REGIONAL VARIATION IN QUEENSLAND'S UNEMPLOYMENT RATE

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ABSTRACT: This paper provides an analysis of the variation in Queensland regional unemployment rates. This is done using data from the 1996 Census of Population and Housing. A preliminary analysis suggests that the spatial variation in the unemployment rate has exhibited a high degree of stability and that this variation is not randomly allocated over geographic space. The econometric investigation seeks to explain the underlying variables responsible for this variation. This analysis employs spatial econometric techniques in an attempt to determine the significance of various economic and demographic factors in determining differences in regional unemployment rates. It is suggested that these techniques are more appropriate in cases where there is a possibility that variables may be related through geographic proximity, as is generally the case with studies based on regional data.

1. INTRODUCTION

Observed disparities or differentials in unemployment rates are a well documented phenomenon with a relatively large body of literature, following Thirlwall (1966), discussing the nature of these. Marston (1985) notes that, broadly speaking, there are two explanations of these disparities, these being the equilibrium and disequilibrium explanation. The equilibrium explanation of regional unemployment differentials assumes that labour mobility is relatively free between areas. In this situation, excess labour in the area will vanish quickly unless workers are compensated in some way that induces them to stay voluntarily. For this reason, any persistent geographic unemployment differentials are not evidence of uneven labour demand, but reflections of workers underlying preferences for certain areas. In contrast, in the disequilibrium explanation, economic and social barriers may separate local labour markets. If these barriers restrict mobility severely, then weak labour demand in one geographic area will raise the unemployment rate above the level in areas with strong labour demand.

These radically different explanations purport to account for unemployment differentials between areas. Additionally, Trendle (2001) notes that public policies based on either one of these explanations will contradict polices based on the other. In the disequilibrium explanation, for example, there is a role for regionally targeted policy. Armstrong and Taylor (1993) presume that regional unemployment disparities in Britain are the result of slow adjustment processes; in this case regionally targeted employment programs can have a long term or permanent effect. However, in the case where disparities are the result of equilibrium factors, there is no role for regionally targeted employment programs. In the case of the equilibrium explanation, Marston (1985) notes that economic disturbances or shocks may move actual regional differentials away from their mean values, but such disequilibrium movements are short lived, and regional differentials will converge back to their equilibrium means. In this case, regionally targeted programs will merely attract more workers into an area, until the initial unemployment differentials reappear.

The aim of this paper is to determine the factors that contribute to these observed disparities in regional unemployment rates. The starting point for this analysis is data available from the 1996 Census of Population and Housing. Regional data from the Community Profile component of this database provides the core of the analysis. This database includes a time series component for the 1986, 1991 and 1996 censuses based on the place of enumeration, along with a collection for 1996 based on the place of usual residence, with this latter dataset forming the basis of the econometric analysis. However, some preliminary work, in particular a descriptive analysis of the regional data, is presented in section 3 using the time series collection. While this data is not ideal, it provides a useful starting place for the analysis of regional unemployment disparities as it allows a comparison of regional unemployment by Queensland Local Government Areas (LGA's) over three successive censuses.

Section 2 provides a brief introduction to spatial econometrics, the technique used in this study. This is followed in Section 3 with a preliminary investigation of the data. Section 4 provides an explanation of the variables likely to influence regional unemployment rates. This section summarises some of the literature on regional unemployment disparities noting the variables thought responsible for these disparities. This is followed in Section 5 by the results of the estimation of a relationship between regional unemployment and the explanatory variables. A brief conclusion is provided in Section 6.

2. AN INTRODUCTION TO SPATIAL ECONOMETRIC ANALYSIS

Studies incorporating the use of small area data in cross sectional analysis are something of a rarity in Australia with a notable exception being Lawson and Dwyer (2002) which looked at regional labour market adjustment. In the international literature there are numerous studies that have attempted to explain disparities in regional unemployment rates using cross section data. These include Metcalf (1975), Marston (1985), Partridge and Rickman (1995 and 1997), Malizia and Shanzi Ke (1993) and Molho (1995).

All but the last of these employed standard regression techniques, while Mohlo (1995) on the other hand, employs techniques from the developing field of spatial econometrics. These techniques are ideally suited to the study of regional data and are employed in this study. The importance of taking these effects into account was reviewed extensively by Anselin (1988a) and since then a growing literature attests to the importance of the problem and the consequences of errors in misspecification that can occur if spatial issues are ignored in cross sectional data analysis involving geographical units.

The field of spatial econometrics has developed only relatively recently with one of the early contributors being Cliff and Ord (1973) where the idea of spatial autocorrelation was introduced. Positive spatial autocorrelation occurs when similar values for a variable are clustered together in space while negative autocorrelation appears when dissimilar values are clustered in space. Lesage (1997) notes that OLS estimators are biased and inconsistent in sample data that contains spatial dependence. Spatial autocorrelation also implies the absence of independence among observations in cross-sectional data and can be taken to mean the existence of a functional relationship between what happens at one point and elsewhere.

Magalhaes *et al.* (2000) suggest that the problem may originate as a measurement problem stemming from the fact that the data has been divided into artificial spatial units that do not coincide with the real spatial dimension of the phenomenon, or alternately, spatial autocorrelation can originate as a result of a true spatial interaction among the variables. There may also be problems that stem from the lack of homogeneity of the spatial units themselves. Different units (i.e. cities, rural regions, etc) have different shapes, densities and sizes which can generate measurement errors that can cause heteroscedasticity, or in the case of spatial econometrics, spatial heterogeneity. Anselin and Rey (1997) and Magalhaes *et al*. (2000) note that it is not easy to differentiate between spatial autocorrelation and spatial heterogeneity. They suggest that in a cross sectional setting, the two effects might be equivalent. Generally speaking, whatever the source of the spatial error process, it is dealt with in the same way i.e., the explicit inclusion of space in the estimated equation.

