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Spatial dependence in regional unemployment in Australia

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1. Introduction

This paper introduces measures of spatial association (spatial autocorrelation) and spatial econometric techniques to analyse the dependence of regional unemployment rates in the major coastal regions of New South Wales as a precursor to a wider study of the importance of local interactions and social networks in Australian regional labour market outcomes. Australian Bureau of Statistics (ABS) census data from 1991, 1996 and 2001 is used for 69 Statistical Local Areas (SLAs) comprising Greater Metropolitan Sydney and its adjacent coastal regions of the Illawarra (south) and the Hunter (north). The study area is consistent with the findings in Watts (2004), in that it encompasses coherent local labour market boundaries. We investigate evidence of spatial dependencies in regional unemployment rates, and controlling for demand and supply effects we explore whether disparities in regional unemployment rates are partly owing to spillovers between neighbouring regions.

This study is motivated by evidence that differentials in regional employment growth rates and regional unemployment rates have persisted in Australia since the early 1990s (Productivity Commission, 1999; ALGA, 2002; O'Connor, *et al.*, 2001; Lloyd *et al*, 2004; Ramakrishnan and Cerisola, 2004), despite relatively robust growth in the Australian economy overall, which might have promoted convergence in regional labour market outcomes (Mitchell and Carlson, 2003a and 2003b). Disparities in Australian unemployment rates are more apparent the greater the level of spatial disaggregation employed (Borland, 2000: 20). While Keynesian macroeconomics typically argues that regional employment variations are a function of variations in the distribution of industries across space and that the impact of aggregate factors is largely uniform within those industries, Mitchell and Carlson (2003b) found regional factors to be independently significant. Even after controlling for industry composition, low growth regions experience stagnant labour markets and negative shocks appear to endure for a long time. These findings contradict Debelle and Vickery (1999) who found a high correlation between national and state unemployment rates but are consistent with Dixon and Shepherd (2001) and Lawson and Dwyer (2002).

Neoclassical explanations for the poor rates of convergence in regional outcomes tend to focus on wage differentials, low labour mobility and related structural impediments. Most recently in Australia's case, the award system and the 'structure of federal government transfers to households and sub-national governments' (giving rise to work disincentives that in turn impact adversely on regional labour market participation) have been identified as causal factors (Ramakrishnan and Cerisola, 2004). This conclusion fails to explain the role of the persistence of demand constraints (not enough jobs being produced) across most regional labour markets and the fact that regional unemployment rates are highly related (inversely) to regional employment growth (see Mitchell and Carlson, 2003a, 2003b). Ramakrishnan and Cerisola (2004: 3) also argue structural reforms in the Australian economy may have lead to greater adoption of new technologies in higher income states versus low income states accelerating the process of growth in real per capita income and output in certain states, although results indicate that the impact of skill-biased technological change is unclear.

A growing body of international research is developing new ways to think about space Regional disparities have received renewed emphasis in the emerging growth theory and in 'new economic geography', starting with Romer (1986, 1990), Lucas (1988) and Krugman (1991). Spatially disaggregated analysis of the labour market appears to provide beneficial insights into internal forces and the ways external forces are transmitted via economic, social and political linkages (Maierhofer *et al.*, 2001). There is renewed interest in models of social interaction and dependence among economic agents (Shields *et al.*, 2003; Jensen *et al.*, 2003; Durlauf, 2003; Glaeser *et al.*, 1996; Akerlof, 1997) and spatial spillovers (Anselin, 2002:1). Local interactions need not be defined geographically, but can exist across a 'social distance',

with a set of neighbours defined by an economic or social distance metric, such as occupation or race (Topa, 2001). These studies have forced econometricians to reconsider regional econometric techniques.

