UNEMPLOYMENT VARIATION IN METROPOLITAN BRISBANE – THE ROLE OF GEOGRAPHIC LOCATION AND DEMOGRAPHIC CHARACTERISTICS

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ABSTRACT: This paper provides an analysis of unemployment variation within the Brisbane Statistical Division. The uneven distribution of urban unemployment is of serious concern for government policymakers. Several previous studies of unemployment rates across urban areas in Australia have noted that neighbourhoods of high or low unemployment may be clustered together in geographic space. However, the analysis adopted in these studies has not explicitly accounted for these neighbourhood effects. In contrast, in this study tools from the rapidly developing field of spatial data analysis have been used to explore the variation of urban unemployment within the Brisbane Statistical Division. These effects are important, having implications not only for the validity of the estimated model and its interpretation, but also its policy implications.

1. INTRODUCTION

Observed disparities in regional and urban unemployment rates are a well documented phenomenon with a relatively large body of literature, following the work of Thirlwall (1966), discussing the nature of these disparities. Furthermore, Kelly and Lewis (2000a and 2000b) note that the evidence is mounting that the underlying relationships between family and neighbourhood need to be addressed if employment outcomes for disadvantaged groups within the labour market are to be improved. These authors have also noted that there are important linkages between the socioeconomic status of neighbourhoods and their labour market performance.

In addition, evidence from international studies suggests that the demographic composition of regions varies across geographic space and is associated with a number of undesirable outcomes. For example, Malizia and Ke (1993) and Molho (1995) have noted that residents of poorer regions are more likely to have on average, lower levels of educational attainment, earn lower incomes, be employed in less skilled jobs, have lower levels of labour force participation and finally, be more likely to be unemployed.

Supply and demand side polices have been proposed to mitigate these disparities in urban neighbourhood performance. Supply side policies include employment education and training programs in addition to programs designed to increase the residential and transport mobility of residents in pockets of high

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[1] The views expressed in this document are those of the author(s) and should not be considered as necessarily representing the views of the Department of Employment and Training or the Queensland Government.

unemployment, providing them with better access to jobs outside their immediate vicinity. Demand side policies on the other hand, include economic development efforts that create or retain jobs in an area. More specifically, economic development may involve creating jobs throughout an entire metropolitan area or, alternatively, more specific job creation projects in and around geographic pockets of high unemployment.

Some authors, notably, Bartik (1991) and Freeman (1991), argue that positive labour demand shocks to metropolitan economies improve the employment and welfare of low income/high unemployment neighbourhoods. Immergluck (1998) however, suggests that this type of analysis does not argue convincingly that metropolitan job growth will permanently reduce unemployment in small areas. The same author argues that neighbourhood job creation policies can bee seen as a more direct demand side attack on the problem of concentrated unemployment than metropolitan wide efforts. Such policies are concerned more with the spatial distribution of jobs and much less with the aggregate growth of jobs across the entire metropolitan area.

The following section of this paper provides an outline the spatial variation of unemployment within metropolitan Brisbane, here defined as the Brisbane Statistical Division (SD). This section applies tools from the field of spatial data analysis to explore the regional variation in unemployment. This is followed in section 3 with an outline of a theoretical model of urban unemployment variation, the data for this model is also described. This model is presented and the results discussed in section 4. A brief conclusion is presented in section 5.

2. VARIATION IN UNEMPLOYMENT RATES IN METROPOLITAN BRISBANE

To examine the determinants of urban unemployment rates across the metropolitan Brisbane, we examine cross sectional data collected from the Australian Bureau of Statistics, 2001 Census of Population and Housing at the SLA level. Analysis at this level of spatial geography raises a number of issues, particularly in relation to what is known as the Modifiable Areal Unit Problem. Messner and Anselin (2004) note that this problem consists of two, interrelated issues, firstly, there are issues regarding the spatial scale of the phenomenon being studied, and secondly, there are issues around the interpretation of results from spatial analysis.

The first of these problems may arise if there is a mismatch between the scale of the phenomenon being studied and the spatial units of analysis. This can be addressed by testing for spatial autocorrelation and applying appropriate techniques if it is found to exist. The second problem is frequently called the problem of *ecological fallacy* and follows from the uncertainty of choosing aggregated zonal units. Different units of geography may produce different results, making generalisations difficult. In the current study, we have followed Messner and Anselin (2004) and based our analysis at the spatial scale for which policy intervention may be designed, i.e. the SLA's of Brisbane.