In spatial econometrics the notion of space is introduced into the estimation process through the spatial weight matrix. This matrix, usually denoted *W*, is used to capture the adjacency patterns of regional units. In the simplest case, a symmetric matrix is defined by having the element *(i*, *j*) set equal to 1 if *i* and *j* are neighbours and 0 otherwise. By convention, the diagonal elements are set to zero, $w_i = 0$. Before use in estimation the weight matrix is standardised, denoted by the superscript *s*, with each of the non-zero elements being defined as $w_{ij}^s = w_{ij} / \Sigma_j w_{ij}$. In this matrix, the elements of the rows sum to one. Besides facilitating the interpretation of the weights as an averaging of neighbouring values, this manipulation ensures the comparability between models of the spatial parameters in many spatial stochastic processes (Anselin and Bera, 1998). There are other more complex specifications of weight matrices based, for instance, on the inverse of distance from a capital city or on economic variables such as known trade flows.

Magalhaes *et al.* (2000) note that the main reason for the use of the spatial weight matrix is to associate a variable, at one point in space, to the observation of the variable in other spatial locations. In contrast to time series, where the relation in time can be expressed by the simple notion of a lag operator *L*, where $L^s y = y_{t-s}$ shifts y_t, *s* periods back in time, in space the problem becomes more complicated. The additional complication stems from the fact that there are many possible directions over which the spatial shift operator can be applied. One solution that has been offered to this problem is the use of the concept of a spatial lag operator L^s. The idea is to use a weighted sum of the values of neighbouring units. In matrix notation this can be written as:

$$L^s y = W^s y \tag{1}$$

It is also possible to define higher order spatial lag operators. By multiplying W by Wy is equivalent to generating W^2y, a second order spatial lag.

The lack of a unique procedure to select a weight matrix has generated alternative approaches to address the problems caused by the misspecification of such a matrix. Griffith (1996) notes that the statistical qualities of the maximum likelihood estimators are affected by misspecification problems, creating problems for spatial statistical analysis. The same author provides some general guidelines that can be applied when specifying a weight matrix. In particular, Griffith (1996) considers it better to posit some reasonable geographic weight matrix than to assume all entries are zero, i.e., ignoring spatial dependence is not the best alternative. In addition, the same author also suggested that a simple specification, such as a first order contiguity matrix is, in many situations, to be preferred to more complicated spatial structures, such as distance decay.

A number of alternative frameworks exist for dealing with the problem of spatial autocorrelation. The most comprehensive framework is the general spatial model, shown in Equation (2);

$$\begin{gathered} y = \rho W_1 y + X\beta + \mu \\ \mu = \lambda W_2 \mu + \varepsilon \\ \varepsilon \approx N(0, \sigma^2 I_n) \end{gathered} \tag{2}$$

Where y contains a vector of cross sectional dependent variables and X represents an $n \times k$ matrix of explanatory variables. W_1 and W_2 are known $n \times n$ spatial weights matrices, usually containing contiguity relations or functions of distance.

From this general model the imposition of restrictions can be used to derive additional models. For example, setting W_2 = 0 in Equation (2) produces a spatial autoregressive model shown in Equation (3). This model is analogous to the lagged dependent variable model in time series. Here we have an additional explanatory variable in the X matrix to explain variation in y over the spatial sample of observations.

$$\begin{gathered} y = \rho W_1 y + X\beta + \varepsilon \\ \varepsilon \approx N(0, \sigma^2 I_n) \end{gathered} \tag{3}$$

Letting W_1 = 0 from Equation (2) results in a regression model with spatial autocorrelation in the disturbances as shown in Equation (4). This model is generally known as the spatial error model.

$$\begin{gathered} y = X\beta + \mu \\ \mu = \lambda W_2 \mu + \varepsilon \\ \varepsilon \approx N(0, \sigma^2, I_n) \end{gathered} \tag{4}$$

The spatial autoregressive model shown in Equation (3) is clearly related to a distributed lag interpretation, in that the lagged dependent variable, *Wy*, can be seen as equivalent to the sum of a power series of lagged dependent variables stepping out across a map, with the impact spillovers declining with successively higher powers of ρ. This may be termed a structural autoregressive relationship, and one would expect it to be based on economic processes. In contrast, the spatial error model presupposes a shared spatial process affecting all of the variables, and is more often interpreted as indicating missing variables.

A recent line of research in the analysis of spatial data has focussed on how to establish the characteristics of the dependence between observations, whether dependence can be demonstrated and how it ought to be represented. One of the earliest tests for spatial autocorrelation of the residuals of a regression relationship was the Moran *I* statistic presented in Cliff and Ord (1973), this tests takes the form:

$$I = \frac{e'W_1 e}{e'e} \tag{5}$$

where e is a $n \times 1$ vector of regression residuals from the OLS estimation of an equation. Inference for this test is carried out on the basis of an asymptotically normal standardized *z*-value, obtained from subtracting the expected value and dividing by the standard deviation.

Anselin *et al.* (1996) note that while the Moran *I* statistic is a very powerful test it does not provide any information about the nature of the spatial relationship. This has lead to the development of new tests, these being the Lagrange Multiplier spatial error and lag tests and robust versions of these tests.

The Lagrange Multiplier spatial error test (LM-ERR) was developed by Burridge (1980). This test has the form:

$$LM - ERR = \frac{\left(e'W_1 e / s^2\right)^2}{T_1} \tag{6}$$

where $s^2 = e'e/n$, and $T_1 - tr(W_1^{'}W_1 + W_1^2)$, with *tr* as the matrix trace operator. This statistic is distributed as χ^2 with one degree of freedom.

