are inconsistent for this procedure in the presence of significant state heterogeneity. Our findings are that the component state data for many variables do have significant impacts on the aggregate procedure. Thus we conclude that state heterogeneity does indeed matter, implying biased estimates in our aggregate procedure.

In our third and final procedure, which acts as as a comparison to the pooled panel and the aggregate procedures, we estimated our four equation model for each state separately and obtained mean group estimates for all parameters. These mean group estimates are consistent for panels with a sufficiently large number of observations across time and states. Thus Pesaran and Smith (1995) recommend estimating individual micro (state) relationships separately when studying panels large in the time dimension. Since we only have a small number of states in our macro panel, a small sample bias may exist in our mean group results.

Having submitted our basic structural model to three procedures (pooling, aggregating and mean group estimates) we can then ask which performs best. Since each procedure suffers from some bias, the answer to this question is not obvious. If states are genuinely independent, then the mean group estimates will do best. If their shocks are perfectly correlated and their economies are identical, then aggregating the states for national macromodelling is appropriate. If they are not independent, their shocks are imperfectly correlated, and not identical in structure, it becomes an empirical issue to decide whether the pooled procedure will dominate the other two. The loss from imposing parameter equality restrictions has to be weighed against the gain from accounting for the covariances of the error processes. Therefore we obtain an answer by comparing the out-of-sample forecasting performance of the three procedures. Our results from the forecasting exercise (in terms of either root mean square errors or Theil's *U* statistic) indicate that even though we are unable to reject state heterogeneity, our pooled model is the most preferred model. This suggests that the gains from accounting for the error covariances across states dominate the losses removed by dealing with state parameter heterogeneity, and that aggregation of the data is too heavy-handed.

In the next section we provide a theoretical framework for the dynamic models that will be estimated. In Section III, we discuss the key features of the data and see whether the labour market experiences of the various states were statistically different. In Section IV, we explain the tests that we use for panel unit roots and panel cointegration. Section V presents the results, and then some concluding comments are offered in Section VI.

2. A Theoretical Framework for Estimation

In this section, we outline a dynamic macroeconomic equilibrium model of many states with temporary wage and price rigidities. From this framework, we obtain dynamic equations for wage and price inflation, employment and the labour force in the first four sub-sections. After explaining the framework, we discuss the empirical implementation of the model, which is in the form of a dynamic vector error correction system in sub-section *5*. In *II.6*, we explain how we test for heterogeneity and how we compare the three procedures.

2.1 Nominal Wage-Setting

Nominal wages[3], W, are set by processes involving insider (or firm-specific) factors such as productivity, and outsider factors such as the state of the labour market.[4] The theories behind this approach include bargaining, search, contract and efficiency wage models.

[3] All variables are in logarithms unless stated otherwise.

[4] For a detailed analysis of this approach, see Layard et al (1991) Chapters 8 and 9.

Representing the insider factors, we use the gap between the real wage (*W-P*, where *P* is the price level) and the marginal product of 'inside' labour, *MPL,* ie of those workers who are party to the wage bargain. This marginal product should depend on employment, *EM,* and other factors, though unfortunately, data on other factors (and output) at the state level are unavailable in Australia.

The outside factors include the change in unemployment, ΔU (measured as ΔLF-ΔEM, where *LF* is the labour force), the gap between the level of unemployment, *U*, relative to its long run value, *U**, and the expected future inflation rate, $E_t[\Delta P_{it+1}]$. The change in unemployment may matter because the competition for jobs can be more intense from the recently unemployed than from the long-term unemployed. We consider *U** to be a function of the real wage, and a deterministic trend following the 'wage curve' hypothesis of Blanchflower and Oswald (1994).[5] There are a number of justifications for the negative relationship between real wages and unemployment.[6] We test to see whether the 'wage curve' hypothesis is supported in our more aggregated macroeconometric panel, which has more information in the time dimension than the normal microeconometric panel.[7]

[5] Blanchflower and Oswald show that this hypothesis of a negative correlation in the logarithmic levels of real wages and unemployment appears to be supported statistically by micro-level panel data for many countries, using repeated and pooled cross-sections (though see Card (1995) for a critical survey).

[6] A number of justifications can be provided to explain the negative relationship between real wages and unemployment. One could be the efficiency wage model of Shapiro and Stiglitz (1984). Another explanation can arise in a union bargaining context – higher unemployment lowers the union's threat point, leading to a lower equilibrium wage bargain. Another could be based on a search model of frictional unemployment

[7] Kennedy and Borland (2000) study the 'wage curve' hypothesis in the Australian context, using microeconometric cross-sections and panels. They work with the Australian Bureau of Statistics Income Distribution Survey for 1982, 1986, 1990 and 1994/5. Their data involves a very wide cross-section at the individual level, and so is quite different to our data set. They are able to find extensive Australian evidence in support of the Blanchflower and Oswald (1994) hypothesis of a static negative elasticity of –0.1 between individual wage levels and various more aggregate measures of unemployment. The robustness of their result depends on the inclusion of state fixed effects.

Given that contracts across a state are formed at different times of the year to last for varying periods, we get a staggered wage setting relation that anticipates the effects of future inflation on the expected real wage. We assume that expected future inflation, $E_t[\Delta P_{it+1}]$, is a linear projection of currently available information. Since there is no reason to assume a more restricted model for expectations (such as static, adaptive, or rational expectations), we prefer to allow a general linear projection. Given our particular state dataset, the available information set will be restricted to include lagged wage and price inflation, employment, the labour force, plus exogenous oil prices and the external terms of trade. As a consequence of the above analysis, the wage-setting equation takes the form:

$$\Delta W_{it} = c_1 + ec1_1 (W_{it-1} - P_{it-1} - MPL_{it-1}) + ec2_1 (U_{it-1} - U^*_{t-1}) + w_1(L)\, \Delta W_{it-1} + p_1(L)\, \Delta P_{it-1} + em_1(L)\, \Delta EM_{it-1} + lf_1(L)\, \Delta LF_{it-1} + tot_1(L)\, \Delta TOT_t + oil_1(L)\, \Delta POIL_t + v_{1it} \quad (1)$$

where the parameter functions (shown in lower case) are polynomial distributions of the lag operator, L (for example, $w_1(L) = w_{11}L + w_{12}L^2 + \ldots$); c_1 is a constant, i is an index for the particular state, t is the index for time, TOT is the external terms of trade, $POIL$ is the local currency value of the world oil price and v_{1i} is a random wage shock.

2.2 Price-Setting

On the price-setting side, we assume that there are imperfectly competitive firms that set their prices optimally, recognizing that the frequency of future price adjustment is constrained by a fixed Calvo-type probability rule. This probability leads to a gradual adjustment of aggregate prices to deviations of real marginal cost from its steady state value, mc_{it}. In addition price changes will depend on expected future price changes, $E_t[\Delta P_{it+1}]$ and shocks, u_{it}, arising on the demand side[8] :

$$\Delta P_{it} = \delta\, mc_{it} + \beta\, E_t[\Delta P_{it+1}] + u_{it}$$

[8] See Clarida et al (1999) for more detail on this relationship.

We shall assume that mc_{it} can be driven by the lagged gap between unemployment and its long run value, by the deviation between the real wage and marginal labour productivity, and on other cost-push shocks, such as oil prices. If unemployment is unusually high, demand and therefore output will be lower, which will put downward pressure on marginal cost. Oil prices pick up an exogenous cost of production that may be partly passed on to final goods consumers. The terms of trade is a possible external demand shock - higher world output enhances national export demand, and thus export prices and the terms of trade. This will be associated with higher national and state incomes and demand, leading to pressure on goods prices (as well as a rise in employment). If expected future inflation, $E_t[\Delta P_{it+1}]$, is some projection of currently available information, then the price inflation equation[9] takes the form:

$$\Delta P_{it} = c_2 + ec1_2 (W_{it-1} - P_{it-1} - MPL_{it-1}) + ec2_2 (U_{it-1} - U^*_{t-1}) + w_2(L)\, \Delta W_{it-1} + p_2(L)\, \Delta P_{it-1} + em_2(L)\, \Delta EM_{it-1} + lf_2(L)\, \Delta LF_{it-1} + tot_2(L)\, \Delta TOT_t + oil_2(L)\, \Delta POIL_t + + v_{2it} \quad (2)$$

where v_{2i} is a random price shock.

2.3 Employment Determination

Output supply in each state is produced by labour, EM_{it}, and other factors, via a standard constant returns production function. In the short run, if the demand for state goods is temporarily less than supply, inventories build up until eventually firms reduce production by layoffs and allowing spare capacity. Absorbing inventories into real investment, the goods market equilibrium is where state demand equals actual production and is thus demand-driven in equilibrium. If the demand constraint does not bind, profit-

[9] Gruen, Pagan and Thompson (1999) study the Phillips curve for wages and prices in Australia. For price and unit labour cost in an expectations-augmented Phillips curve, they find a role for the level of unemployment (related to the NAIRU) and its rate of change (the 'speed limit' effect). Beechey, Bharucha, Cagliarini, Gruen and Thompson (2000) estimate a small model of the Australian economy using single equation methods. Amongst five key variables, they estimate Phillips curves for unit labour cost and price. In both of these papers, their preferred equations include very complex lags as well as various forcing variables.

maximising employment is where the real wage equals the marginal product of labour. In the short run, deviations might be tolerated but they could be gradually corrected by wage adjustments and by hiring or firing. If demand exceeds supply, inventories are run down, leading to abnormally high employment, and eventually an increase in capacity. Over time then, the state goods market equation may include both demand factors and the wage-productivity gap.

Aggregate state demand arises from a number of sources - state residents, other state residents, foreign residents. Aggregate consumption of state residents includes their imports from other states and other countries. Thus aggregate state demand is the sum of state consumption, real investment, the balance of trade with every other state, the balance of trade with other foreign countries, and a random shock. We shall now explain how these five are determined in our model.

First, with the representative state household optimising an intertemporal utility function, we can obtain the standard, first order or Euler condition for state consumption, which exhibits some degree of smoothing over time. Log-linearising this, the log of consumption obeys a random walk with a drift explained by the rate of time preference and the expected real interest rate. Second, the representative firm chooses a real investment path to maximize expected intertemporal profits, subject to the production function and convex costs of installation. Given the forward-looking properties of the shadow (or market) price of capital, the equilibrium is found on a saddlepath relating investment to the price. When demand is not a constraint, log-linearised investment becomes a random walk with a drift explained by the expected real interest rate. When demand is constrained, the level of demand also affects investment[10]. Third, the balance of trade with other states may depend on relative state prices, but should be driven more by macroeconomic factors. We will assume that these are picked up by multiplier factors, which we cannot identify in our dynamic panel model. Interstate shocks will be accommodated in our estimations through the error variance-covariance matrix. The fourth factor, the balance of foreign trade for the state, is determined by the terms of trade and oil prices. Finally, the random shock to state output may arise from innovations in fiscal policy or unspecified supply and demand factors coming from other states or countries.

Bringing these five relationships into the goods market equilibrium condition that has been log-linearised and expressed in first differences, we can obtain a dynamic IS equation.[11] Current output depends on expected future output, the expected real interest rate, the terms of trade and oil prices. If the expected values of future variables are some projection from currently available state information, we can express actual output growth as a linear function of lags of itself, of inflation, the changes in the terms of trade and oil prices, perhaps the unemployment gap, plus a random error.