Figure 1 displays a thematic map of Queensland depicting the quintiles of unemployment rates for each of the SLA's within the metropolitan Brisbane.

SLA's in the highest quintile are predominantly clustered in the outer areas of the city, particularly the cities northern, eastern and southern areas (i.e. the Beaudesert, Caboolture, Ipswich, Pine Rivers, Redcliffe and Redland shires and Logan City). In contrast, clusterings of low unemployment rates can be seen in Brisbane's northwest and inner southeast areas.

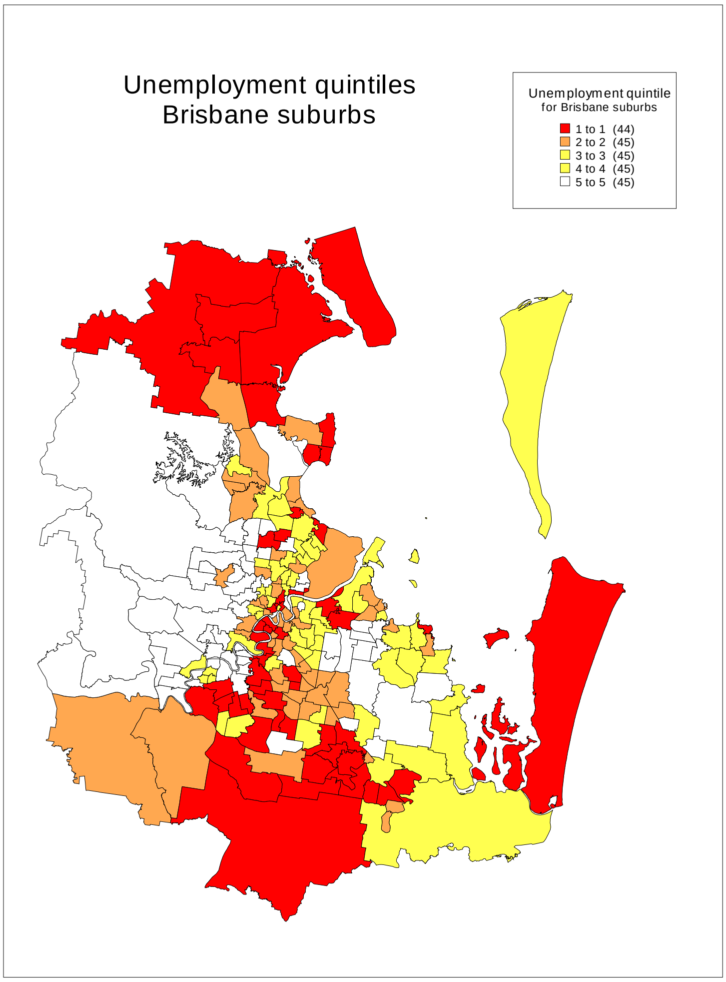

Figure 1. Unemployment Quintiles in Brisbane Statistical Division

The data presented in the quintile map suggests that there is some spatial dependence in the distribution of unemployment rates across the SLA's of metropolitan Brisbane, i.e. that the unemployment rate is not randomly distributed across geographic space but some spatial clustering occurs. One way of testing if this clustering is significant is through the Moran scatter plot and Moran I statistic.

Figure 2 provides a Moran scatter plot, here each SLA's difference from the average unemployment rate is plotted against the unemployment rate of its nearest geographic neighbour[2]. The figure is split into four quadrants. Quadrant 1 represents SLA's with low unemployment rates surrounded by high unemployment rate neighbours; Quadrant 2 has high unemployment rate SLA's with high unemployment rate neighbours; Quadrant 3 has low unemployment rates with low unemployment rate neighbours and Quadrant 4, high unemployment rates with low unemployment rate neighbours.