The robust version of the spatial error tests (RLM-ERR) owes its origin to Bera and Yoon (1992). This test is robust to local misspecification in the form of a spatial lag term and is computed as:

$$RLM - ERR = \frac{\left(e'W_1 e / s^2 - T1(R\tilde{J}_{\rho-\beta})^{-1}(e'W_1 y / s^2\right)^2}{\left(T1 - T_1^2 (R\tilde{J}_{\rho-\beta})^{-1}\right)} \tag{7}$$

with:

$$(R\tilde{J}_{\rho-\beta})^{-1} = \left[T_1 + (W_1 X\beta)' M (W_1 X\beta)\right] \tag{8}$$

where $W_1X\beta$ is a spatial lag of the predicted values from the initial OLS regression and $M = I - (X(X'X)^{-1}X$ is the projection matrix. Just as with the LM-ERR this statistic is distributed as χ^2 with 1 degree of freedom.

The Lagrange Multiplier test for spatial lag dependence (LM-LAG) is due to Anselin (1988b). This test statistic is derived as;

$$LM - LAG = \frac{(e'W_1 y / s^2)}{(R\tilde{J}_{\rho-\beta})} \tag{9}$$

again, this statistic is distributed as χ^2 with 1 degree of freedom.

The robust version of this test (RLM-LAG) is the counterpart of the robust version of the spatial error test and again owes its development to Bera and Yoon (1992). This test allows for the testing of spatial lag dependence robust to local misspecification in the form of a spatial moving average process and is defined as:

$$RLM - LAG = \frac{(e'W_1 y / s^2 - e'W_1 e / s^2)^2}{(R\tilde{J}_{\rho-\beta} - T_1)} \tag{10}$$

with the statistic again distributed as χ^2 with 1 degree of freedom.

These tests allow the researcher to determine the appropriate way in which to incorporate spatial dependence into the estimated relationship. Anselin, Florax and Yoon (1996) conduct Monte Carlo experiments on these tests and conclude that they have good power for detecting spatial dependence and also provide insight into the way this spatial dependence should be modelled. This is an important consideration, as Anselin (2001) demonstrates. Some forms of spatial interaction such as that represented by a spatial autoregressive model imply that changes or shocks to the model in one region have a global effect or will, in our case alter all regional unemployment rates with the amount of the effect being inversely related to the distance from the region receiving the initial impact. On the other hand, the spatial dependencies represented by the spatial error model have only local effects, flowing only to immediate neighbours.

3. UNEMPLOYMENT DSPARITIES IN QUEENSLAND – A DESCRIPTIVE ANALYSIS

The starting point for this analysis is the small area data from the 1996 Census of Population and Housing, and in particular the Community Profiles component of this database. This database includes a time series component, incorporating small area data from the 1986, 1991 and 1996 censuses. Ideally, data collected on a usual residence basis would be desirable. Unfortunately, the time series data refers to the place of enumeration, or place staying on the night of the census, while not ideal, this provides a useful starting place for the analysis of regional unemployment disparities.

Table 1. Descriptive statistics: Regional Unemployment Rates, 1986 to 1996.

	1986	**1991**	**1996**
Average UE rate	10.10	9.96	8.47
Highest	24.03	28.59	23.56
Lowest	0.00	2.57	1.04
Range	24.03	26.03	22.52
Sample SE	4.80	4.83	4.57
Correlation		0.75	0.72
Speamans rank correlation stability		-8.64	-8.11

Table 1 provides summary statistics for the regional unemployment rates of Queensland over the period 1986 to 1996. This table shows that the average unemployment rate has decreased over the ten year period from 10.1% in 1986 to 8.5% in 1996, a decrease of 1.6 percentage points. The range of unemployment rates has also decreased marginally from 24.0% in 1986 to 22.5% in 1996.

This small decrease in both the average and the range of unemployment rates has been accompanied by a high level of stability in the correlation of regional unemployment rates, with both the correlation coefficients and the Spearman's test of rank order stability being significant for unemployment rates between each census period[1]. This suggests that regions have retained their relative ranking, with high unemployment rate regions remaining high unemployment rate regions over the period while regions with relatively low unemployment rates have retained their status as low unemployment rate regions. This suggests a high degree of persistence in the observed unemployment structure.

An alternate perspective on regional unemployment is provided by the Moran scatter plots provided in Figure 1. These figures plot each LGA's difference from the average unemployment rate against their spatial lag, i.e., a weighted average of the unemployment rates of neighbouring regions. The four different quadrants of the Moran scatter plot identify four types of spatial association between a LGA and its neighbours: quadrant 1 shows low unemployment rate LGA's surrounded by high unemployment rate neighbours; In quadrant 2 high unemployment LGA's with high unemployment neighbours appear; quadrant 3 records low unemployment rate LGA's surrounded by low unemployment rate neighbours while quadrant 4 shows high unemployment rate LGA's with low unemployment rate neighbours.

Concentrations of observations in the top right hand corner and bottom left hand corner indicate that regions with high unemployment rates tend to be adjacent to regions with high unemployment rates and regions with low unemployment rates are likewise clustered together in space. The trend line through the scatter diagrams suggests that this spatial clustering of regions

[1] These correlation coefficients refer to the regional unemployment rate for the year referred to by the specific column's correlation to the 1986 regional unemployment.