One model of local interactions (Wilson, 1987: 57 cited in Durlauf, 2003: 2) proposes that in areas where the majority of people experience spells of long-term joblessness, social isolation works to exclude residents from the job network of other neighbourhoods, and exclusion from networks results in less effective job-search. Labour market outcomes experience a greater decline than would otherwise be the case, welfare dependency increases and poverty traps result, with the process becoming self-perpetuating. So while the problem is in its source a lack of job opportunities largely due to erroneous macroeconomic policy, the hysteretic effects on individual motivation entrench the problem and increase the costs (see Mitchell, 2001). Meanwhile intergenerational effects retard the development of 'cognitive, linguistic and other education related skills' (Wilson, 1987: 57) in children, teachers become frustrated and exit the neighbourhood, accelerating the decline. Also young people may, based on observation of neighbourhood employment outcomes, make incorrect inferences about future returns to education and under-invest in human capital, leading to poorer employment outcomes in the future. Neighbourhood effects can exist through peer (where an individual is influenced by its cohort and the effects are reciprocal) or role model effects (where an individual is affected by earlier behaviours of older members of his social group). Durlauf (2003: 4) notes this 'imitative behaviour' may be due to psychological factors, a desire to behave like others, interdependencies which act as constraints and make costs dependent on the behaviour of others, or interdependences in information transmission. He identifies a number of sources of neighbourhood effects in the United States: classroom effects, social capital, segregation, social attitudes, homeownership and individual behaviour and geography and social customs.[2]

One of the few Australian studies looking at concepts of local interactions as they relate to unemployment (see also Gregory and Hunter, 1995; Hunter, 1996; Jensen *et al*., 2003; Shields *et al*., 2003) for studies of neighbourhood effects in Australia), suggests that there are links between neighbourhood information spillovers and unemployment rates amongst youth. In examining the job search behaviour of unemployed local youths, Heath (1999) finds that unemployed youth are much less likely to directly contact employers and much more likely to use indirect methods such as newspapers or employment agencies. She finds that higher overall neighbourhood unemployment rates decrease the probability of using direct search methods and increase the probability of using a labour market intermediary. In cases where the quality of local job-information networks (which may depend of the proportion of residents who are already in jobs) is low then the effectiveness of direct search methods may also be lessened. Heath (1999) concludes that the presence or absence of local job-information networks may also help explain the increasing concentration of unemployment documented by Gregory and Hunter (1995).

In the context of regional labour markets, theoretical explanations of spillovers also relate to capital accumulation processes and knowledge externalities which create agglomerations influencing firm locational decisions, and models of herds and information cascades (Audretsch and Feldman, 1996; Banerjee, 1992). Such 'local information spillovers' (Topa, 2001) ensure the spread of local shocks to neighbouring regions. Regional spillovers are most likely to exist in regions tightly linked by interregional migration, commuting and trade (Niehbuhr, 2003). Spillover effects ensure the spread of local shocks to neighbouring regions (Topa, 2001). If regions start with a steady-state pattern of local unemployment rates, any disturbance will impact on the local state and ripple out to the neighbouring regions (Molho, 1995). Higher degrees of spatial autocorrelation will increase the persistence of any regional

shock. Topa (2001) argues that neighbourhood stratification and widening inequalities accompany these endogenous spatial dependencies.

Exploration of such endogenous processes has clear policy relevance. Durlauf (2003: 6) notes political intervention, such as provision of scholarships, will be more effective where social multipliers work to magnify the policy's initial impact. Peer group effects within neighbourhoods will result in additional take-up of education over and above the scholarships provided, and role-model effects will see higher rates of human capital investment in the future. The parallel in employment policy is obvious, direct intervention in the form of job creation programs in regions with strong spillovers or interactions will promote higher overall employment growth, as effects ripple out to neighbours magnifying the initial growth stimulus. The development of economies of agglomeration, improvement in the size and efficiency of information flows (including technology and job-networks), increased market efficiency and associated higher levels of capital investment will lead to greater resilience against economic shocks for the region and its neighbours.