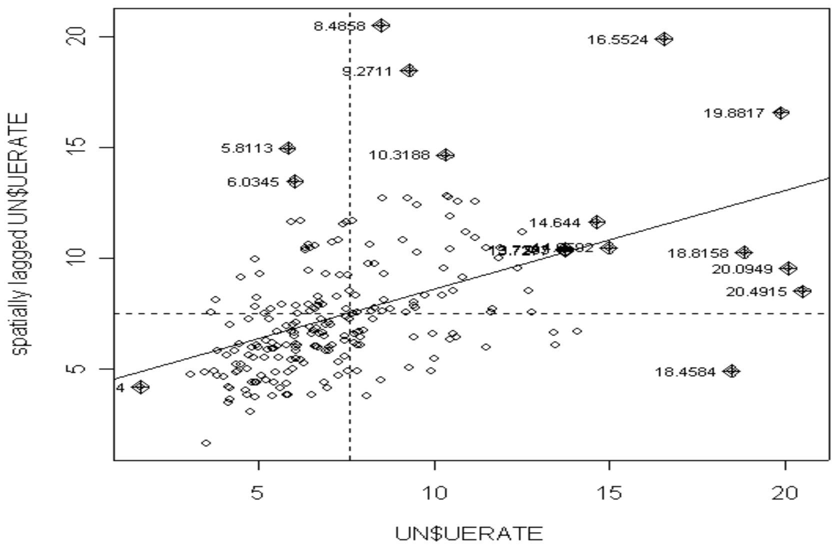

Figure 2. Moran Scatter Plot of Unemployment Rates in Brisbane Statistical Division

The points in the figure suggest a clustering in quadrants 2 and 3, i.e. SLA's with high unemployment rates are adjacent to other SLA's with high unemployment rates, while SLA's with low rates of unemployment tend to be adjacent to other SLA's with low unemployment. The trend line through the scatter plot suggests that the spatial clustering is significant and that the urban variation of the unemployment rate is not randomly distributed throughout the

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[2] In all the spatial data analysis conducted within this project a spatial weight matrix representing the nearest neighbours of each SLA has been used.

Brisbane SD. The significance of spatial dependence is confirmed using the Moran *I* test, producing a test statistic of 5.91, with a probability <0.0000.

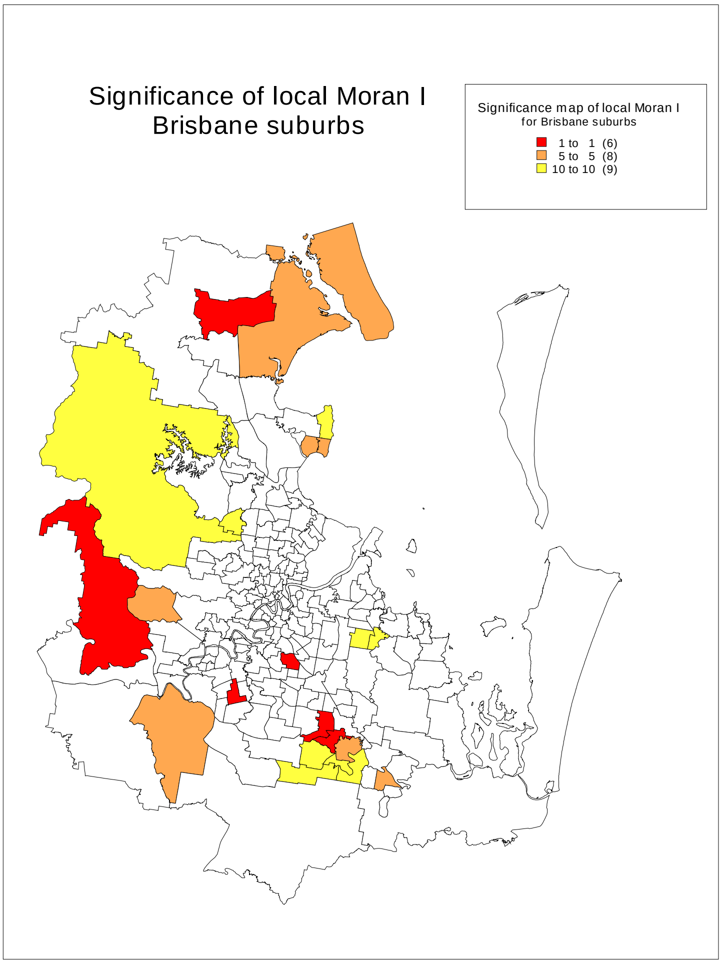

Figure 3. Significance Map – Geographic Clustering of Unemployment Rates

Further insight into spatial clustering can be gained through the use of local indicators of spatial association. These latter measures include the Ord and Getis

(1995) *G*-stat and the Local Moran *I* Statistic (see Anselin, 1995). In this section the Local Moran *I* statistic is used to analyse the spatial clustering. The Local Moran *I* statistic is an extension of the Moran *I* statistic, and decomposes the global measure into contributions for each location, referred to as LISAs or Local Indicators of Spatial Association.