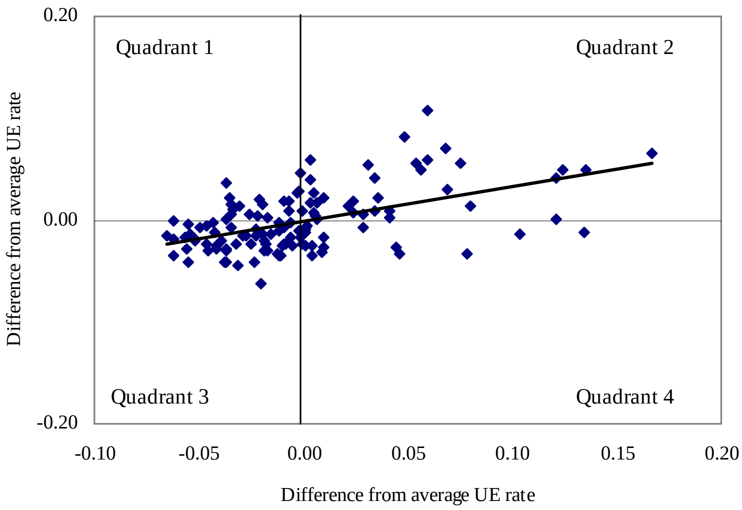

Figure 1. Moran Scatterplot – Regional Unemployment Rates.

Table 2. Moran I Tests for Spatial Autocorrelation.

Test	Moran *I*
Value	6.1593
Marginal probability	0.0000

sharing similar unemployment rates is significant, or that variations in regional unemployment do not occur randomly over Queensland's geographic space. This conclusion is confirmed by the test results shown in Table 2 where the results of the application of the Moran *I* test are presented.

In this case, the Moran *I*-statistic takes the form;

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{11}$$

The Moran *I* statistic is tested using analytical expectations and variances based largely on the neighbourhood structure assumed in the spatial weighting matrix and are asymptotically distributed. The significance of the Moran *I* statistic is assessed by a standardized *z*-score that follows a normal distribution and is computed by subtracting the theoretical mean from *I* and dividing the remainder by the standard deviation.

4. A MODEL OF LOCAL UNEMPLOYMENT

As noted in Section 2 there have been many cross sectional studies attempting to determine the variables responsible for the variation in regional unemployment rates. The variables that have been found significant in explaining regional variation in unemployment rates can be classified into three categories, these being; industry or product market variables, demographic variables and regional factor endowments.

4.1 Industry Variables

A number of industry variables have been found to be significant in explaining differences in regional unemployment rates. These variables include the regional industry structure, in particular the extent of industrial concentration within the regional economy and shares of employment within particular industries within the regional economy. There are a number of ways in which industrial concentration can be measured; Malazia and Shanzi Ke (1993) for example, use the Entropy index of industrial concentration while Partridge and Rickman (1995) incorporate the Herfindahl index of industrial concentration.

Generally it is considered that regions with a higher measured industrial concentration are likely to have higher unemployment rates than industrially diverse regions. Malazia and Shanzi Ke (1993) suggest that regions with greater diversity are more likely to be able to absorb adverse economic shocks and so, all things being equal, should have a lower unemployment rate than the more industrially concentrated regions. In this study, the variable HERFINDAHL, being the Herfindahl index of industrial concentration has been incorporated to determine if regional variation in employment concentration across industries has influenced the rate of unemployment experienced in regions. This index has been calculated for all regions using the first division Australian New Zealand Standard Industry Classification (ANZSIC) data provided in the CPROFILE database. This data provides a disaggregation of 17 industry categories.

Employment concentrations in particular sectors of the economy have also been found to have a significant influence on variations in the regional unemployment rate. Different industries may be at different stages of their economic cycle, thus, regional unemployment rates may vary because of the variations in the economic bases of the regions. In this study this is controlled for through the inclusion of variables capturing the shares of employment in various sectors of the economy. The variables included to capture the effect of the variation in regional economic bases consisted of; the percentage of the labour force employed in agriculture (PERAGR), in addition to the percentage of the non-agricultural labour force employed in manufacturing (PERMAN), the percentage of the non-agricultural labour force employed in services excluding Public administration and defence and Electricity, gas and water (PERSER) and the percentage of the non-agricultural labour force employed in mining (PERMIN). In the final model, PERSER and PERMIN were excluded on the basis that they were insignificant in all preliminary equations.

Differences in regional incomes are also thought to be significant in explaining regional variations in unemployment rates. Partridge and Rickman (1995) note that the association between wages and unemployment may be ambiguous. For example, these authors note that there may be a hedonic wage-unemployment tradeoff or there may be wait unemployment where workers queue for high wage jobs. In this study the natural log of average regional income is incorporated (LINCOME). Data to construct this variable is available from the Australian Taxation Office and following Mohlo (1995) it relates to the preceding year in order to avoid problems of endogeneity associated with using the income variable available in the CPROFILE dataset.

A final group of variables that may influence regional unemployment rates that fall into this category relate to the growth of the regional economy. The growth of the regional labour market will act to reduce unemployment, it may also attract additional labour into the region so that the final effect on the regional unemployment rate is not clear. In this study two variables are incorporated, these being the regional labour market growth rate over the intercensal period 1991-96 (GROWTH) and the average rate of growth of neighbouring regions (WGROWTH) derived by multiplying GROWTH by the row standardized spatial weight matrix (*W*).

4.2 Demographic Variables

A number of demographic variables have also been found to be significant in explaining differences in regional unemployment rates. These variables include the education levels of the population in a region, the proportion of the labour force comprised of females and the proportion of migrants, especially from non-English speaking backgrounds. In this study the percentage of the population with bachelor degrees or above (PERBACH) and the proportion of the labour force made up by females (PERFEM) are included. Initially, attempts were made to incorporate variables that measured the extent of migration into regions, from both interstate and overseas, but in all cases these variables were found to be insignificant.