This paper focuses on the exploration spillovers or interactions between regions (rather than the smaller neighbourhood unit) stemming from geographic proximity. More detailed spatial analysis is planned for the next phase of the project. This work should be viewed as an introductory investigation into the problem. Traditionally, regional cross-sectional data are viewed as being conceptually identical to cross-sectional data on individuals or businesses at a single location. However, spatially adjacent observations are likely to exhibit spatial interdependence, owing to dynamics (such as those above) which accompany proximity. This emerging consensus begins with Tobler's (1970) maxim that 'everything is related to everything else but near things are more related than distant things'. Ignoring dependence between neighbouring regions will lead to biased regression results (Anselin, 1988). Also in many cases direct analysis of the interactions between regions is not possible, due to the scarcity of data, and this "requires us to apply a method that allows us to analyse the effects of spatial interaction without quantitative information on the different linkages between labour markets" Niebuhr (2003: 5). In the last twenty years, a range of spatial regression techniques have been developed to measure latent forces of interaction and handle data that violate standard statistical assumptions of independence (Cliff and Ord, 1981; Anselin, 1988; an excellent summary can be found in Goodchild *et al.*, 2000: 141).

While there has been growing recognition of differing patterns of labour market outcomes for households, local and regional areas in Australia, there has been little direct empirical consideration of the impact of interaction between neighbourhoods and regions on labour markets (Borland, 1995; Heath, 1999; O'Connor and Healy, 2002; are some exceptions). In this paper we estimate a model of changes in regional unemployment rates to test whether there is evidence of spillover effects, and whether these spillovers can be said to result in a "spatial dependence of labour market conditions" (Niebuhr, 2003: 4).

The paper is laid out as follows: Section 2 introduces the stylised facts of unemployment and employment growth in the regions that comprise the study area. There is significant visual evidence of spatial concentration. Section 3 outlines the concept of spatial autocorrelation and provides an introduction to spatial weight matrices, which are used in spatial statistics and spatial econometrics. Section 4 performs preliminary statistical analysis and confirms the presence of significant spatial dependency among regional unemployment rates. Section 5 presents a series of spatial econometric models while Section 6 formally investigates the proposition that regional unemployment is spatially dependent. We find that with a number of supply and demand controls added to the regressions, there is still some remaining spatial dependency. Concluding remarks follow.

2. Stylised facts from ABS census data

Figures 1 and 2 map the official unemployment rate for Statistical Local Areas (SLAs) in the Hunter, Sydney and Illawarra regions for 1991 and 2001, respectively.[3] Figure 1 records unemployment in 1991, a recession year. Rates range from 4.9 per cent in Baulkham Hills per cent to 21.8 per cent in Fairfield. SLAs in the Hunter, particularly the Great Lakes SLA, record high rates of unemployment in 1991, as do SLAs in the Illawarra Statistical Region, notably Shoalhaven. SLAs in Inner-Sydney and surrounding region, particularly Eastern Suburbs and the North Shore, record below average rates of unemployment (bottom quintile). However there are still some SLAs within the Sydney metropolitan region that occupy the top quintile, largely in Western Sydney (see inset).

Figure 2 maps unemployment rates for 2001. The growth over the 1990s saw the average unemployment fall by 3.8 per cent (10.4 to 6.6 per cent) between 1991 and 2001. The Hunter's relative position worsens in 2001 (unemployment rate of 9.1 per cent overall). This is concentrated in the Newcastle SLA, but also further south outside the Hunter in Gosford. SLAs of outer Western Sydney fare better, as evidenced by the shrinking numbers of SLAs in the top quintile, although some remain in the top two quintiles of SLAs. The better performing SLAs are concentrated in Inner, Eastern and Northern Sydney. The standard deviation for rates decrease over the period from 3.9 to 2.6, and this provides a crude indication that concentration of rates may have increased although it tells us nothing about the spatial concentration.

The other stylised fact worth noting is that between 1991 and 2001 employment grew by 22 per cent overall but was unevenly distributed across the 69 regions (see Figure 3 for graphical analysis). From 1996 to 2001 employment grew by 10 per cent, plotted by SLA in Figure 4. SLAs of Inner Sydney, Camden, Liverpool and Blacktown all experienced strong employment growth. The Hunter performed relatively poorly, particularly the Northern Hunter – Merriwa, Murrurundi, Gloucester and Muswellbrook all recorded negative growth, and Fairfield in Western Sydney remained sluggish. An examination of the data also shows that there is no significant regression to the mean operating in the data between 1991 and 2001 (see Figure 5). SLAs with high unemployment do not have the largest changes in unemployment rates.