This statistic can be represented as:

$$I_i = x_i S\, w_{ij} x_j \tag{1}$$

where x_j is the difference between the value of the variable under consideration for area *i* and the mean value for that variable, w_{ij} is a weight representing the strength of connection between areas *i* and *j*, developed from neighbour information. The Local Moran *I* statistic can be used to identify those “hot spots” where there is a significant spatial clustering of similar values of the variable. The values of I_i are positive when values at neighbouring locations are similar and negative if they are dissimilar.

The significance map presented in Figure 3 indicates regions with Local Moran *I* statistics that are significant at the 1, 5 and 10 percent levels of significance. In this significance map it can be seen that the clustering of high rates of unemployment in the Logan City region, are significant between the 1 and 10 percent levels. Similarly, the SLA's with high rates of unemployment in the Pine Rivers Shire in Brisbane's north appear to be among a significant cluster. In contrast, the clustering of regions in Brisbane's north and west are SLA's with low rates of unemployment.

The results of this analysis suggest that rates of urban unemployment are not randomly allocated across geographic space. Instead, the quintile map, Moran scatter diagram and Moran *I* statistic all suggest that the variable is spatially dependent, while the local Moran *I* statistic provides an indication of where significant clusterings of similar rates of unemployment occur. Overall, this suggests that geographic location cannot be ignored, as in much empirical research conducted at the urban level, further, this may need to be considered in our formal model of urban unemployment rate determination.

3 EXPLAINING VARIATION IN URBAN UNEMPLOYMENT RATES

Numerous studies have explored the geographic variation in unemployment rates. Following Kain (1968) many of these studies have explored the role played by the accessibility of urban areas, formally testing the spatial mismatch hypothesis (see, for example, Raphael 1995, Rogers 1997, Arnott 1998 Giuliano 1998 and Immergluck 1998). This hypothesis seeks to explain how housing choices of low income groups impacts on their earnings and labour force status. In particular, it is suggested that low income persons, being limited to either public or low cost housing, may locate in residential areas isolated from employment opportunities. As a consequence, high commuting costs and the lack of linkages into informal job networks, due of geographic isolation, reduce the chances of employment for these persons.

Other authors have sort to explain cross sectional variation in unemployment, including Metcalf (1975), Partridge and Rickman (1995 and 1997), Malizia and Shanzi Ke (1993), Molho (1995), Kelly and Lewis (2000a and 2000b) and Trendle (2002). While the current study uses cross sectional regression techniques to model the variation in urban unemployment rates, it incorporates elements of the spatial mismatch hypothesis.

In the current study, the variables used to explain variation in the unemployment rate across metropolitan Brisbane can be divided into four groups, labour market mismatch variables, (*MISMATCH*), demographic variables (*DEMOG*), housing tenure variables (*HOUSE*) and educational level variables (*EDUC*). Thus, the rate of unemployment for the *r*th SLA can be written as:

$$UE_r = \alpha + (MISMATCH_r) + \beta(DEMOG_r) + \kappa(HOUSE_r) + \zeta(EDUC_r) + \sigma_r + \varepsilon_r \quad (2)$$

where α is the constant term, the subscript *r* refers to the region or SLA, and σ represents region specific effects and ε is an error term.

Since the seminal work of Kain (1968), a large amount of work has been undertaken aimed at determining the effect of space on employment. In the current study, a modeling strategy initiated by Immergluck (1998) is used. Rather than using commute distances or times, as in much of the work exploring the spatial mismatch hypothesis, this author looks at the differences that exist between the characteristics of local residents and local jobs.