In U.S. studies (see, for example, Malazia and Shanzi Ke 1993, and Partridge and Rickman 1995, and 1997), the proportion of the population of African origin is also found to be a significant determinant of differences in regional unemployment rates. In this study the proportion of the population of indigenous origin (PERIND) is included, it is likely that indigenous Australians have a more difficult time finding work, consequently the unemployment rate for this demographic group is likely to be higher. For this reason, it might be expected that regions with a high proportion of the population from an indigenous background would have a higher unemployment rate.

Other studies have incorporated variables to measure the shares of the labour force made up by different age groups into the analysis of regional variation in unemployment. For example, Metcalfe (1975) notes that young and old workers experience different patterns of unemployment to prime age workers. Regions with different age distributions of the labour force will, for this reason, experience different rates of unemployment. If workers of certain age groups are more or less likely to leave high unemployment regions than other groups this may result in a strong statistical relationship between the proportion of the labour force comprised of these age cohorts and the unemployment rate. In this analysis two age variables were tested, these being the proportion in the 15 to 24 age cohort (PERYNG) and the proportion in the 54+ age cohort (PEROLD).

4.3 Regional Factor Endowments

In addition to economic and demographic variables, a number of region specific variables are thought to influence the unemployment rate. These are variables that influence the amenity value of regional economies. Marston (1985) notes that differences in the amenity value of a region are thought to make a region a more or less desirable place to live. Consequently, it is suggested that persons may be prepared to live in certain regions that have a relatively high level of these amenities and accept a higher risk of remaining or becoming unemployed. Thus, higher levels of desirable regional amenities may be associated with higher unemployment rates. The particular variables that make up this category range from the climate of the region, through to house and land costs and the availability of education and health care facilities.

Some studies, including Partridge and Rickman (1995 and 1997) incorporate regional population to capture regional amenity values. These authors suggest that regions with larger populations may have amenity values due to access to more schools, entertainment, health care facilities etc. Additionally, it could be that a higher population has negative regional amenity values associated with increased congestion and pollution. In this study the natural logarithm of population (LPOP) is included in the estimated relationships. It is hypothesised by Partridge and Rickman (1995 and 1997) that, other things being equal, regions with a higher population will have a higher amenity value, thus it is expected that the coefficient of this variable will be negative as persons are prepared to accept higher rates of unemployment in return for greater local amenity values.

Additional variables that have been tested in this study to capture the effect of region specific amenities comprise the population density and a dummy variable for proximity to the coast. Both of these variables were tried in the initial stages of this study but found to be insignificant.

5. SPATIAL ECONOMETRIC ANALYSIS OF QUEENSLAND UNEMPLOYMENT

The use of variables to capture the effect of differences in regional economic, industrial and demographic characteristics in a purely cross section study may, as noted by Molho (1995), be considered equivalent to picking up the regional fixed-effects which appear in a pooled cross-section/time-series study. These fixed effects influence the underlying equilibrium pattern of employment rates that would be expected to exist in the absence of any demand shocks. For this reason, the modelling undertaken in this study could be seen as attempting to explain the equilibrium distribution of regional unemployment rates within Queensland.

The first stage in the process of determining the significance of spatial autocorrelation is to conduct a series of tests on the residuals of the OLS version of the model incorporating the variables discussed in section 4. A wide range of tests is available, including the Moran *I* statistic, Lagrange Multiplier (LM) error,

Table 3. Tests for Spatial Autocorrelation in the Residuals of the OLS Equation[2].

Test	**Moran *I***	**LM Error**	**LM Lag**	**RLM Error**	**RLM Lag**
Value	2.2324	3.0814	9.8770	1.8771	8.6726
Marginal Probability	0.0330	0.0792	0.0017	0.1707	0.0032

LM lag and robust versions of these latter two tests. The results of applying these tests to the residuals of the OLS equation are presented in Table 3.

The results of these five tests suggest that we can reject the hypothesis of spatial independence due to the small marginal probabilities for the Moran *I* test and the LM lag and robust form of the LM lag test, and conclude that the residuals from the OLS estimation exhibit spatial dependence, best represented by the spatial autoregressive model.

The Moran *I* test is perhaps the most commonly used specification test for spatial autocorrelation. Anselin *et al*. (1996) note that this test consistently outperforms other tests in terms of power in simulation results. A limitation of the test however, is that it provides no indication of whether the spatial autocorrelation present in the residuals is due to a true spatial process, best represented by a spatial autogressive model, or an error process, best represented by a spatial error model. On the other hand, the Lagrange Multiplier tests, especially the robust tests provide a means of discriminating between the spatial autoregressive or error model.

The strategy used in the model selection process in this study has been to estimate several versions of the models presented in Equations (2) through (4). These models included both spatially lagged dependent variables, spatially lagged error terms or both spatially lagged dependent variables and error terms. In addition, 1st and 2nd order spatial weight matrices were tried. All weights matrices used were based on the simple contiguity matrix, i.e., with the elements (i, j) of the 1st order matrix set to 1 if i and j are neighbours and 0 otherwise. It was found that, based on the value of the log-likelihood function and $\overline{R}^2$ the spatial autoregressive model seemed to be the most appropriate, performing marginally better on these criteria than competing models and confirming the results of the specification tests presented in Table 3. However, further tests of the residual of the spatial autoregressive model indicated that residual spatial autocorrelation existed. For this reason a spatial autoregressive model estimated using the 2nd order spatial weight matrix was selected as the final version of the model.