State output growth translates to an equivalent employment growth equation by inverting the production function. To the resultant employment growth equation, we add the error correction term, reflecting the real wage-productivity gap that may also drive employment when demand constraints do not bind[12]. The general form of the employment equation for estimation becomes:

$$\Delta EM_{it} = c_3 + ec1_3(W_{it-1} - P_{it-1} - MP_{i-1t}) + ec2_3(U_{it-1} - U^*_{t-1}) + w_3(L)\,\Delta W_{it-1} + p_3(L)\,\Delta P_{it-1}$$
$$+ em_3(L)\,\Delta EM_{it-1} + lf_3(L)\,\Delta LF_{it-1} + tot_3(L)\,\Delta TOT_t + oil_3(L)\,\Delta POIL_t + v_{3it} \qquad (3)$$

where v_{3i} is a random employment shock..

2.4 Labour Force

Finally, the labour force growth in a state is assumed predetermined, but can adjust over time through a myriad of national factors, such as immigration, net births, net retirements etc, and through inter-state migration if there are

[10] For example see Obstfeld and Rogoff (1996) for detailed derivations of the consumption and investment paths.

[11] Clarida et al (1999) apply similar arguments to establish a dynamic IS curve.

[12] Russell and Tease (1991) test an error correction model for Australian employment from 1969 to 1987. The restrictions implied by this model on a more general 2nd order model cannot be rejected, though a first order Koyck model's restrictions for the error correction one cannot be rejected.

changes in relative expected real income after discounting for the associated costs. Thus if expected real wages are seen to rise permanently in a state, both immigration to that state and the participation rate in the state should increase. However if real wages are seen to rise only temporarily, this might be seen as reducing employment opportunities, and thus may discourage participation. The same argument may apply to oil price increases. A lower value of lagged employment change in a state (or higher unemployment) is likely to discourage some people from participating in the labour force. This is the 'discouraged worker' hypothesis. It is also possible that this hypothesis may operate through the wage-productivity gap and the unemployment gap. Bringing all of the above together, we obtain the following first difference relationship:

$$\Delta LF_{it} = c_4 + ec1_4 (W_{it-1} - P_{it-1} - MP_{i-1t}) + ec2_4 (U_{it-1} - U^*_{t-1}) + w_4(L)\, \Delta W_{it-1} + p_4(L)\, \Delta P_{it-1} + em_4(L)\, \Delta EM_{it-1} + lf_4(L)\, \Delta LF_{it-1} + tot_4(L)\, \Delta TOT_t + oil_4(L)\, \Delta POIL_t + v_{4it} \quad (4)$$

where v_{4i} is a random labour supply shock.

2.5 Estimation of the Dynamic Four Equation Model Across Seven States

The dynamic model that we will test is based on (1)-(4), and to implement the tests we use a two step procedure. The first step involves establishing possible cointegrating relationships among our variables, which are often interpreted as hypotheses of the long run. At the most general level, we can test for the long run cointegrating relationships by running separate regressions for each state involving nominal wages, W_{it}, prices, P_{it}, employment, EM_{it}, the labour force, LF_{it}, a trend, and a constant picking up fixed effects[13]. Arising from the theoretical framework given above are only two possible cointegrating vectors[14], which are the terms attached to the parameters $ec1_i$ and $ec2_i$ in (1)-(4).

EC1: The real wage-marginal productivity relationship

Labour market pressure may arise on the demand for labour side, yielding a long run relationship between the real wage and the marginal productivity of labour. If the real wage is excessively high, then the current level of employment will exceed the underlying long run value, and there will be negative labour market pressure that should encourage gradual reductions in wages, maybe rises in prices and possible declines in employment. The estimated error for each state i and time t from the (FM-OLS) regression of this relationship is defined as $E\hat{C}1_{it}$, and its lagged value enters the dynamic model as a generated regressor for the first error correction effect:

$$E\hat{C}1_{it} = W_{it} - \hat{p}_{0i}\, P_{it} - e\hat{m}_{0i}\, EM_{it} - \hat{t}_{0i}\, TREND - \hat{c}_{0i} \quad (5)$$

Since other factor inputs and output data are unavailable at the state level, the trend term in (5) is likely to pick up scale effects as well as changes in total factor productivity.

EC2 – The unemployment gap

A second possibility is that outside labour market pressure arises from the difference between actual unemployment and its long run trend value, U^*. This gap may be associated with the 'wage curve' that negatively relates the level of real wages to unemployment. If the actual real wage rises, the long run level of unemployment falls, creating negative labour market pressure that may force down wage and price inflation, and possibly even reducing labour force participation. For this possible cointegrating relationship, we represent unemployment as $LF\text{-}EM$ and expect the parameter estimate on the wage rate to be negative, and on the price level to be positive

[13] In addition, one could include time dummies in the panel cointegration model, which would eliminate the effects of all common global trends without explaining the source of exogenous aggregate shocks. Without time dummies, one runs the risk of omitted variable bias. However that is a risk in any macroeconometric model. Further, Fortin, Keil and Symons (2001) in a study of unemployment in a panel of regions and demographic groups in Canada, use a Hausman test for the omitted variable bias related to missing Canada-wide trends and find that these missing trends are not a problem (with a p-value of 15%) for three out of four demographic groups, and not for the fourth at 1%.

[14] We did try to estimate a cointegrating relationship between the labour force and the real wage, representing a long run labour supply function. However the estimates led us to reject this hypothesis.

in the absence of money illusion[15]. The estimated error, defined as $\widetilde{EC2}_{it}$, becomes the second error correction regressor:

$$\widetilde{EC}2_{it} = LF_{it} - EM_{it} - \widetilde{w}_{0i} W_{it} - \widetilde{p}_{0i} P_{it} - \widetilde{t}_{0i} TREND - \widetilde{c}_{0i} \qquad (6)$$

At the second step, we estimated the short run dynamic model, substituting the lagged estimated errors from (5) and (6) as regressors in place of the wage-productivity and unemployment gaps as shown in (1)-(4). Our general error correction system has four endogenous labour market variables (m=1,..4) for each of the seven states (i=1,..7) over the time period of 107 quarters (t=1972:3,..1999:1). The error variables (v_1,, v_2 ,v_3,, v_4) shown in (1)-(4) may be correlated across states and across labour market variables, but independent through time. In each of the dynamic equations, seasonal dummies are also included (with a structural break assumed for wages from 1981 – see footnote 18 below) but not shown in (1)-(4). The dynamic models were estimated using non-linear least squares, which is equivalent to SUR in this context. We resorted to non-linear estimation because of the many cross-equation restrictions that are imposed (and subsequently singly tested). The SUR method implies that unexplained correlations across states for each variable (which may arise from aggregate shocks) and across variables, can be accounted for in the estimation of the error variance-covariance matrix. Though our least squares estimates are consistent under relatively weak assumptions, in case heteroscedasticity and/or serial correlation remain, we use the Newey-West correction (with a fourth order moving average) for the standard errors and the covariance matrix.

2.6 Aggregation Tests

Though the general model allows all estimated parameters to differ across states, we do not have enough degrees of freedom to attempt that. Instead, for our first procedure, we restricted all parameters in (1)-(4) to be constant across states, thus obtaining pooled estimates. Then we tested the state equality restriction for each parameter of the dynamic panel model, one at a time. These results will give us one answer to the question about whether state heterogeneity exists. If it does, our pooled estimates will be flawed. As shown by Pesaran and Smith (1995), pooled estimators are inconsistent with a heterogenous dynamic panel. By wrongly ignoring heterogeneity in the presence of serially correlated regressors, the errors become serially correlated, which implies inconsistent estimates of dynamic models even as the number of observations in time grows. The asymptotic bias is greater for a larger degree of heterogeneity.

A second approach to that question is obtained by aggregating the state data on each endogenous variable, and then estimating the four equation model with the same general structure as the panel model. To test for state heterogeneity, we then added the individual state component variables into the model for this second procedure, one variable at a time; if the aggregation is adequate, these component variables should have no significant effect in the aggregate model. As an example of our procedure, consider AR(1) models of two variables, x_1 and x_2, with AR parameters, ρ_1 and ρ_2. Aggregating to $x = x_1 + x_2$, the model for x becomes:

$$x_t = \rho\, x_{t-1} + (\rho_1 - \rho)\, x_{1t-1} + (\rho_2 - \rho)\, x_{2t-1} + u_t$$

If the aggregation is appropriate, the parameter estimates for the component variables should be insignificant. As it is possible that the best model for the aggregate data does not have the same structure as the one that has arisen in a panel context, these tests can only be suggestive of possible aggregation problems. If we cannot reject the hypothesis of state heterogeneity in the aggregate context, the aggregate estimates are not consistent for the same reason as for the pooled estimates.

As a standard for comparison (as suggested by Pesaran and Smith (1995)), we estimated the model separately for each state and then average coefficients across the group of states. In this procedure, though complete parameter heterogeneity is assumed, it ignores possible correlation of shocks across states, generating a possible simultaneous equation bias. The group mean estimates from this third procedure are otherwise consistent for samples large in both the time and cross-section dimension. Unfortunately, since the

[15] This issue does not appear to be of concern in the micro-based studies of the wage curve. There, goods prices are assumed to be identical within and across regions (eg see Blanchard and Katz (1997)), and so are assumed to be picked up by time dummies. We prefer to include regional prices and to treat them as jointly endogenous variables.

number of states is relatively small in our sample, our mean group estimates will suffer from some small sample bias.

Having explained our theoretical framework and our procedures for estimating the model, we now examine the key features of the data.

3. Key Features of the Data

In this section, we describe the data used in our analysis in terms of descriptive statistics. These statistics also suggest we should be concerned about the effects of cross-sectional heterogeneity in macro-economic models. From the model in the previous section, our focus is on four key endogenous variables (average weekly earnings, consumer price indices, total employment and the labour force) and two exogenous ones (the price of oil and the terms of trade).[16]. The wage and price variables are available for each capital city[17] of the states, while the labour quantity data are measures for the state. Thus we will miss any changes that may have taken place between rural and urban Australia arising from relative real wage factors – however our guess is that these will be insignificant.

Our focus is on the period from September 1972 to March 1999. It covers a number of very significant events or aggregate shocks such as: the oil price hikes in 1974 and 1979; the wage explosions of 1973 and 1974 based on collective bargaining decisions; the introduction of wage indexation from 1975 to 1981; the wages pause of 1982; the Prices and Incomes Accords from 1983 to 1995 between the peak union (ACTU) and the Labor government with its emphasis on the safety net for the lower-paid; the deregulation and liberalisation of financial markets epitomised by the floating (and subsequent depreciations) of the Australian dollar from 1983; the growth in over-award payments leading to widespread enterprise bargaining in the 1990s; the major recessions in the early 1980s and early 1990s; the decline in inflation cemented in by the introduction in 1994 of explicit inflation targeting by the Reserve Bank of Australia; and the Asian financial crisis from 1997 to 1998.

National aggregates for wages and prices showed a positive but declining trend over the sample representing the general fall in inflation. The real wage grew by an average of 0.26% per quarter, and in total over the 27 years by 27.2%. Consistent with the fall in inflation, wage and price growth rates exhibited declining variance. This is particularly evident for wages after 1981, which might be explained in part by the Accords between the ACTU and Labor governments[18]. National employment and labour force measures are based on the monthly Labour Force Survey, and they had positive trends that may have shifted down marginally in the 1990s. Apart from cyclical and seasonal phenomena, their growth rates seemed to retain a consistent shape over the period.