Using the framework of Immergluck (1998), the variable *JOBRATIO* was created. *JOBRATIO* is the ratio of the number of low skilled jobs in the LGA to which each SLA belongs relative to the number of low skilled workers residing in the region. Here, low skilled is defined as ASCO Labourers and related workers, and Elementary sales and service workers. Around 60 percent of these lower skilled workers in metropolitan Brisbane are employed within the LGA in which they reside, compared to an average of 53.9 percent of all workers in metropolitan Brisbane. Unlike Immergluck (1998) who had access to journey to work data at the US quarter section level, which seems most closely related to the Collection District level of Australian census data, only LGA journey to work data was available in the current study. This meant that a number of other variables could not be constructed and so were omitted from the analysis.

A number of demographic variables have also been found to be significant in explaining differences in regional and urban unemployment rates. These variables may include the proportion of the population that are migrants, especially from Non-English speaking backgrounds. Further, 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 has been found to be a significant determinant of differences in regional and urban unemployment rates. The current study incorporates the proportion of the SLA population that is of indigenous origin (*PERIND*), along with the proportion that is of a non-English speaking background (*PERNESB*), to capture differences in the demographic composition of the population. Other variables, comprising the percent of females and the percent aged less than 25 in each SLA's labour force, were also included in some preliminary versions of the model. However, these variables were found to be insignificant and were omitted from the final version presented in Table 1.

Home tenure is likely to have a significant influence on urban unemployment variation. Several studies, (see, for example, Marston 1985 and Molho 1995) note that that home ownership reduces geographic mobility. The availability of public housing has also been found to reduce labour market adjustment and has been found to be associated with higher levels of regional and urban unemployment (see, for example, Molho 1995 and Kelly and Lewis 2000a). In the current study *PUBHOUSE*, the percentage of regional households in public housing, has been included.

Geographic mobility is likely to reduce attachment to the labour market (see, for example, Immergluck 1998). Persons that have moved in to an urban area are likely to have less contacts in the region. To the extent that many job opportunities are passed along informal networks, it is likely that migrants are less likely to be informed of many job offers. As a consequence, the percentage of the working aged population that has moved into each SLA within the last year (*PERMOV1*), has been included as is likely to be positively associated with the unemployment rate.

The education levels of urban areas within the Brisbane metropolitan area vary significantly. Differences in levels of education have long been known to influence employment outcomes. In this study two variables, *PERBACH*, the percentage of the regional population with a bachelor degree or higher and *PERVOC*, the percentage of the regional population with a vocational qualification have been included to capture variation in the education profile of urban areas.

As suggested by Kelly and Lewis (2000a and 2000b) neighbourhood effects may be important. This is also suggested by the findings of Section 2, where it was found that clusterings of similar values of our dependent variable, the unemployment rate, occur across metropolitan Brisbane. The existence of these neighbourhood effects can be formally tested using spatial econometric techniques. In particular, if such effects are significant, testing the residuals from a model estimated using Ordinary Least Squares (OLS) should suggest that a spatially lagged representation of our model is most appropriate.

Finally, it is important to note that 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.

4. A MODEL OF URBAN UNEMPLOYMENT VARIATION

Regional science has always recognised the role of space in determining regional economic performance. Space is also increasingly being recognised in empirical modelling through the use of techniques that formally incorporate a role for geographic location. These techniques allow the specification and testing of models that incorporate geographic spillover effects, or specify a dependence between observations at different points in geographic space. Collectively, these techniques form the field of spatial econometrics and range from simple descriptive statistics, which can be used to determine if similar values of a variable are clustered together in geographic space, through to methods for the estimation of structural equations that formally recognise the role of geographic location.

In this study two types of spatial econometric models were considered, being the spatial lag and error models. The spatial lag model takes the form:

$$Y = \rho Wy + X\beta + \varepsilon \qquad (3)$$
$$\varepsilon = N(0, \sigma^2 I_n)$$

while the spatial error model is defined as:

$$Y = X\beta + \varepsilon \qquad (4)$$
$$\mu = \lambda W\mu + e$$
$$\varepsilon = N(0, \sigma^2 I_n)$$

where Y is a vector of N observations of the dependent variable, X is a $N * K$ matrix of observations of the explanatory variables, β is a vector of regression coefficients, ε is a vector of residuals, μ is an independently and normally distributed error term with constant variance, and W is an $N * N$ spatial weight matrix. Anselin (2002) notes that these models require specialised estimation techniques, such as maximum likelihood or instrumental variables. In this study, maximum likelihood techniques have been used, implemented through the R statistical software package.