In the analysis of cross section data, heteroscedasticity is often a serious problem and Lesage (1997) notes that Bayesian estimation is well suited to spatial econometric problems, with a large Bayesian literature that deals with the problem of heteroscedastic disturbances. The same author also notes (see Lesagee, 1997 and 1999) that the presence of a few outliers in the data will produce a violation of the assumption of normality in small samples. This is the

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[2] A description of these tests can be found in Anselin 1988, p. 108.

type of problem that the heteroscedastic modelling approach of Geweke (1993) based on Gibbs sampling estimation is designed to address.

Gibbs sampling has greatly reduced the computational problems that plagued previous applications of the Bayesian methodology, with this technique providing a way to sample data from a multivariate probability density based only on the densities of subsets of vectors conditional on all others. Lesage (1997) suggests that this sampling method proves useful for Bayesian estimation of spatial autoregressive models, where data exhibit heterogeneity over space, or the spatial data sample is small and contains outlying observations. In these cases, the assumption of normality and the asymptotic arguments used to derive maximum likelihood estimates of the precision of the parameters are not met.

The form of the Bayesian spatial autoregressive model is presented in Equation (12).

$$\begin{gathered} y = \rho W_1 y + X\beta + \mu \\ \varepsilon \approx N(0, \sigma^2 I_n) \\ V = diag(v_1, v_2, \ldots. v_n) \\ \rho \sim N(c, T) \\ r / v_i \sim ID\chi^2(r)/r \\ r \sim \Gamma(m, k) \\ \sigma \sim \Gamma(v_0, d_0) \end{gathered} \tag{12}$$

Where *W* is a spatial contiguity matrix that has been standardised to have row sums of unity. *X* represents an $n \times k$ matrix of explanatory variables, while the ε are assumed to be normally distributed random variables that have a non-constant disturbance. This formulation allows for an informative prior on the spatial autoregressive parameter ρ, the heteroscedastic control parameter *r* and the disturbance variance σ.

To implement the Bayesian estimation, priors must be placed on the parameters β and a diffuse prior on σ, the variance. The relative variance terms $(v_1, v_2, \ldots. v_n)$ are assumed fixed but unknown parameters that need to be estimated. Lesage (1997) notes that the thought of estimating the *n* parameters $(v_1, v_2, \ldots. v_n)$, in addition to the *k*+1 parameters, β and σ using *n* data points seems problematical from the degrees of freedom perspective. However, Bayesian methods overcome this problem by relying on an informative prior for the v_i parameters. This prior distribution for the v_i terms will take the form of an independent $\chi^2(r)/r$ distribution. This allows the estimation of the additional *n* parameters, v_i in the model by adding the single parameter *r* to the estimation procedure.

The specifics regarding the prior assigned to the v_i term can be motivated by considering that the mean of the prior equals unity and the variance of the prior is 2/*r*. This implies that as *r* becomes very large, the terms v_i will all approach unity, resulting in $V = I_n$, the traditional Gauss-Markov assumption. Lesage (1997) notes that the role of $V \neq I_n$, is to allow the derivation of more robust estimates by down weighting outliers and observations containing large variances.

Large *r* values are associated with a prior belief that outliers and non-constant variances do not exist, since this prior would produce $V = I_n$. Large values, such as $r = 30$ or $r = 50$ produce v_i estimates that are close to unity, forcing the model to take on a homoscedastic character and producing coefficient estimates similar to those from the maximum likelihood spatial autoregressive model. Small values of *r*, around 2 to 7, allow for a non-constant variance and are associated with a prior belief that outliers or non-constant variances exist.

Table 4 provides three versions of the model of regional unemployment. The first two columns relate to the model when estimated using OLS with the estimated coefficients and *t*-statistics provided. Columns three and four of this table provide an estimate of the maximum likelihood version of the spatial autoregressive model along with the relevant *t*-statistics. This model incorporates the same explanatory variables with the addition of ρ, the coefficient of the spatially lagged dependent variable. Columns five and six of this table provide an estimate of the same model estimated using Bayesian techniques with a heteroscedastic prior. Prior to estimating this model a Bayesian model was estimated using a homoscedastic prior. For the homoscedastic model, *r* was set to 40. The results of this model were close to replicating the estimates from the maximum likelihood model. In the heteroscedastic disturbance model *r* has been set to 4, allowing ample opportunity for the v_i parameters to deviate from unity[3].

In Table 4 some notable differences can be seen in the estimated coefficients and the significance of these coefficients. For example, in moving from the OLS version of the model to the maximum likelihood version of the model, the average absolute size of the coefficients change by 12.2% while the difference between the coefficients in the OLS and Bayesian version of the model differ by 28.0%. The differences between the maximum likelihood and Bayesian version of the spatial autoregressive model are no less significant being 26.0% in

[3] The justification for this formulation of the model was the plot of the posterior estimates of the relative variance terms (v_i) which indicated that there are a number of outliers in this sample, providing evidence that the data contradicts the homoscedastic prior, thus suggesting that the heteroscedastic prior is more appropriate. A strong justification for the acceptance of the model estimated using the heteroscedastic prior is also provided by the results. If heteroscedasticity had not been a problem the estimated coefficients would have almost been identical to those in the model estimated using maximum likelihood techniques.

Table 4. Maximum Likelihood and Bayesian Spatial Autoregressive Model Estimates[4].