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[16] The average weekly earnings (AWE) series is taken from ABS Table 6302 and is for total earnings of all male employees. For further details, see http://www.abs.gov.au/Ausstats/abs@.nsf/Lookup/NT000096DA. We were forced to choose male earnings because state data on female employees are available only after December 1981 - however the correlation for total and male earnings after 1981 was greater than 99.5%. The price data is taken from ABS Table 6401-1b. For further details, see http://www.abs.gov.au/Ausstats/abs@.nsf/Lookup/NT00004DBE.
The employment and labour force data is taken from ABS Table 6202 –H5. For further details, see http://www.abs.gov.au/Ausstats/abs@.nsf/Lookup/NT0000FB22. The oil price data was the West Texas crude oil price (converted to Australian dollars) which was sourced from http://www.economagic.com/em-cgi/data.exe/var/west-texas-crude-long. The external terms of trade was computed as the relative price of exports to imports and taken from ABS Table 1364.0.15.003:29, also available from the ABS website.

[17] Data on the CPI for the Northern Territory and its capital Darwin are available only from September 1980, and so, to keep the panel balanced, we excluded this Territory from the analysis. Being relatively small (its employment share in the aggregate reached only 1% by 1999), its exclusion should not make too much difference.

[18] However there is another compelling explanation. The wages series is for average weekly earnings, that is average gross before-tax earnings, and was affected by the proportions of full-time, part-time, casual, junior and overtime employment. As a consequence, this data does display substantial seasonality and will also be driven by the business cycle. Prior to August 1981 it was based on payroll tax returns, and after that on a survey of employer units. Since companies with a small number of employees did not pay payroll tax, the high variance of the earlier segment reflects larger company employment practices (such as the greater use of overtime). To deal with this, we treat the seasonality components of average weekly earnings as different for the two periods.

Our state analysis may be worth conducting if there were some significant differences in the experiences of the states relative to the national aggregate. Figures 1 to 4 and Tables 1 (and 2) present graphs and basic statistics of the deviations in log levels (and growth rates) of each of the seven states from the national aggregate for four variables.[19]

The deviations of mean wage and price levels for all states are statistically significant, though the deviations of mean growth rates are not. This suggests different local factors are at work (eg. state taxes, geographical distance etc.), but the changes on average and thus in the long run, may largely be driven by national factors. Queensland (QLD) exhibits significant relative skewness in wage levels and growth, and Tasmania (TAS) in wage growth. Victoria (VIC) shows significant negative relative kurtosis in wage levels, while South Australia (SA), TAS and Australian Capital Territory (ACT) suffer this (positively) in wage growth. For deviations of prices growth, New South Wales (NSW), Western Australia (WA), TAS and ACT have significant (and positive for all but NSW) skewness and (positive) kurtosis. These higher moment results provide additional evidence to support the notion that there are important differences in wage and price processes across the cities and through time.

The significant deviations of mean employment and labour force levels merely indicate the varying sizes of the states. The deviations of the growth rates are largely associated with population migration within the country, and there have been significant relative gains in QLD and WA, and losses in SA. The distributions over time of relative employment levels in NSW, VIC, TAS and the ACT (and for the labour force in the last three) were significantly skewed (negatively for all but the first). The levels of both showed negative kurtosis for VIC, QLD and SA. The growths of both were significantly positively skewed for TAS, while the ACT suffered negative skewness for labour force growth. This is further evidence that the stochastic processes for labour quantities differ significantly across states and through time.

To get a deeper understanding of the differences across states for the four variables, we conducted analysis of variance tests for common means and variances across states and/or time for a panel of each. In Table 3, the results for these tests are reported. For the growth rates of wages and prices, the hypothesis of equal means across states cannot be rejected, however, the equality of means for the growth rates of employment and labour force can be rejected. If we consider the time means, our result is uniform: we are always able to reject the null hypothesis of equality of means through time for all the series under consideration. For the growth rate of prices, we cannot reject the equality of variance across states. The failure to reject the equality of variances across states for prices only may be explained by the relatively high degree of integration of goods markets across Australia. For the labour market, variances differ significantly across states for growth rates of wages, employment and the labour force. These tests imply that there are important state-specific effects impacting on our labour market variables. Overall, we conclude that there is likely to be extra useful information in panels of state-wise components of labour market variables.

Given the time series dimension in our data, it is important to check the non-stationarity properties of the various series. We discuss these issues in the next section.

4. Testing for Panel Unit Roots and Cointegration

This section is divided into two sub-sections: sub-section 1 analyzes the procedure for testing for the presence of a panel unit root along with the results for each of the variables in our model. Subsection *IV.2* discusses the case of panel cointegration.

4.1 Panel Unit Root Tests

Early studies, which employed univariate unit root tests from Dickey and Fuller (1979, 1981, hereafter ADF) and Phillips and Perron (1988), very rarely rejected the unit root null hypothesis in favour of a stationary

[19] Here the test is conducted on the deviations of state series from national data. Although we will show that the data in levels is nonstationary, one may also argue that if both (a state series and the national series) are I(1), then the deviation may turn out to be I(0).

alternative. These results, however, are typically attributed to the tests' low power over short time spans of data. To increase the power of unit root tests, one solution is to allow for additional cross-sectional variation using panel methods. This approach has been used extensively to test for the presence of 'PPP', growth and inflation convergence. We explore this approach in our paper by employing the panel data unit root test as proposed by Im, Pesaran and Shin (1995)[20] – henceforth referred to as IPS - and estimate the following equation:

$$\Delta x_{it} = \alpha_i(\beta_i + 1) + \beta_i x_{it-1} - \beta_i \delta_i t + \sum_{j=1}^{k_i} \gamma_{ij} \Delta x_{it-j} + \varepsilon_{it} \qquad (6)$$

where i is the index for the N (=7 in our case) states, t indexes time over the sample period of length T (=107), and x is the variable under consideration. In the above equation we have allowed the intercepts as well as the slope coefficients to differ across states. We have also included a heterogenous trend term in our equation (given by $-\beta_i\delta_i t$). The inclusion of different intercepts accounts for possible unobserved heterogeneity across states. The lag-length was selected by the Campbell and Perron (1991) procedure starting with a maximum lag length of 16 and using the 10% critical value of asymptotic normal distribution to assess the significance of the last lag. The null and the alternative hypothesis under the IPS tests can be expressed as:

$$H_0: \quad \beta_i = \beta = 0$$
$$H_1: \quad \beta_i < 0 \ \ for\ some\ i$$

The above formulation makes it clear that the IPS test allows heterogeneity across cross-section units, i.e. states in our case.[21]

Let t_{iT} denote the individual t statistic for testing $\beta_i = 0$ in (6). The group mean of the n individual t-statistics, called the *t-bar* statistic, is defined as follows:

$$\bar{t}_{nT}(k_i) = (1/n) \times \sum_{i=1}^{n} t_{iT}(k_i)$$

where the lag length, k_i, has been determined optimally. The standardized *t-bar* statistic is defined as:

$$T_t = \frac{(n)^{1/2}\{\bar{t}_{nT}(k_i) - \frac{1}{n}\sum_{i=1}^{n} E[t_{iT}(k_i) \mid \beta_i) = 0]\}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} Var[t_{iT}(k_i) \mid \beta_i) = 0]\}}} \qquad (7)$$

T_t is asymptotically distributed as a standard normal distribution. The mean and the variance adjustment terms in (7) depend on lag length and whether a constant and/or a trend are included in the model, and are given in IPS (1995).

The results for the individual unit root along with that of panel unit root tests are presented in Table 4. We cannot reject the null hypothesis of a unit root in almost all the individual series with the exception of NSW's employment (at the 5% level). The results from the panel unit root test reveal the same picture: for all the series we are able to do not reject the unit root in a panel context at the 5% level with the exception of the employment series. From these results, we shall take the cautious route, and assume that all of our four variables are integrated of order one.

4.2 Panel Cointegration Tests

As in the univariate testing of unit roots, the power of the single equation approach to cointegration is low and, as with our unit root testing, we shall appeal to the additional power delivered by the panel approach. If the coefficients in the cointegrating relationship were known *a priori* rather than having to be estimated, the Levin and Lin (1992) procedure could be applied to the estimated error variables in a panel framework. However, just as Dickey-Fuller critical values are not applicable to generated residuals from a

[20] Bowman (1998) and Maddala and Wu (1999) provide evidence that the IPS test has more power than the Levin-Lin test for panel unit roots.

[21] By introducing cross-section variation information to unit root testing, there is a gain in power, but the hypothesis being tested in the panel context is somewhat different to that in the univariate tests – in the IPS test, the null of the panel unit root may be rejected on account of just one member of the cross-section, even if it could not be rejected without that member. Thus these panel tests are useful for testing the general applicability of a theoretical hypothesis, but they do not add power to the univariate methods that test hypothesis of specific applicability – only more powerful univariate tests can do that.

cointegrating regression, Levin and Lin critical values are (usually) inappropriate in a panel context. Furthermore, as Pedroni (2001) notes, while in the single series case the dependency of the residuals on the distributional properties of the estimated coefficients in the spurious regression can be accounted for by simply altering the critical values, the effect can be harder to remove in a panel because of the cross-sectional dimension to the structure of the residuals. The effect of this dependency hinges crucially on the alternative hypothesis. Consider a homogeneous panel:

$$y_{it} = \alpha_i + \gamma_t + \delta_i \, t + x_{it}\beta + e_{it} \quad (8)$$

In the above equation, although we allow for unobserved state heterogeneity, we capture this only by the presence of a different intercept term (α_i). The term γ_t captures the presence of aggregate shocks or the time dummy, whereas the term t allows for the presence of a heterogenous trend across states. We estimated the above equation both with a trend term and without it.[22] We also estimated equation (8) in two cases: in one case $\gamma_t = 0$ (without time dummy model), and in the other where $\gamma_t \neq 0$ (with time dummy model). In (8), we have assumed that the cointegrating vector, β, is the same across different cross-sectional units (ie the states). Pedroni shows a superconsistency-type result whereby the asymptotic distributions of unit root tests are invariant to whether the residuals are known or estimated. However, in the more general heterogeneous panel

$$y_{it} = \alpha_i + \gamma_t + \delta_i t + x_{it}\beta_i + e_{it} \quad (9)$$

where the cointegrating relationship (in terms of β_i) can differ between individual panellists, the standard panel unit root test statistic does not converge, with serious implications for the test.

Pedroni (1999, 2001) develops three tests of the null hypothesis that the e_{it} are nonstationary: $Z_{\hat{\rho}_{NT}}$ based on residual autoregressions, and $Z_{t_{\hat{\rho}_{NT}}}$ based on a t test with corresponding to an Augmented Dickey-Fuller and the other to a Phillips-Perron type test. Pedroni (1999) refers to the t statistic as the panel-cointegration statistic when the slope coefficient in the cointegrating relationship is the same for the cross-sectional units, and as the group statistic when the slope differs across the units. The group statistic is based on the average of individual statistics.

We tested for panel cointegration in the heterogeneous model allowing the cointegrating vector slope terms and the intercept term to differ between individual panel members. We also tested for separate time trends and for time dummies to account for aggregate shocks. As in the case of the unit root test, we started with $k = k_{max} = 9$ and used the 10% critical value of asymptotic normal distribution to assess the significance of the last lag.

If our panel cointegration tests reject the null of no cointegration amongst a particular set of variables, we used the estimated errors in the context of a dynamic error correction model. Though the least squares estimator of the cointegrating vector is known to be superconsistent (so that the two step estimator of the error correction model has the same asymptotics as when the cointegrating vector is known), its asymptotic distribution suffers from nuisance parameters arising from regressor endogeneity and serial correlation of the errors. To obtain unbiased estimates of the cointegrating vector, we used the fully modified OLS (FM-OLS) estimator of Phillips and Hansen (1990) which introduces non-parametric corrections for the nuisance problems.