The weighting matrix W shows the interconnectedness of the areas in the sample; each element W_{ij} in W tells us the strength of interaction between the pair of regions i and j. Generally, it is expected that neighbouring areas would have a stronger interaction (larger W_{ij}) compared to geographically distant areas.

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 geographic 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 $L_s y_t = y_{ts}$ 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, with the idea being to use a weighted sum of the values of neighbouring units. In this study the spatial weight matrix has been derived using the nearest neighbour. In this case the matrix is defined as having the element (i, j) set equal to 1 if i and j are nearest neighbours and 0 otherwise.

The spatial lag model, shown in equation (3), is related to the distributed lag interpretation of time series economics. 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 of 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 an economic process. An alternate specification might be the spatial error model, shown in equation (4). This model presupposes a shared spatial process affecting all variables. This spatial process is frequently interpreted as indicating missing variables. In this model, λ is the residual spatial autocorrelation coefficient and represents unmodelled shocks. These sorts of effects include regional characteristics that are not part of the model but affect neighbouring regions similarly. Anselin (1999) notes that this type of regression incorporates a special case of a non-spherical error term. In this situation, OLS remains unbiased, but it is no longer efficient and the classical estimation of standard errors will be biased.

From this discussion it can be seen that the inclusion of spatial effects into an applied econometric model is typically motivated either on theoretical grounds, following the formal specification of spatial interaction in an economic model, or on practical grounds, due to the peculiarities of the data.

Another consideration arises out of the discussion presented in Section 2. Figures 1 and 3 suggest that there may be systematic differences in the unemployment rates across the SLA's of the Brisbane metropolitan area. In particular, those SLA's on the urban fringe seem to be characterised by higher unemployment rates. Consequently there is a possibility of a number of spatial regimes operating. Anselin (1992) notes that spatial regimes are formalised as varying coefficients between spatial subsets of data. The simplest way that this variation can be expressed as through the inclusion of an intercept dummy, with interaction dummy variables and spatial Chow tests also possible[3].

The first step in modelling involved the estimation of the model using conventional OLS techniques. The result of this exercise are presented in Table 1. The next stage of the investigation involved determining whether spatial autocorrelation was present in the residuals of the equation estimated using OLS, and if so, whether it is best represented by a spatial lag or spatial error model.

A series of tests have been developed and the results derived from the application of some of these tests are also presented in Table 1. The tests used here comprise the Moran *I* statistic and Lagrange Multiplier (LM) error and LM lag tests. The results of the Moran *I* test suggest that we can reject the hypothesis of spatial independence due to the small marginal probability associated with this test and so conclude that the residuals from the OLS estimation exhibit spatial dependence.

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

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3 Spatial lag and error models, represented in equations 3 and 4 can incorporate different spatial regimes.

represented by a spatial lag model, or an error process, best represented by a spatial error model. On the other hand, the LM tests provide a means of discriminating between the spatial lag or error model.

The higher test statistic derived from the LM lag test and the robust version of this test, coupled with the insignificance of the robust version of the spatial error test, can be taken as suggesting that the spatial lag version of the model is the most appropriate (see, for example, Anselin et al 1996). Table 1 presents the estimated coefficients and diagnostics of the OLS version of the model (estimated after correcting for heteroscedasticity) along with the spatial lag model estimated using maximum likelihood techniques. The second and third columns in this table provide the estimated coefficients and *t*-statistics of the OLS version of the model, while columns four and five provide the coefficients and *z* values of the spatial lag model, estimated using maximum likelihood techniques.