	OLS		Maximum Likelihood		Hetroscedastic Prior	
Variable	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
Inpt	1.7095	4.8177	1.5140	4.7266	1.3108	3.4910
LINCOME	-0.1096	-3.3138	-0.0996	-3.3454	-0.0828	-2.3052
LPOP	0.0090	0.8819	0.0064	0.6977	0.0114	1.1857
PERBACH	-0.8337	-3.3819	-0.7129	-3.2303	-0.6181	-2.2904
PERIND	-0.0386	-1.2863	-0.0263	-0.9787	-0.0233	-0.7276
PERAGR	-0.1205	-2.8621	-0.1028	-2.7281	-0.1101	-2.4743
PERMAN	-0.2083	-3.0859	-0.2137	-3.5368	-0.1754	-2.5812
HERFINDAHL	-0.1539	-3.1329	-0.1539	-3.4934	-0.1092	-2.0522
PERFEM	-0.2468	-1.5209	-0.2464	-1.6958	-0.1555	-0.9235
GROWTH	0.0468	1.7223	0.0412	1.6939	0.0175	0.6112
WGROWTH	0.0248	2.6764	0.0178	2.0955	0.0137	1.5156
PERYNG	-0.4075	-2.5855	-0.3538	-2.5021	-0.3075	-1.8637
PEROLD	-0.3671	-2.0661	-0.2981	-1.8736	-0.3596	-1.8225
Rho	n.a.	n.a	0.4190	4.3671	0.4671	3.6151
R^2	0.4946		0.5481		0.5204	
Adjusted R^2	0.4405		0.4997			
Sigma^2	0.0012		0.0010		0.0008	
Log-likelihood	n.a.		299.3181		r = 4	

absolute terms. Thus, it appears that the incorporation of Bayesian techniques to make the results more robust has led to some changes in the estimated coefficients with these changes providing a strong justification for the use of this methodology.

Additionally, the results indicate that moving from the OLS through to the Bayesian version of the spatial autoregressive model has seen the significance of some of the variables change. In particular the variable GROWTH while significant at the 10% level in the OLS model is insignificant in the maximum likelihood and Bayesian versions of the spatial autoregressive model. The variable WGROWTH is significant at the 5% level of significance in the OLS model but its significance declines to 10% in the maximum likelihood version of the spatial autoregressive version of the model and then becomes insignificant even at this level in the Bayesian version of the spatial autoregressive model. Lawson and Dwyer (2002) note that strong regional growth does not necessarily mean that regional unemployment rates will decline. They find that the regions

[4] The Bayesian model in this table has been derived using 3,500 passes through the Gibbs sampler with the first 1,100 used to burn in the estimates. It is important in applying Bayesian techniques to ensure that the process has converged to a stable solution. A discussion of the convergence diagnostics for the estimation of the heteroscedastic model is presented in Appendix 1.

with strong employment growth over the 1986-96 period tended to also have experienced high regional unemployment rates. This result suggests that policies aimed at stimulating regional growth with the intention of reducing regional unemployment are not necessarily going to achieve their objective, and are not supported at all by the Bayesian version of the model presented in Table 4.

The two variables capturing the age structure of the labour force, while significant at the 5% level in the OLS and Maximum likelihood model can only be accepted as significant in the Bayesian version of the model at the 10% level. Both of these variables have negative coefficients, this is in contrast to the conclusions of Metcalf (1975) who believed that younger workers were more inclined to leave the workforce and contribute to frictional unemployment. Metcalf (1975) also found that the coefficient of the proportion of the labour force made up by older workers was positive as these workers tend to have a longer average duration of unemployment. The findings of Metcalf (1975) in conjunction with the significance and sign of the coefficients of PERYNG and PEROLD in the Bayesian model suggests that it is difficult to support the idea that the age structure of the labour force is a significant factor in explaining regional unemployment rate disparities in Queensland.

Some of the results presented in Table 4 are surprising. For example, in none of the estimated equations are the variables PERIND and PERFEM significant. This indicates that, when the other variables are taken into account, these variables do not influence the unemployment rate experienced by a region. The negative coefficient on HERFINDAHL, the Herfindahl index of industrial concentration, is also surprising and suggests that regions with a less diverse industrial base experienced lower rates of unemployment during 1996. This is contrary to mainstream regional economic theory concerning the effect of industrial diversity, with Malazia and Shanzi Ke (1993) noting that it is generally believed that regions with higher industrial concentration are more likely to have higher unemployment rates than industrially diverse regions. These authors suggest that regions with greater diversity are more likely to be able to absorb adverse economic shocks and so, all things being equal, should have a lower unemployment rate than the more industrially concentrated regions. This seems contrary to the findings in this study and can perhaps be attributed to the fact that higher levels of industrial concentration may also be associated with a more specialised labour force or a thinner labour market as is associated with smaller regional economies. Consequently, the loss of a job may mean that the chances of finding a similar job are increased by moving across regional boundaries, perhaps to the larger regions of Queensland. For this reason, smaller regions with more concentrated industrial bases may experience lower rates of unemployment.

For the remaining significant variables, the signs of the coefficients are negative in all cases. For the variable LINCOME this suggests that, all things being equal, regions with higher average incomes are associated with lower unemployment rates. One explanation for this is that the average income may be picking up effects due to regional industry mix not captured by the variables included to capture these effects. This explanation seems to be supported by a simple regression to explain LINCOME that includes UERATE and a number of other explanatory variables from the models in Table 4. The results of this exercise suggest that the rate of unemployment in a region is not significant in explaining regional income variation while variables capturing differences in regional industrial structure and demographic characteristics, including education, are significant.

For the variable PERBACH, the result suggests that regions with a higher proportion of the population with bachelor or post bachelor qualifications tend to experience lower rates of unemployment. The size of the coefficient indicates that, on average, an additional 1.62 percentage point increase of the population with a bachelor or post bachelor qualification is associated with a 1 percentage point lower rate of unemployment.