Having established with our panel unit root tests (in the previous sub-section) that we cannot reject non-stationarity for the levels of our four variables, we present in the next section our error correction models results. We began by testing for the cointegrating vectors that arise from our long run hypotheses of the labour market, and then if they could not be rejected, we estimated a dynamic error correction model based on the theoretical framework discussed in Section II.

5. Estimation Results and Forecast Performance

We begin in sub-section *V.1* with the long-run results from the first step estimation of the two conjectured cointegrating vectors, (5) and (6), using the

[22] Note that the trend term is different to a time dummy.

panel cointegration tests, and the associated FM-OLS estimators. Sub-section *V.2* presents the results for the second step estimation of the short-run dynamic model in (1)–(4) in three ways, namely the pooled, unrestricted aggregate and mean-group estimates procedures. Sub-section *V.3* conducts a forecasting exercise for the three procedures.

5.1 Panel Cointegration and FM-OLS Results for (5) and (6)

The results of applying the panel cointegration test (Pedroni (1999)) are given in Table 5. The first 3 rows report test statistics for the model with a common slope coefficient whereas the next 3 represent the case for heterogeneous slope coefficients. We present the results for the most general model: model allowing for time dummies and with and without a trend term. However, our results are more or less invariant to alternative specifications.[23] There is clear evidence of cointegration in this framework since all the test statistics are significant at standard confidence levels.

Table 6 reports the unbiased individual FM-OLS estimates of the cointegrating vectors, as well as the group FM-OLS estimates[24]. The asymptotic covariances are estimated individually for each member i of the cross section using the Newey-West estimator. For the lag length of the band width, we employ the data-dependent scheme recommended in Newey and West (1994), which is to set the lag truncation to the nearest integer given by $K = 4*(T/100)^{2/9}$, where T is the number of time observations.

With regard to (5), we infer that the elasticity of the state CPI is significantly different from one (and zero) for all the states, except NSW and QLD. This is not surprising because there are different state taxes affecting the real product wage. The employment variable exerts a significant negative impact in all but WA. However, the elasticity estimates are significantly different from one (and zero) for the CPI and from zero for employment in the panel context. When we include time dummies in our model, the state CPI remains significantly different from one and zero, but the employment parameter loses some significance (6%). The deterministic trend is positive (and only insignificant for SA and TAS) partly reflecting technological progress.

For the unemployment gap estimates of (6), each state's elasticity of the nominal wage on (long run) unemployment is estimated to be positive (which is not as predicted by the wage curve hypothesis), but is significant only for NSW, QLD and TAS. The group estimate, without time dummies included, is significantly positive. However when time dummies are included (effectively removing aggregate shocks), the wage elasticity becomes significant with the expected negative sign. In general, the price elasticity estimates are not significant, and it would appear that it is the nominal and not the real wage that matters for long term unemployment. However it may be that wages are compared to a nominal benefit rate instead. After accounting for wages and prices, the trend in long run unemployment is significantly negative (apart from ACT).

In summary, our results suggest that the real wage-marginal productivity relationship appears to hold in the long run, while the wage curve hypothesis gets support provided aggregate shocks are purged from the data.

5.2 Estimates of the Dynamic Model

The short run dynamic model, (1)-(4), was estimated by non-linear least squares, which is equivalent to SUR. For our pooled panel procedure, 28 equations were estimated simultaneously, with cross-equation restrictions applied so that each elasticity is the same across states. There were 107 observations for each variable in each of the 7 states. After accounting for 2 lags[25] on all variables in the model and some missing observations, we ended

[23] Detailed results are available on request.

[24] See Phillips and Hansen (1990) for properties of the FM-OLS estimator. For the group FM-OLS estimator, see Pedroni (2000).

[25] For the dynamic model, the maximum number of lags on all variables had to be set to 2. With 3 lags, the iterative procedure for estimating the model could not reach convergence. In Table 7, the test for setting the second lags of all variables to zero rejected the restriction at less than 1%.

up with 91 usable observations. No estimates of seasonal dummies are reported though most were highly significant.

The results are shown in Table 7. The pooled panel estimates (with standard errors) for each of (1)-(4), where all parameters are constrained to be equal across states, are shown in the 2nd and 5th columns. For the wage growth equation, only 4 parameters are significant (and 3 at less than 5%). These are the parameters for the first error correction effect from (5), the second lag of wage change, the second lag of price change and of oil price change. If the gap between the wage and labour productivity increases by 10%, wage change in the next period will decline by 2.05%. This persistence of this process will be directly influenced by the lagged wage parameter, estimated to be 0.175. The lagged price change parameter arises largely from expected inflation effects, and its estimated value of 0.973 is not significantly different from 1. The negative oil price change effect (significant at 10%) suggests that wage setters expect a recession impact from oil price increases. Since the change in lagged unemployment was not significant, there was no 'speed limit' effect on wage or price inflation (or a first difference form of the wage curve hypothesis).

The significant parameters in the price inflation equation are for the unemployment gap, the wage mark-up, own lags that deliver persistence, the second lag of employment change (with a negative sign, but only 10% significance), the second lag of the terms of trade growth and oil price inflation. If the level of unemployment rises above its estimated long run value by 10% (equivalent to about 0.7% in unemployment in 1999), inflation would fall by 0.09%. The wage mark-up occurs after 1 lag, and the parameter is modest in size (0.07). An improvement in the terms of trade raises inflation after 2 periods, consistent with our interpretation that the Australian terms of trade are driven positively by global output. The net effect of higher oil prices is to raise inflation as an expected cost-push factor.

Employment change is driven significantly by a constant, negatively by the first lag of real wage change (since the absolute value of the parameters for the nominal wage and price changes are not significantly different), and also by the second lag of the nominal wage change. The first lag in the change in unemployment very significantly reduces employment growth (with a parameter between -0.206 and –0.189). This is consistent with our interpretation of a short run aggregate demand factor operating through a multiplier on employment. The terms of trade has a significant (at 10%) and positive effect on employment after 2 periods, similar to prices, and consistent with an external demand-driven interpretation. The second lag of the oil price is significant (at 5%) and negative, and is likely to be due to a rise in production costs.

Labour force growth is explained by a constant, negatively by lagged nominal wage growth, positively by lagged price growth, positively by the first lag of employment growth, negatively by its own lags, and negatively by the terms of trade and oil prices. The negative wage and positive inflation effects as well as the negative terms of trade effect may be surprising. Labour force participation might fall after a rise in the real wage because it is recognised that employment opportunities will be reduced. This means that the discouraged worker hypothesis, working via expected future employment, dominates the direct incentive effects on labour supply of a wage rise. The employment and labour force signs are also consistent with the discouraged worker hypothesis. The negative terms of trade effect might arise because exports are not relatively labour-intensive, though this is not consistent with the positive effect on employment discussed in the previous paragraph. Higher oil prices reduce labour force participation because they will reduce employment opportunities, as established in the employment equation.

The results of our first approach to test for state heterogeneity are given in columns 3 and 6 in Table 7, which are based on the estimates from the dynamic pooled panel model of 28 equations. We ran a series of pooled regressions in which each parameter alone was allowed to vary across states, and then we tested for equality of those 7 state parameters. A strongly significant fixed effect exists only in the labour force equation, and very weakly in the price equation. For the wage equation, of the 4 significant parameters, only 2 differ across states. For the price equation, all significant parameters appear to differ across states (at 10% or less). In the employment equation, 3 out of the 8 significant parameters exhibit state heterogeneity, and in the labour force equation, we have 5 out of 10. In each equation, there are a number of instances where a restricted parameter was not significantly different from 0, but the parameter was significantly different across states. From our first approach, we conclude that state heterogeneity certainly exists.

Our second approach to the state heterogeneity problem involved estimating the same structural model with aggregated data (reducing the system from 28 to 4 equations). We report the parameter estimates for this aggregate national macro procedure in Table 8. The parameter estimates are not much different to those reported in columns 2 and 5 in Table 7. For each parameter in question, we ran a separate model regression including the associated state variables, and test to see if these are jointly significant. The results are in columns 3 and 6 of Table 8. In the aggregate wage growth equation, for each of the 3 significant parameters on lagged endogenous variables, the inclusion of the relevant state variables cannot be rejected (at 10% or less). For the aggregate inflation equation, state variables make a difference for only 1 out of 5 relevant variables, and that is the own second lag. For employment growth, we have 3 out of 5 relevant variables, and for the labour force, 6 out of 8. These results suggest that aggregation is not serious when modelling price inflation, but may be of concern for models of wages, employment and the labour force.

The results from the tests for state homogeneity indicate that we can reject the null hypothesis of state homogeneity in both the pooled as well as the aggregate national context. Therefore the pooled as well as the aggregate estimates are not consistent in the presence of state heterogeneity. Given heterogeneity, and following Pesaran and Smith (1995), we also compute the mean group estimates of our dynamic model by running the model separately for each state and then averaging coefficients across the group of states. Here, the standard errors of the parameter estimates are the square root of averages of the cross-section variance of the estimates.

The results from the mean group estimates procedure are given in columns 2 and 4 of Table 9. Compared to our pooled procedure (as reported in Table 7) or the aggregate procedure (as reported in Table 8), we note that that for the wage growth equation, several coefficients of the variables are significant. These include the second lag of wage changes, the first and second lag of both price and employment changes as well as both lags of terms of trade and oil price changes. For the price equation, the significant parameters are the unemployment gap, the wage mark-up, own lags that deliver persistence, the second lag of employment change (with a positive sign), both lags of the terms of trade growth and the first lag of oil price inflation. The wage mark-up occurs after 1 lag and continues in the second lag, and the sum of the two lags of the wage mark-up is 0.09. An improvement in the terms of trade raises inflation after 1 period, whereas the effect of higher oil prices is to raise inflation as an expected cost-push factor. Employment change is driven significantly by the terms of trade after 2 periods. An increase in the change in nominal wage significantly reduces the change in employment (the first lag is significant at one percent level), as well by the lag of changes in unemployment. The equation for the labour force growth is positively affected by the first lag of price growth, positively by the lagged employment growth, negatively by its own lags and negatively by the first lag of wage growth.

Knowing that all three procedures will suffer from bias in some form, we now present the results from our out-of-sample forecasting exercise for all three estimated procedures.

5.3 Forecasting Performance of the Three Procedures

This sub-section discusses the forecasting performance of the pooled, aggregate and mean-group estimates procedures. We computed twelve-step ahead forecasts based on a series of rolling regressions. First, we estimated the model until 1996:1 (95^{th} observation) and then used the estimated coefficients to forecast for the next 12 periods. We then re-estimated the model by adding one more observation and forecasted the model for the next eleven steps and so on. The computed statistics are based on the number of available observations for each step, 1 to 12.

To compare the three procedures, we first aggregated the forecast results for the pooled and mean group estimates procedures. We evaluated the forecasting performance in two ways: by the root mean square error (*RMSE*) and by using Theil's *U* statistic. Theil's *U* statistic is a ratio of the root mean square error for the model to the root mean square error for a naïve forecast of no change. This is preferred to *RMSE* because it is independent of the scale of the variable in question. Values of Theil's U less than 1 indicate a technique is better than using a naïve forecast.

We summarize the results from our first forecasting exercise in Figure 5. The pooled procedure dominates the other two for each variable at all steps less than 12 in terms of the *RMSE.* The pooled procedure performs better than a naïve forecast of no change (i.e. Theil's $U < 1$) for employment and the labour force at all forecast steps less than 12. For wages, it performs better for about half the number of steps (particularly between 6 and 9 steps), but for prices it does only as well at the 4^{th} quarter step. The other two procedures never do better than a naïve forecast for any of the endogenous variables for steps less than 12. Beyond a 2 step horizon, the mean group procedure performs in most cases better than the aggregate one except for the price growth equation.