Table 1. OLS and Spatial Lag Model Estimates

	OLS model estimate			Spatial lag model estimate		
	Estimate	t value		Estimate	z - value	
Intercept	0.130	7.710	***	0.113	6.644	***
JOBRAT	-0.035	-5.842	***	-0.030	-5.033	***
PERIND	0.840	6.052	***	0.803	6.013	***
PERNESB	0.076	4.327	***	0.071	4.192	***
PUBHOUSE	0.042	1.976	*	0.041	2.040	*
PERSINGF	0.136	4.429	***	0.135	4.589	***
PERMOV1	0.062	3.191	**	0.055	2.915	**
PERBACH	-0.053	-2.186	*	-0.045	-1.927	*
PERVOC	-0.366	-5.269	***	-0.340	-5.081	***
Rho:	n.a.	n.a.		0.113	8.086	***
	Residual s.e. 0.016 on 215 d.f.			Log likelihood = 612.89		
	R-Squared = 0.74			R-Squared = 0.74		
	Adjusted R-square = 0.73			Adjusted R-square = 0.73		
	F-stat (8, 215) = 75.87, p-value <0.0000			ML res var = 0.0002, sigma = 0.016		
	Moran I = 2.15, p-value = 0.02			AIC = -1203.8, AIC for LM = -1197.7		
	Lmerr = 4.19, p-value = 0.04			LM test for residual autocorrelation		
	Lmlag = 7.86, p-value = 0.01			test value = 0.04, p-value 0.85		
	RLMerr = 0.03, p-value = 0.87			Breusch-Pagan test = 14.61, p-value = 0.07		
	RLMlag = 3.70, p-value = 0.05					

Notes: *** indicates significance with p > 0.001, ** indicates significance with p > 0.01, *indicates significance with p > 0.05 and . indicates significance with p > 0.1.

Several versions of a spatial regimes model were also trailed in an attempt to uncover systematic coefficient variation. These versions included intercept dummy variables for the peripheral shires of the Brisbane metropolitan area (i.e.

Beaudesert, Caboolture, Gold Coast, Ipswich, Logan, Redlands and Redcliffe), along with interaction variables created by multiply the dummy variable with the post school education variables, *PERVOC* and *PERBACH*. In all cases no significant differences were uncovered.

The results for the OLS model and the spatial lag version of the model indicate that these variables explain around 73 percent of urban variation in regional unemployment rates. In addition, it can be seen that the test for residual spatial autocorrelation of the error term of the spatial lag model suggests that the lag specification has overcome this problem. However, the Bruesch-Pagan (BP) test indicates that heteroscedasticity is a problem in the maximum likelihood version of the spatial lag model. Estimation techniques to correct this problem are not generally available within the spatial lag modelling framework. However, it should be remembered that while heteroscedasticity results in inefficient parameter estimates, these estimates remain unbiased.

The results presented in Table 1 indicate that all variables are significant and of the expected sign in both versions of the model. For example, the two variables included to capture urban differences in demographic composition, the proportion of the regional population from a Non-English speaking background (*PERNESB*) and the proportion of the population of an indigenous origin (*PERIND*) are both significant and have a positive sign. The positive sign indicates that higher proportions of these characteristics are associated with higher rates of urban unemployment.

Of these coefficients, the coefficient of *PERIND* (0.80) is the largest and indicates that a 1 percentage point increase of the share of the urban population of an indigenous origin is associated with an 0.80 percentage point increase in the unemployment rate. In contrast, the smaller coefficient for *PERNESB* suggests that the unemployment rate is less sensitive to changes in this variable, i.e. a 1 percentage increase in the share of the population from a Non English speaking background is associated with only a 0.07 percentage point increase in the unemployment rate.

The housing variables *PUBHOUSE*, the proportion of households in public housing has a significant positive coefficient in both models. This indicates that higher proportions of households in public housing are associated with higher rates of urban unemployment across metropolitan Brisbane.

Similarly, the variable incorporated to capture the impact of the mobility of the regional population has a significant positive coefficient in both versions of the model. The variable (*PERMOV1*) is the proportion of the population that has moved in to the region over the last year. The positive coefficient for this variable indicates that the greater the proportion of the urban population that has recently arrived, the higher the unemployment rate. There may be a number of factors driving this result. One explanation can be found in the spatial version of the job matching hypothesis which suggests that persons that are newly arrived to a region will have fewer informal links and therefore, be less aware of job offers in local labour markets (see, for example Immergluck 1998). In this case, a higher proportion of recent in-migrants would be associated with higher rates of unemployment as appears to be the case within metropolitan Brisbane.