The negative coefficients on PERAGR and PERMAN indicates that regions with larger shares of the labour force employed in agricultural and manufacturing industries tended to experience lower rates of unemployment. This result may indicate that employment had grown relatively strongly in these industries in the period leading up to the census. An alternative explanation for PERAGR is that regions with relatively large shares of their labour force in this industry tended to be in the sparsely settled western and far northern regions of Queensland and thus, this variable may be picking up some negative amenity effect associated with small, isolated regions.

6. CONCLUSION

The results from the tests for spatial dependency presented in Table 3 suggest that this is a problem present in the data. Furthermore, in the models presented in Table 4 the coefficient for the spatially lagged dependent variable is significant. These results suggest that spatial effects are important and need to be incorporated into the estimation procedure. The results presented in this analysis tend to suggest that the spatial autoregressive model is the most appropriate for the data being analysed.

The acceptance of this finding has at least two implications. Firstly, Lesage (1999) notes that OLS estimators are biased and inconsistent in the face of sample data containing spatial dependence. The actual changes to the estimated coefficient values between the OLS estimate and the two versions of the spatial autoregressive models are considerable when viewed in percentage terms. Secondly, and perhaps of more significance to policy makers, are the implications of the inclusion of variables to capture the spatial dependence uncovered by the tests presented in Table 3. In the two versions of the spatial autoregressive model presented in Table 4, ρ, the coefficient of the spatially lagged unemployment rate is significant. This suggests that a policy designed to reduce unemployment in one region will have flow-on effects to neighbouring regions. These regions unemployment rates, in turn, become an explanatory variable in the unemployment rates of their neighbouring regions; thus, changes in their unemployment rate will have further flow-on effects. In this way, policies affecting any one region will be transmitted to neighbouring regions.

This suggests that regional employment/unemployment policy may have wider implications than suggested by the simple OLS model presented in Table 4. In particular this model failed to take into account spatial dependency and spatial spillover effects. These effects can only be incorporated using techniques from the developing field of spatial econometrics.

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Appendix 1. Convergence Criteria for the Bayesian Estimation of the Spatial Autoregressive Model

It is important in applying Bayesian techniques to ensure that the process has converged and a number of diagnostic tests have been developed to determine if the sample size is large enough to ensure a stable solution for the problem in question. Lesage (1997) notes that for simple models, convergence of the Gibbs sampler tends to occur quite rapidly. One approach to monitor convergence is provided by a series of convergence diagnostics including autocorrelation estimates, Raferty and Lewis (1992) diagnostics, MCMC diagnostics and Geweke's (1992) numerical standard errors. In Table A1, two sets of diagnostics are provided, these being the autocorrelation estimates and the diagnostics proposed by Raftery and Lewis (1992).

To interpret these diagnostics some explanation is required. In time series, autocorrelation estimates provide an indication of how much independence exists in the sequence of ρ and σ parameter draws. A high degree of autocorrelation indicates that more draws may be required to achieve a sample of sufficient size. The results presented in the top half of Table 6 indicate that the draws for the parameter ρ exhibit large autocorrelations at lag 1 but then tail of rapidly at lags 5, 10 and 50. The autocorrelation structure for σ shows a smaller value at lag 1 and also tails of rapidly.

An alternative approach has been proposed by Raftery and Lewis (1992) who designed a set of diagnostics to determine the length of the number of draws required based on some predetermined view of the desired accuracy of the posterior summaries desired by the user. The methodology designed by Raftery and Lewis (1992) requires that the user specifies three pieces of information, with the first being the quartiles of the marginal posteriors the user is interested in. This is generally set at 2.5% because this provides the basis for a 95% interval estimate. The second piece of information is the minimum probability needed to achieve the accuracy goals. In this study this has been set at 95%. Finally, the user is required to specify how much accuracy is desired in the estimated quartiles. In this implementation this has been set at 2% because Raftery and Lewis (1992) specify this using the area to the left of the reported cumulative density function. Setting this at 2% with a nominal reporting based on a 95% interval should result in posterior values that lie between 0.93 and 0.97.

In the literature, it is suggested that a number of the initial draws should be discarded, these are referred to as the 'burn-in' draws for the sampler. Starting from arbitrary parameter values makes it unlikely that the initial draws come from the stationary distribution needed to construct posterior estimates. Another practice followed by researchers involves saving every third, fifth, tenth etc, draw since the draws from a Markov chain are not independent. This practice is labelled thinning. The results presented in Table 6 suggest that the thinning estimate required by the Raftery and Lewis (1992) diagnostics is 1 which is

Table A1. Convergence Diagnostics from Bayesian Implementation of Spatial Autoregressive Model.

Markov Chain Monte Carlo Autocorrelation Estimates					
Variable		**Lag 1**	**Lag 5**	**Lag 10**	**Lag 50**
Rho		0.666	0.017	-0.052	-0.018
Sigma		0.190	0.032	-0.026	-0.019
Raftery-Lewis Diagnostics					
Variable	**Thin**	**Burn**	**Total (n)**	**(Nmin)**	***I*-stat**
Rho	1	10	2830	937	3.020
Sigma	1	10	2830	937	3.020

consistent with the fact that the autocorrelation estimates tail of rapidly for both ρ and σ. The third column reports that only 10 draws are required for the 'burn-in', which is quite small. The forth column shows the total number of draws needed to achieve the desired level of accuracy for each parameter. This is given as 2830; inside the 3500 used in the estimation presented in Table 4. The Nmin in the fifth column represents the number of draws that are required if the draws represented an *iid* chain, which is possibly not true in the current case because of the observed autocorrelation structure. Finally the *I*-statistic in the final column is the ratio of the fourth and fifth columns. Raftery and Lewis (1992) suggest that values much above 5 are indicative of convergence problems and may suggest that more draws should be carried out, this is obviously not a problem in this exercise.