In a second forecasting exercise, we compared the state forecast performances for each variable using the pooled procedure and from the separate state regressions of the model. We took the difference in the Theil U statistics for these. These are presented in Figure 6. Overall the pooled procedure is preferred, although understandably not always for NSW (being the largest state entity).

We conclude that our original pooled panel procedure is preferred to the aggregate macro procedure and to the mean group and individual results of the independent state models. Thus even though state heterogeneity exists, the gain from the simultaneous estimation of the 28 equation model exceeds the costs of ignoring parameter heterogeneity in terms of making out-of sample forecasts.

6. Conclusions

The objective of this paper was to consider whether cross-section information improves the information content of dynamic macroeconometric modelling of the Australian labour market. We took a disaggregation by state of key labour market variables. The resulting macroeconometric panel was far longer in the time than the cross-section dimension, in contrast to microeconometric panels.

Using modern methods of panel cointegration with a two-step procedure, we estimated dynamic error correction models for the Australian state labour markets. For the long run relationships, we tested two models: a labour demand-side relation for which the real wage should equal the marginal product of labour; and an unemployment relation based on the wage curve hypothesis. Both models yielded cointegrating vectors. The demand-side model had the correct signs and significance in all the tests (ie univariate, panel unit root, with and without fixed state and time effects) using FM-OLS estimation. The wage curve hypothesis suggests a negative relationship between unemployment and wages, and this could only be detected when time dummies were included, that is when aggregate effects had been factored out.

The short-run dynamic model delivered a significant expectations-augmented Phillips curve in wages and prices, with the latter exhibiting stickiness and including mark-up, and external demand and supply-side effects. The employment growth equations showed significant short-term Keynesian demand-side features through unemployment and the terms of trade growth, as well as supply-side effects through oil prices. Labour force growth exhibited migration differences across states, and the estimates also supported the discouraged worker hypothesis. Decisions to participate in the labour force appeared to depend on what was perceived to influence employment opportunities.

Our tests for state heterogeneity suggest that it certainly existed in our sample. In the dynamic pooled panel model, we detected fixed effects for quantity variables, as well as differential slope effects for many of the regressors in each equation. Further, when using aggregate data with the same structural model, we showed that the inclusion of state-level data was statistically important. This was particularly true for our labour market variables, though not so for inflation. We conclude then that state heterogeneity in labour markets does exist. This is an important result because it is known that the state homogeneity assumption implicit in pooling or aggregating dynamic panels is not innocuous – significant heterogeneity may create serious biases in estimates. One resolution of that problem may be to estimate state relationships individually, and then obtain state averages of the parameter estimates. Two problems may arise in this context. First, the number of component states may be quite small (as in the case of Australia, but probably not the US) leading to small sample biases, and second this procedure assumes state independence, which is not likely.

With each procedure suffering from some bias, our way of selecting amongst them was to see which performs best in out-of-sample forecasting tests. Our results for Australian labour markets show that the pooled model is definitely the most preferred model even though by pooling it ignores the parameter aspects of state heterogeneity.

Data is usually available for much longer time spans and many more variables at the national level than at the state level. Our results are sufficiently promising to encourage government agencies around the world to provide more detailed data at the state level. Much remains unexplained, and this paper as only begun to address the important issue of comparing the performance of macroeconometric models using national aggregate data with those using disaggregated data. Even though the particular model that we worked with may be improved upon, we conjecture that our conclusions on aggregation will not easily be over-turned. Although our empirical model is applied to Australian data, our result that the pooling procedure is preferred to aggregation and group means may well hold, or at least should be tested, for many other countries.

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TABLE 1: Descriptive Statistics for Level Deviations from National Data, 1972:3-1999:1

		Probability Values (and Sign) of		
Deviations from National Data	**Mean**	**Mean**	**Skewness**	**Kurtosis**
Wages				
ACT (Canberra)	.116	.00	.94	.90
NSW (Sydney)	.035	.00	.21	.21
QLD (Brisbane)	-.043	.00	.01 (-)	.48
SA (Adelaide)	-.067	.00	.28	.29
TAS (Hobart)	-.065	.00	.38	.28
VIC (Melbourne)	-.013	.00	.38	.01 (-)
WA (Perth)	.010	.00	.56	.95
Prices				
ACT (Canberra)	.009	.00	.83	.62
NSW (Sydney)	-.004	.00	.13	.21
QLD (Brisbane)	.012	.00	.94	.12
SA (Adelaide)	.011	.00	.07	.56
TAS (Hobart)	.011	.00	.78	.07
VIC (Melbourne)	-.003	.00	.77	.14
WA (Perth)	-.007	.00	.49	.65
Employment				
ACT	-4.05	.00	.02 (-)	.11
NSW	-1.07	.00	.02 (+)	.18
QLD	-1.83	.00	.65	.02 (-)
SA	-2.45	.00	.49	.12
TAS	-3.64	.00	.01 (-)	.51
VIC	-1.33	.00	.01 (-)	.02 (-)
WA	-2.38	.00	.61	.04 (-)
Labour Force				
ACT	-4.07	.00	.05 (-)	.06
NSW	-1.07	.00	.13	.09
QLD	-1.82	.00	.80	.02 (-)
SA	-2.44	.00	.45	.06
TAS	-3.64	.00	.00 (-)	.62
VIC	-1.34	.00	.27	.02 (-)
WA	-2.38	.00	.26	.04 (-)

Note: The p-values indicate the strength of evidence against the existence of a zero mean, no skewness or kurtosis.

TABLE 2: Descriptive Statistics for Growth Deviations from National Data, 1972:3-1999:1

		Probability Values (and Sign) of		
Deviations from National Data	**Mean**	**Mean**	**Skewness**	**Kurtosis**
Growth in Wages				
ACT (Canberra)	.00028	.92	.06	.00 (+)
NSW (Sydney)	.00004	.96	.22	.23
QLD (Brisbane)	-.00014	.92	.01 (-)	.42
SA (Adelaide)	.00018	.91	.93	.04 (+)
TAS (Hobart)	.00057	.79	.03 (-)	.03 (+)
VIC (Melbourne)	-.00006	.95	.53	.44
WA (Perth)	.00022	.88	.23	.50
Growth in Prices				
ACT (Canberra)	-.00013	.78	.00 (+)	.00 (+)
NSW (Sydney)	.00001	.96	.01 (-)	.00 (+)
QLD (Brisbane)	-.00006	.87	.51	.31
SA (Adelaide)	.00021	.58	.55	.02 (+)
TAS (Hobart)	-.00007	.87	.00 (+)	.00 (+)
VIC (Melbourne)	.00008	.77	.52	.72
WA (Perth)	-.00011	.82	.00 (+)	.00 (+)
Growth in				
ACT	.0014	.47	.90	.62
NSW	-.0009	.08	.85	.57
QLD	.0029	.00	.94	.96
SA	-.0018	.00	.93	.54
TAS	-.0022	.14	.03 (+)	.46
VIC	-.0008	.14	.19	.55
WA	.0021	.01	.38	.71
Growth in Labour				
ACT	.0015	.41	.03 (-)	.23
NSW	-.0009	.06	.40	.63
QLD	.0030	.00	.38	.74
SA	-.0017	.03	.37	.92
TAS	-.0018	.21	.02 (+)	.60
VIC	-.0009	.12	.34	.96
WA	.0020	.01	.38	.73

Note: The p-values indicate the strength of evidence against the existence of a zero mean, no skewness or kurtosis.

TABLE 3: Analysis of Variance for State Panels

	Probability Values		
Variable	**State Means**	**Time Means**	**State Variances**
Growth in Wages	.99	.00	.00
Growth in Prices	.99	.00	.82
Growth in Employment	.00	.00	.00
Growth in Labour Force	.00	.00	.00

Note: These p-values measure the strength of evidence for whether the means across states and through time and the variance across states differ significantly.

Table 4: Results from Individual and Panel Unit Root Tests
(trend included)

	Individual Unit Root Tests		Panel Unit
Variable	Lag Length, k_i	Test-Statistics	
Wages			
Canberra (ACT)	6	-2.05	--
Sydney	8	-1.35	--
Brisbane (QLD)	8	-1.64	--
Adelaide (SA)	8	-1.22	--
Hobart (TAS)	7	-1.95	--
Melbourne (VIC)	8	-0.62	--
Perth (WA)	4	-1.66	--
Group			1.992
Prices			
Canberra (ACT)	7	0.14	--
Sydney	7	-0.03	--
Brisbane (QLD)	7	-0.49	--
Adelaide (SA)	5	-0.20	--
Hobart (TAS)	7	-0.51	--
Melbourne (VIC)	7	-0.11	--
Perth (WA)	9	-0.32	--
Group			6.157
Employment			
ACT	0	-1.32	--
NSW	8	-4.00**	--
QLD	8	-3.05	--
SA	6	-2.02	--
TAS	7	-2.49	--
VIC	8	-2.80	--
WA	4	-3.06	--
Group			-1.861**
Labour Force			
ACT	8	0.14	--
NSW	8	-2.31	--
QLD	2	-2.05	--
SA	8	-1.36	--
TAS	8	-0.95	--
VIC	5	-1.97	--
WA	4	-1.57	--
Group			2.209

*Notes: Columns 2 and 3 summarize the results of univariate (ADF) unit root tests. The null is the non-stationarity of the time series. Critical values for the univariate unit root tests are taken from MacKinnon (1991). For 107 observations, the critical values at 1% and 5% levels of significance are –4.05 and –3.45, respectively. Column 4 reports the results of the panel unit root test. The critical (standard Normal) values for the panel unit root tests at the 1% and 5% levels of significance are –2.325 and –1.645, respectively.** denotes rejection of the unit root null at the 5% level.*

Table 5: Results from Panel Cointegration Tests

Panel Cointegration Statistics	Equation 5		Equation 6	
	Without Trend	With Trend	Without Trend	With Trend
Panel Rho	-10.74	-10.14	-9.45	-8.87
Panel PP	-7.82	-8.62	-7.14	-7.95
Panel ADF	-12.10	-16.29	-9.08	-10.71
Group Rho	-11.96	-10.34	-9.01	-8.02
Group PP	-9.54	-9.57	-7.77	-7.92
Group ADF	-15.53	-19.47	-11.72	-12.78

Notes: All of these test statistics are standard normal distributed. Sufficiently large negative values lead to a rejection of the null hypothesis that the series are not cointegrated (the critical value is -2.326 at the 1% level).