The two variables incorporated to capture variation in education levels, (*PERVOC*) the proportion of the population with vocational qualifications and *PERBACH*, the proportion with bachelor or above level qualifications have positive estimated coefficients. Numerous studies have found that higher levels of education are associated with better performance in the labour market (see, for example, Malizia and Ke 1993, Molho 1995 and Giuliano 1998). This result is confirmed in this study. Surprisingly the coefficient for *PERVOC* is larger than that of *PERBACH*, suggesting that urban unemployment rates are more sensitive to changes in the proportion of the population with vocational training level qualifications, than to changes in university level qualifications.

Also of importance is the significance of the variable to capture the impact of local labour market imbalances, *JOBRATIO*. *JOBRATIO* is the ratio between the number of low skilled jobs in an LGA and the number of residents in low skilled employment. When this ratio is positive, there are more low skilled jobs than residents employed in low skilled occupations. The significance and negative coefficient of this variable suggests that an imbalance in the number of low skilled jobs and low skilled persons may be contributing to high unemployment rates in some SLA's in metropolitan Brisbane.

Finally, neighbourhood effects are found to be significant in the model. Previous studies in Australia, (see, for example, Kelly and Lewis 2000a and 2000b), have discussed neighbourhood effects but used methods that are inappropriate for the analysis of geographic data. In contrast, spatial econometric techniques, such as those used in the current research, provide an avenue through which such effects can be formally included in the modelling structure. The significance of the coefficient of the spatially lagged dependent variable (*Rho*) and the modelling selection criteria, which indicates that this is the most appropriate specification, suggests that neighbouring regions unemployment rates are important determinants of a regions unemployment rate. More specifically, geographic spillover effects are important in our model of urban unemployment variation. Further, estimation of the model while excluding such effects, as in Kelly and Lewis (2000a and 2000b) has been shown to result in biased parameter estimates (See Lesage (1999) for a discussion of the reasons behind this bias).

5. CONCLUSION

The modelling results presented in Table 1 are of some policy relevance. In particular, the results suggest that both supply side policies, such as improving the training and education levels of local residents and demand side policies, such as the provision of local job creation strategies, may both be beneficial in reducing urban unemployment.

From a supply side policy perspective, the results suggests that programs designed to encourage young persons to enter into education and training programs would be beneficial in reducing unemployment rates in this region. For example, both variables associated with education, i.e. *PERVOC*, the percentage of the population with a vocational training qualification and *PERBACH*, the proportion with a bachelor level qualification or higher, are shown to have a negative coefficient. Higher proportions of the population with these qualifications are therefore, associated with lower levels of unemployment.

In saying this, a qualification needs to be made with regard to the interpretation of the coefficients from the model presented in Table 1. A large volume of literature (for a extensive review of this literature, see Card 1999), investigating the role of education on labour market outcomes notes the problem of self-selection. Persons from different family backgrounds and belonging to different social groups place different values on education. These factors to a degree, determine both their education level and job preferences. In measuring the impact of education on labour market outcomes, account must be taken on these variables; otherwise the impact of education on labour market outcomes is likely to be overstated. This is not possible in the current analysis, so that the impact of education on unemployment rates is likely to be overstated in the modelling results presented in Table 1.

Also of importance from a policy perspective is the variable incorporated in the model to ascertain the significance of job imbalances. The variable *JOBRATIO*, shows the ratio of local jobs (within an LGA) to residents employment in low skilled jobs. Several authors have found that low skilled workers have less geographically expansive job search patterns than high skilled workers and are thus less likely to travel than higher skilled workers (see for example, Giuliano 1998, Immergluck 1998 and Eliasson et al. 2000).

The significance of this variable supports the contention of Immergluck (1998) who also suggests that pockets of high unemployment are not only helped by an improvement in the performance of the labour market across the wider metropolitan area, but that conditions within the local labour market are also important. This is especially so for low skilled workers who have less incentives to travel than higher skilled workers. Thus, this finding is supportive of the use of demand side polices such as local job creation strategies to reduce unemployment in geographic pockets of high unemployment.

Finally, the spatial autocorrelation in the residuals of the OLS version of the model, uncovered in the formal tests, suggest that the spatial lag is the most relevant of our two models. Generally, this form of model is taken to indicate the existence of geographic spillover effects, so that polices designed to decrease unemployment rates in one region will have beneficial impacts on neighbouring regions. This indicates that neighbourhood or geographic spillover effects are significant. Further, estimation of the model while excluding such effects has been shown to result in biased parameter estimates.

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