Table 6: Individual and Group FM-OLS estimates of the Cointegrating Vectors

Equation: **Dependent variable:**	**(5)** **Wages, W_{it}**				**(6)** **Unemployment rate, LF_{it}-EM_{it}**			
State	**CPI**	**Employment**	**Constant**	**Trend**	**Wage**	**CPI**	**Constant**	**Trend**
ACT (Canberra)	1.16 (20.1)	-0.53 (-4.26) ***	3.36 (9.44)***	0.002 (3.79)***	0.11 (0.18)	-0.43 (-0.67)	-1.7 (-1.69)*	0.01 (2.47)**
NSW (Sydney)	1.03 (34.1)	-0.74 (-5.02) ***	6.65 (6.70)***	0.003 (4.33)***	2.83 (3.72) ***	-1.46 (-1.73) *	-11.77 (12.15)***	-0.02 (-6.74)***
QLD (Brisbane)	1.02 (27.3)	-0.89 (-4.38) ***	6.46 (5.41)***	0.006 (4.04)***	1.31 (2.39) **	0.13 (0.21)	-9.85 (-13.10)***	-0.02 (-6.68)***
SA (Adelaide)	1.12 (38.1)***	-0.42 (-3.04) **	3.81 (5.23)***	0.000 (0.36)	1.09 (1.55)	0.20 (0.25)	-8.76 (-11.59)***	-0.01 (-5.95)***
TAS (Hobart)	1.27 (34.3) ***	-0.88 (-5.37) ***	4.79 (6.90) ***	-0.01 (-1.34)	0.91 (2.34) **	0.28 (0.56)	-8.30 (-18.42)***	-0.01 (-5.42)***
VIC (Melbourne)	1.12 (35.7) ***	-0.43 (-2.99) **	4.23 (4.82) ***	0.001 (1.90)*	1.12 (1.29)	-0.29 (-0.29)	-7.45 (-7.72)***	-0.01 (-2.13)**
WA (Perth)	1.11 (30.7) *	-0.28 (-1.36)	2.88 (2.93) ***	0.002 (1.68)*	0.32 (0.53)	1.29 (1.87) *	-8.86 (-12.78)***	-0.02 (-8.78)***
Group – without time dummies	1.12 (83.2) ***	-0.60 (-9.99) ***	4.60 (15.66) ***	0.002 (5.58)***	1.10 (4.54) ***	-0.04 (0.07)	-8.10 (-29.27)***	-0.01 (-12.56)***
Group – with time dummies	0.57 (4.79)**	-0.03 (-1.95) *	-0.04 (-6.95) ***	0.00 (0.59)	-0.76 (-3.19) ***	-0.48 (-0.72)	0.04 (3.05)***	-0.00 (-1.28)

*Notes: The numbers in parenthesis are the t-statistics for the null hypothesis that the coefficient of log of price is one and that of employment or labour force or unemployment rate is zero. *** denotes rejection at 1% level, ** at 5% level and * rejection at 10% level respectively.*

Table 7: Pooled SUR Estimates of the Dynamic System (1)-(4) with 2 lags

Parameter	Panel Estimates (Std Errors)	State Equality Test	Parameter	Panel Estimates (Std Errors)	State Equality Test
Wages (1)			*Prices (2)*		
c1	0.004(0.005)		*c2*	0.001(0.001)	#
ec11	-0.205(0.067)***	#	*ec21*	0.019(0.015)	
ec12	-0.007(0.014)		*ec22*	-0.009(0.003)***	###
w11	0.061(0.080)	###	*w21*	0.070(0.021)***	###
w12	0.175(0.049)***		*w22*	0.027(0.025)	
p11	-0.052(0.287)	###	*p21*	0.296(0.082)***	#
p12	0.973(0.266)***		*p22*	0.463(0.058)***	###
em11	-0.031(0.139)	###	*em21*	-0.002(0.065)	
em12	-0.029(0.124)		*em22*	-0.165(0.087)*	##
lf11	0.055(0.152)	###	*lf21*	0.005(0.076)	##
lf12	0.053(0.137)	##	*lf22*	0.112(0.077)	###
tot11	-0.019(0.061)	##	*tot21*	0.017(0.027)	
tot12	0.056(0.062)	#	*tot22*	0.074(0.030)**	#
op11	-0.002(0.008)	##	*op21*	0.010(0.003)***	###
op12	-0.012(0.007)*	###	*op22*	-0.006(0.002)***	###
Average R^2	0.43		*Average R^2*	0.66	
Employment (3)			*Labour Force (4)*		
c3	0.005(0.001)***		*c4*	-0.005(0.001)***	###
ec31	0.021(0.025)	##	*ec41*	-0.003(0.014)	
ec32	0.003(0.005)	###	*ec42*	-0.001(0.003)	###
w31	-0.066(0.027)**	##	*w41*	-0.073(0.019)***	###
w32	-0.091(0.027)***		*w42*	-0.054(0.023)**	
p31	0.122(0.053)**		*p41*	0.250(0.045)***	###
p32	0.104(0.065)		*p42*	0.099(0.040)**	###
em31	0.206(0.057)***	##	*em41*	0.189(0.044)***	
em32	0.071(0.070)	###	*em42*	0.051(0.047)	###
lf31	-0.189(0.065)***		*lf41*	-0.210(0.041)***	
lf32	-0.105(0.073)	###	*lf42*	-0.140(0.059)**	###
tot31	-0.017(0.030)		*tot41*	-0.070(0.028)**	#
tot32	0.044(0.025)*		*tot42*	0.033(0.022)	
op31	-0.002(0.003)		*op41*	0.000(0.002)	##
op32	-0.009(0.005)**	###	*op42*	-0.016(0.004)***	###
Average R^2	0.18		*Average R^2*	0.34	
	H_0:All 2nd lag parameters=0 : $\chi^2(24)$	*=627****			

*Note: The significance of the test statistic for a null hypothesis of zero for parameters is shown as * at the 10% level, ** at 5%, and *** at 1%.*

#, ## and ### indicate significance at the 10%, 5%, and 1% levels respectively of evidence against the hypothesis that a parameter is equal across states in panel model estimations.

Table 8: Estimates of the Unrestricted Aggregate SUR System (1)-(4) with 2 lags

Parameter	Panel Estimates (Std Errors)	State Equality Test	Parameter	Panel Estimates (Std Errors)	State Equality Test
Wages (1)			*Prices (2)*		
c1	-0.006(0.006)	-	*c2*	-0.002(0.002)	-
ec11	-0.236(0.077)***	@@@	*ec21*	0.047(0.023)**	
ec12	-0.006(0.000)	@@@	*ec22*	0.004(0.005)	
w11	0.073(0.109)		*w21*	0.013(0.032)	
w12	0.186(0.093)**	@@	*w22*	0.065(0.027)**	@@@
p11	0.095(0.406)		*p21*	0.424(0.100)***	
p12	0.822(0.280)***	@	*p22*	0.355(0.081)***	@@@
em11	0.328(0.322)	@@@	*em21*	-0.074(0.140)	@@@
em12	0.500(0.393)		*em22*	0.176(0.141)	
lf11	-0.006(0.366)	@@@	*lf21*	-0.010(0.130)	@@@
lf12	-0.299(0.406)		*lf22*	0.015(0.156)	
tot11	-0.041(0.068)	-	*tot21*	0.039(0.031)	-
tot12	0.006(0.072)	-	*tot22*	0.029(0.042)	-
op11	0.002(0.008)	-	*op21*	0.011(0.004)***	-
op12	-0.005(0.008)	-	*op22*	-0.006(0.004)	-
R^2	0.70		R^2	0.72	
Employment (3)			*Labour Force (4)*		
C3	0.005(0.002)**	-	*c4*	-0.001(0.002)	-
ec31	0.020(0.019)	@@@	*ec41*	0.000(0.000)	
ec32	0.011(0.005)**	@@@	*ec42*	-0.001(0.004)	@
w31	-0.082(0.038)**		*w41*	-0.091(0.038)**	
w32	-0.006(0.034)	@@@	*w42*	-0.008(0.030)	@@
p31	0.145(0.091)	@@@	*p41*	0.218(0.091)**	@@@
p32	0.074(0.080)		*p42*	0.010(0.079)	@
em31	0.505(0.104)***	@@@	*em41*	0.423(0.129)***	@@@
em32	0.698(0.113)***	@@@	*em42*	0.307(0.108)***	@@@
lf31	-0.540(0.135)***	@@@	*lf41*	-0.544(0.164)***	@@
lf32	-0.841(0.117)***	@@@	*lf42*	-0.694(0.125)***	@
tot31	0.003(0.034)	-	*tot41*	-0.031(0.042)	-
tot32	0.012(0.029)	-	*tot42*	-0.004(0.034)	-
op31	-0.003(0.004)	-	*op41*	-0.001(0.004)	-
op32	-0.001(0.005)	-	*op42*	-0.004(0.003)	-
R^2	0.62		R^2	0.73	
	H_0: All 2nd lag parameters=0: $\chi^2(24)$=	*544****			

*Note: The significance of the test statistic for a null hypothesis of zero for parameters is shown as * at the 10% level, ** at 5%, and *** at 1%.*
@, @@ and @@@ indicate significance at the 10%, 5%, and 1% levels respectively of evidence against the hypothesis that a parameter is equal across states in aggregate model estimations

Table 9: Mean Group Estimates of the Dynamic System (1)-(4) with 2 lags

Parameter	Panel Estimates (Std Errors)	Parameter	Panel Estimates (Std Errors)
Wages (1)		*Prices (2)*	
c1	0.002(0.002)	*c2*	0.002(0.001)**
ec11	-0.227(0.009)***	*ec21*	0.047(0.006)***
ec12	0.006(0.002)***	*ec22*	0.000(0.001)
w11	-0.051(0.041)	*w21*	0.020(0.007)***
w12	0.214(0.049)***	*w22*	0.073(0.014)***
p11	0.381(0.113)***	*p21*	0.361(0.020)***
p12	0.594(0.093)***	*p22*	0.319(0.019)***
em11	0.312(0.075)***	*em21*	-0.073(0.051)
em12	0.413(0.166)**	*em22*	0.146(0.052)***
lf11	-0.006(0.093)	*lf21*	0.047(0.046)
lf12	-0.276(0.220)	*lf22*	-0.105(0.059)*
tot11	0.056(0.033)*	*tot21*	0.034(0.008)***
tot12	-0.057(0.027)**	*tot22*	0.067(0.011)***
op11	0.014(0.006)***	*op21*	0.012(0.001)***
op12	0.013(0.005)***	*op22*	0.001(0.002)
Average R^2	0.70	*Average* R^2	0.64
Employment (3)		*Labour Force (4)*	
c3	0.003(0.003)	*c4*	-0.003(0.001)*
ec31	0.004(0.011)	*ec41*	0.000(0.000)
ec32	0.009(0.003)***	*ec42*	-0.004(0.003)*
w31	-0.051(0.012)***	*w41*	-0.066(0.019)***
w32	-0.013(0.023)	*w42*	0.000(0.022)
p31	0.083(0.088)	*p41*	0.142(0.071)**
p32	0.108(0.093)	*p42*	0.125(0.080)
em31	0.238(0.061)***	*em41*	0.242(0.088)***
em32	0.417(0.079)***	*em42*	0.253(0.039)***
lf31	-0.305(0.071)***	*lf41*	-0.399(0.090)***
lf32	-0.597(0.087)***	*lf42*	-0.569(0.057)***
tot31	0.003(0.014)	*tot41*	-0.012(0.011)
tot32	0.023(0.011)**	*tot42*	-0.004(0.010)
op31	-0.002(0.002)	*op41*	-0.000(0.003)
op32	0.001(0.009)	*op42*	0.000(0.008)
Average R^2	0.42	*Average* R^2	0.56
	H_0:All 2nd lag parameters=0 : Average $\chi^2(24)$ =	*347****	

*Note: The significance of the test statistic for a null hypothesis of zero for parameters is shown as * at the 10% level, ** at 5%, and *** at 1%.*

FIGURE 1

Deviations from National AggregateWages

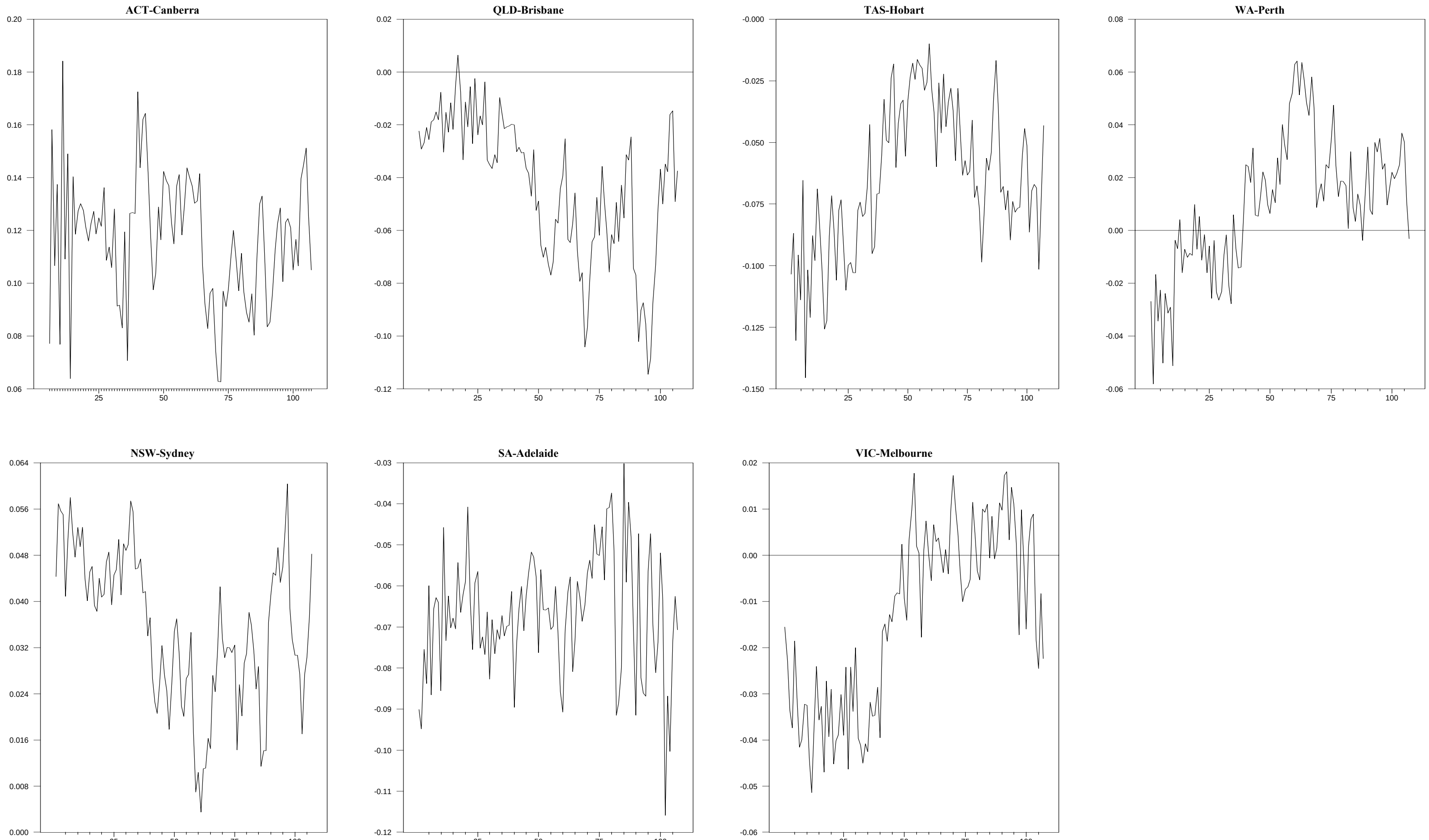


FIGURE 2

Deviations from National AggregatePrices

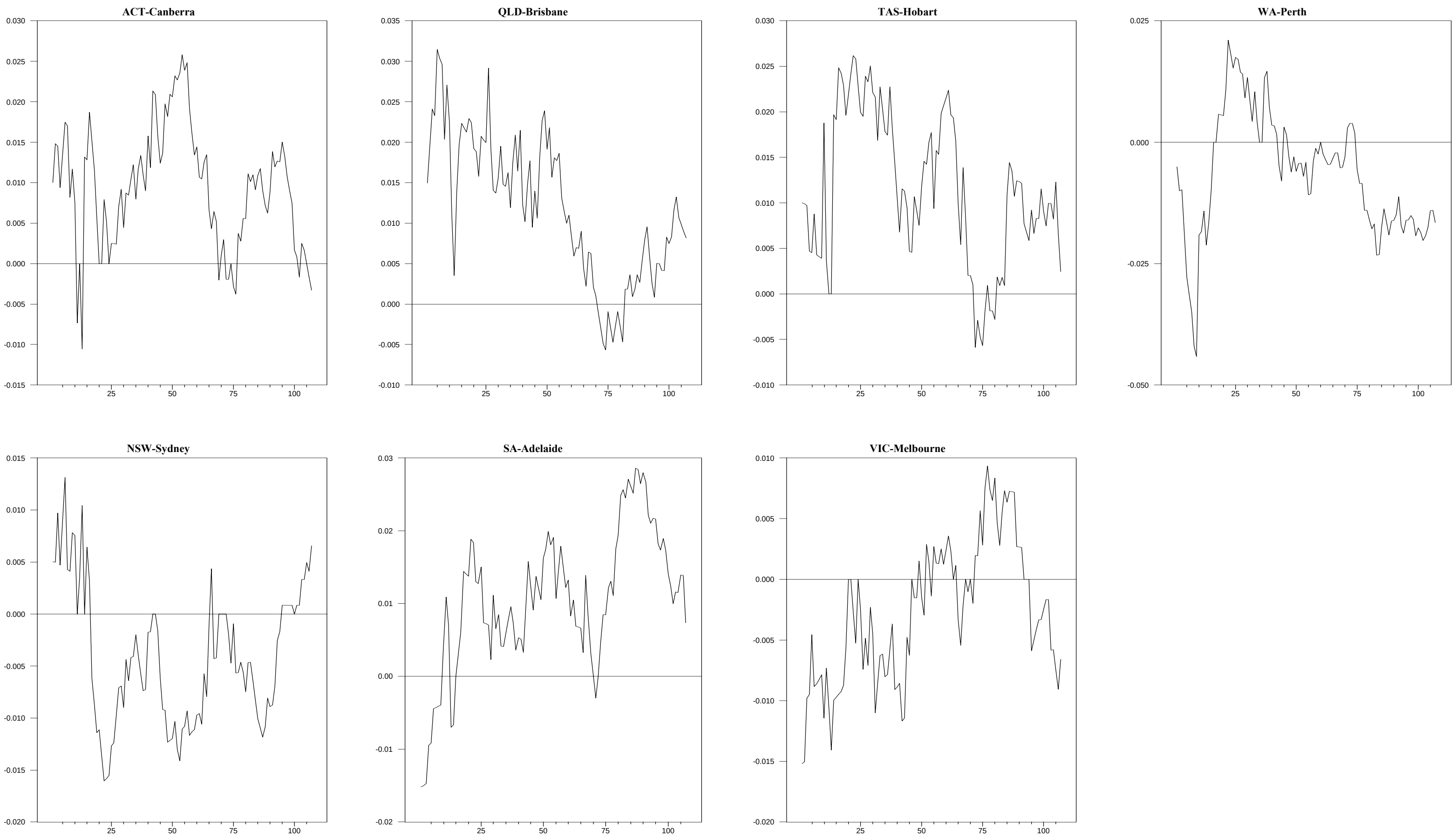


FIGURE 3

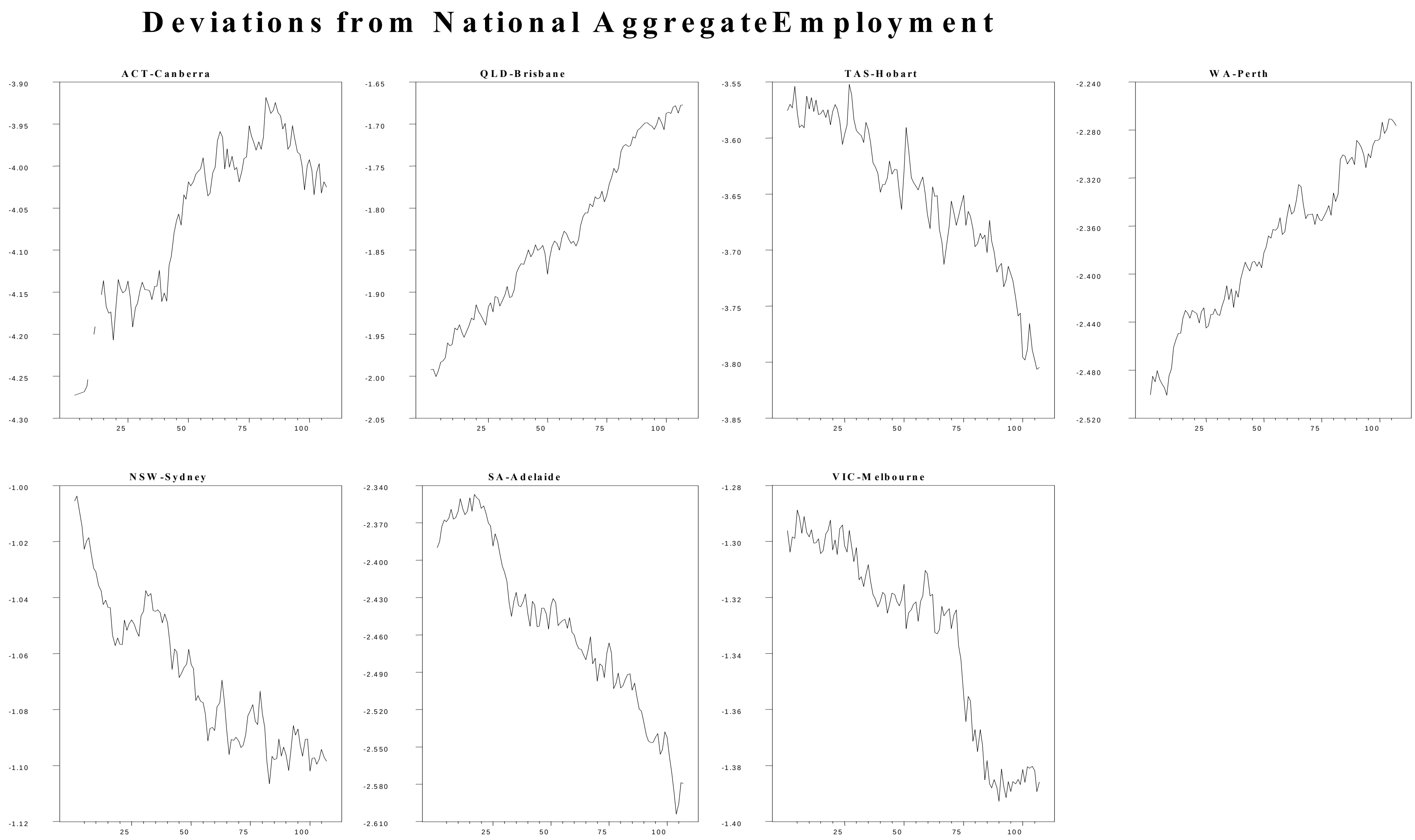

Deviations from National Aggregate Employment
ACT-Canberra
QLD-Brisbane
TAS-Hobart
WA-Perth
NSW-Sydney
SA-Adelaide
VIC-Melbourne

FIGURE 4

Deviations from National AggregateLabourForce

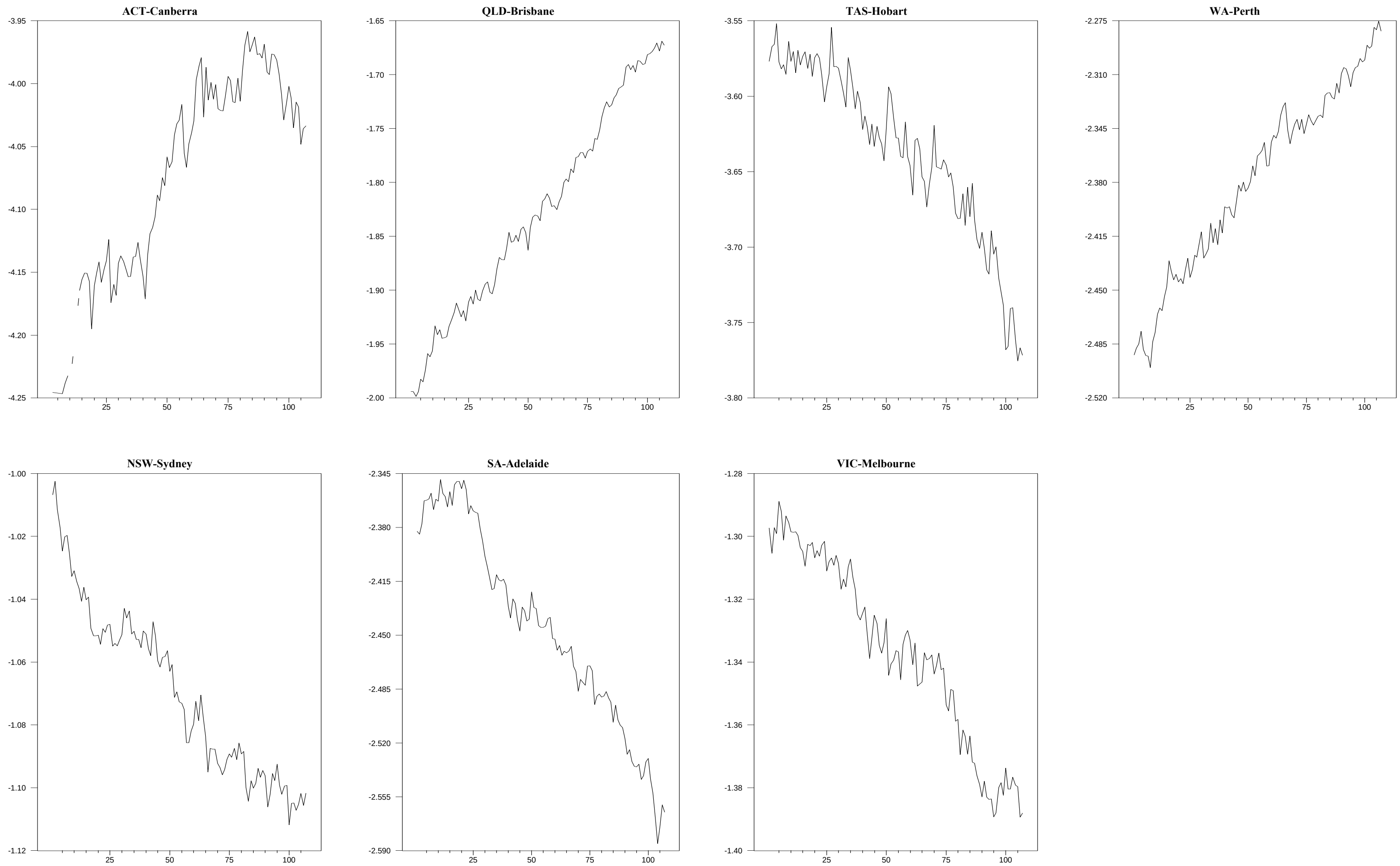
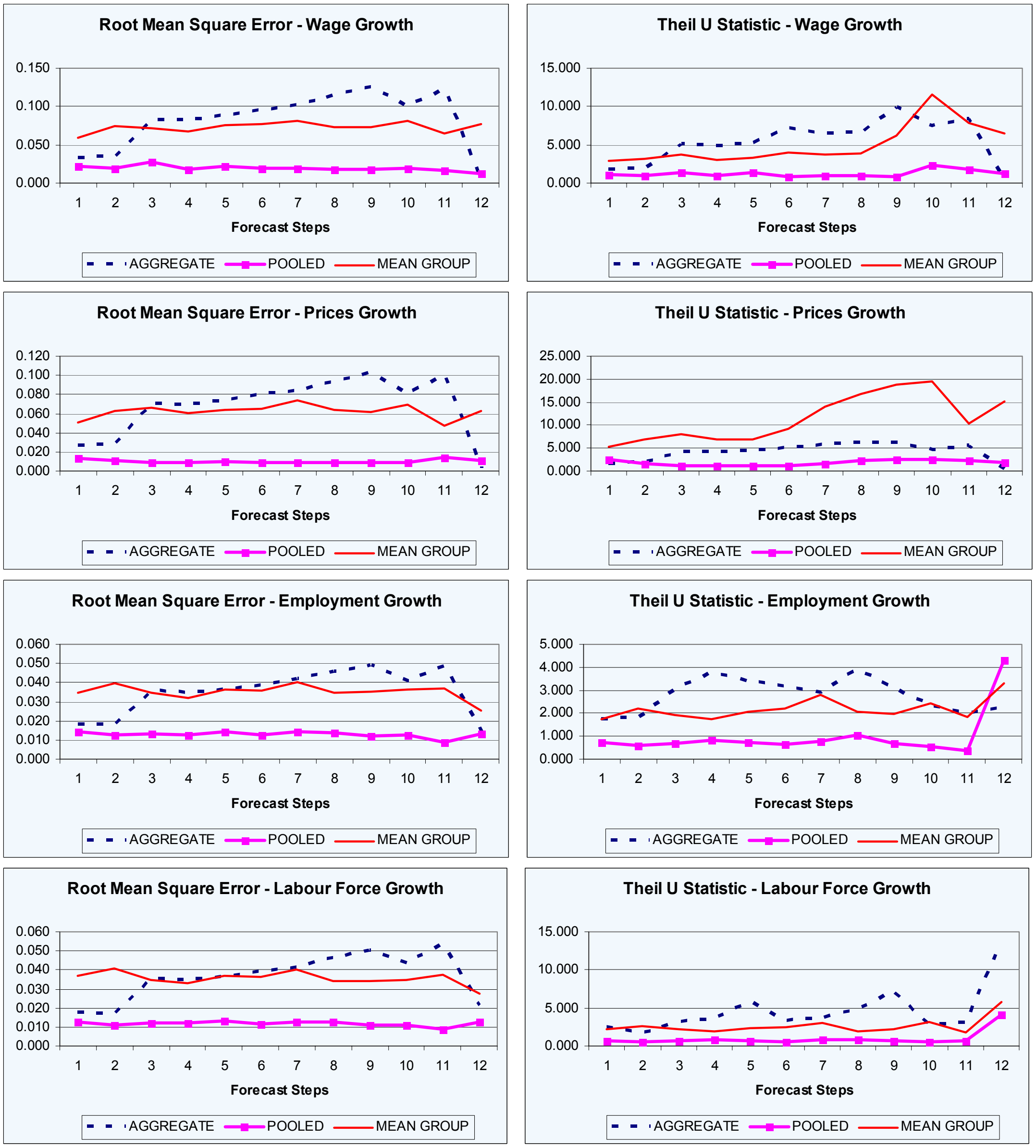


FIGURE 5

Comparing Aggregate Forecast Performances

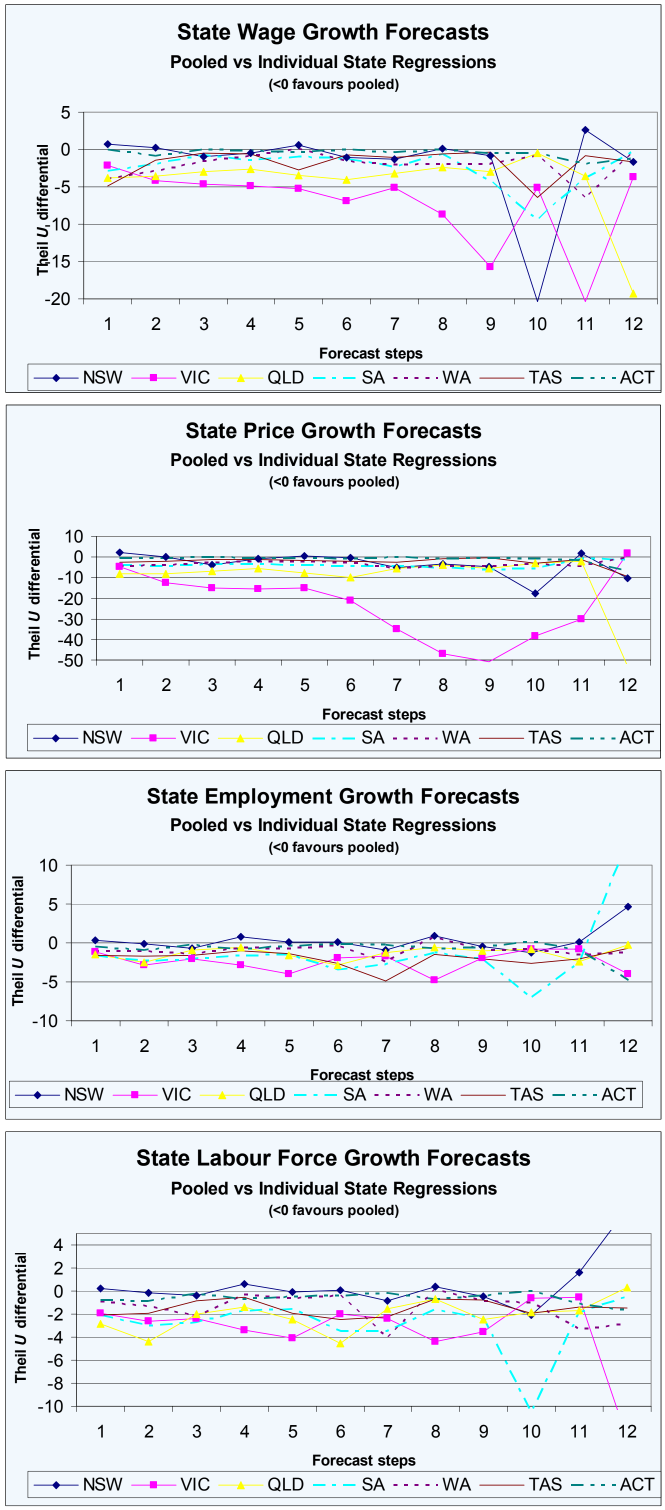
of the Aggregate, Pooled and Mean Group Procedures



Note: The 3 models are first estimated from 1972:3-1996:1, and 1 to 12 quarter step forecasts produced. Then they are re-estimated with one more observation and one less step forecast, until the end of the sample, 1999:1, is reached. The root mean square and Theil statistics are based on the averages available for each step across all the forecasts for a model. Therefore the 12 step forecast statistics are based on only 1 observation while the 1 step statistics are based on 12 observations. The Theil U statistic is a unit-free measure which compares the model forecasts with a no-change forecast, and so a value less than 1 is preferred.

FIGURE 6

Comparing State Forecast Performances of the Pooled and Individual State Procedures



Note: Figure 5. The Theil U differential is the difference between the Theil U statistics for step forecasts of state variables from the pooled procedure and separate state regressions. If the differential is less than 0, the pooled procedure is preferred..