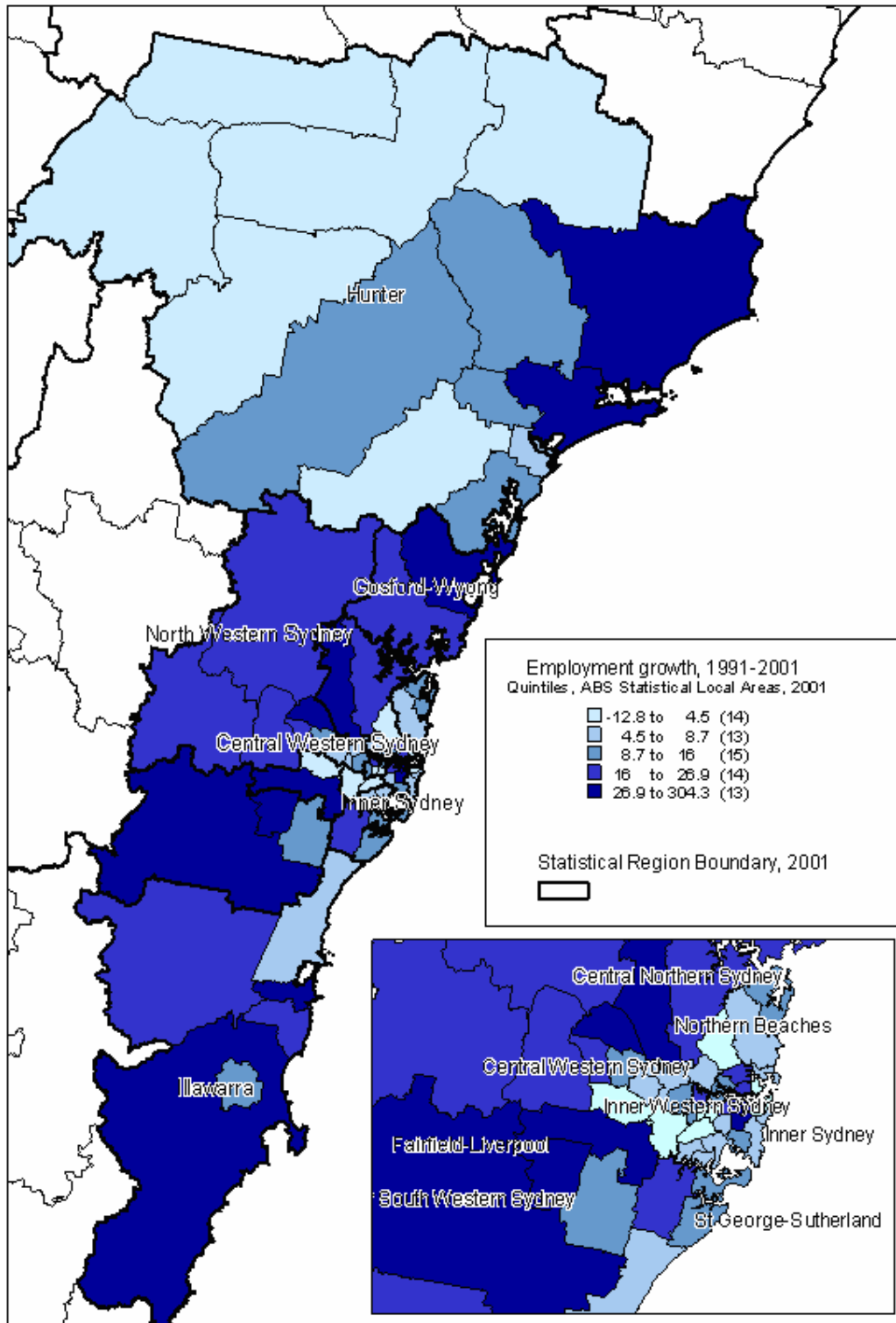Figure 1 Unemployment rates for SLAs in Illawarra, Hunter, Sydney and Inner Sydney, 1991
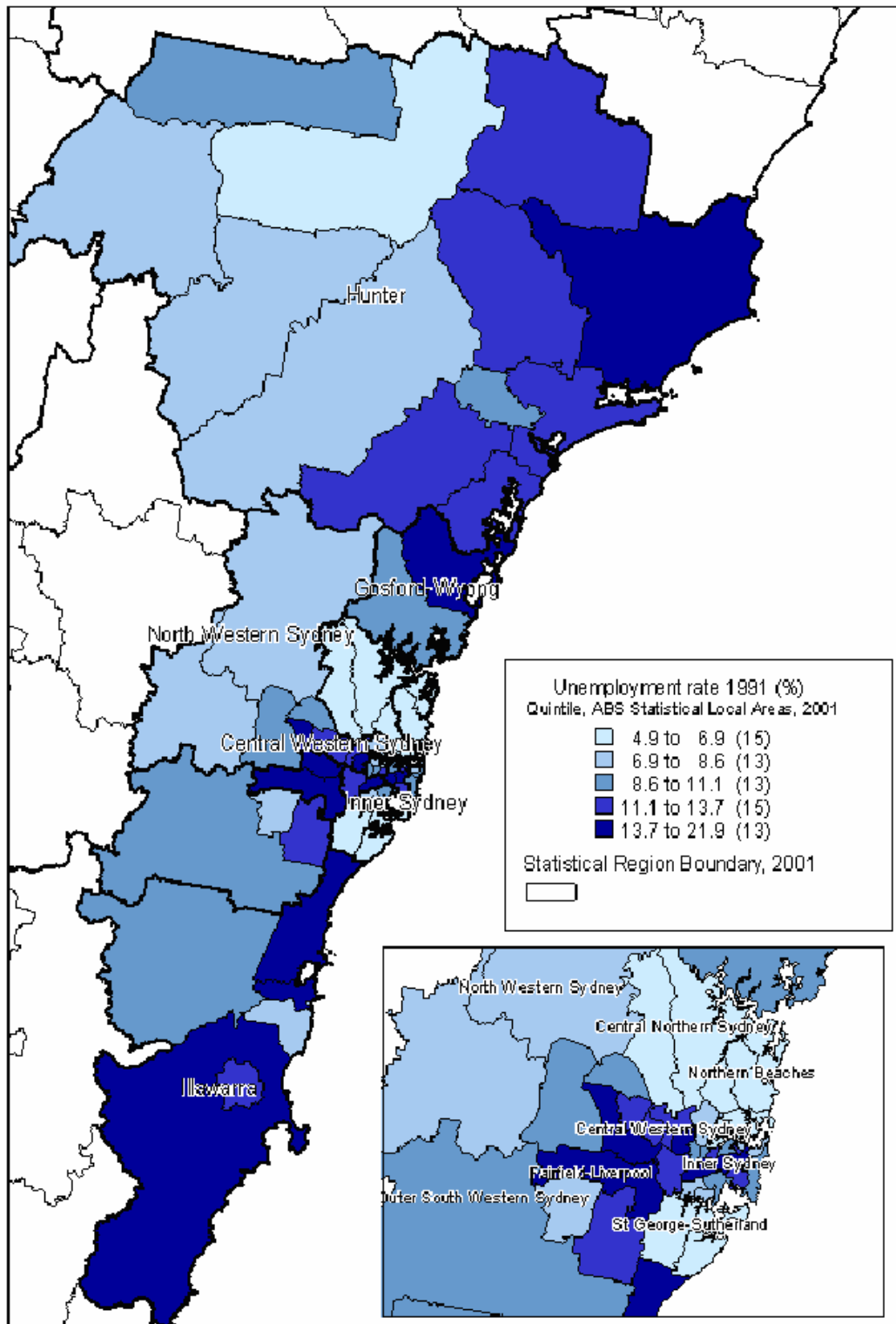
Source: ABS, CDATA: Census of Population and Housing 2001, Time Series Profile – T13 – Age by Labour Force Status (full-time/part-time) by Sex.

Figure 2 Unemployment rates for SLAs in Illawarra, Hunter, Sydney and Inner Sydney, 2001
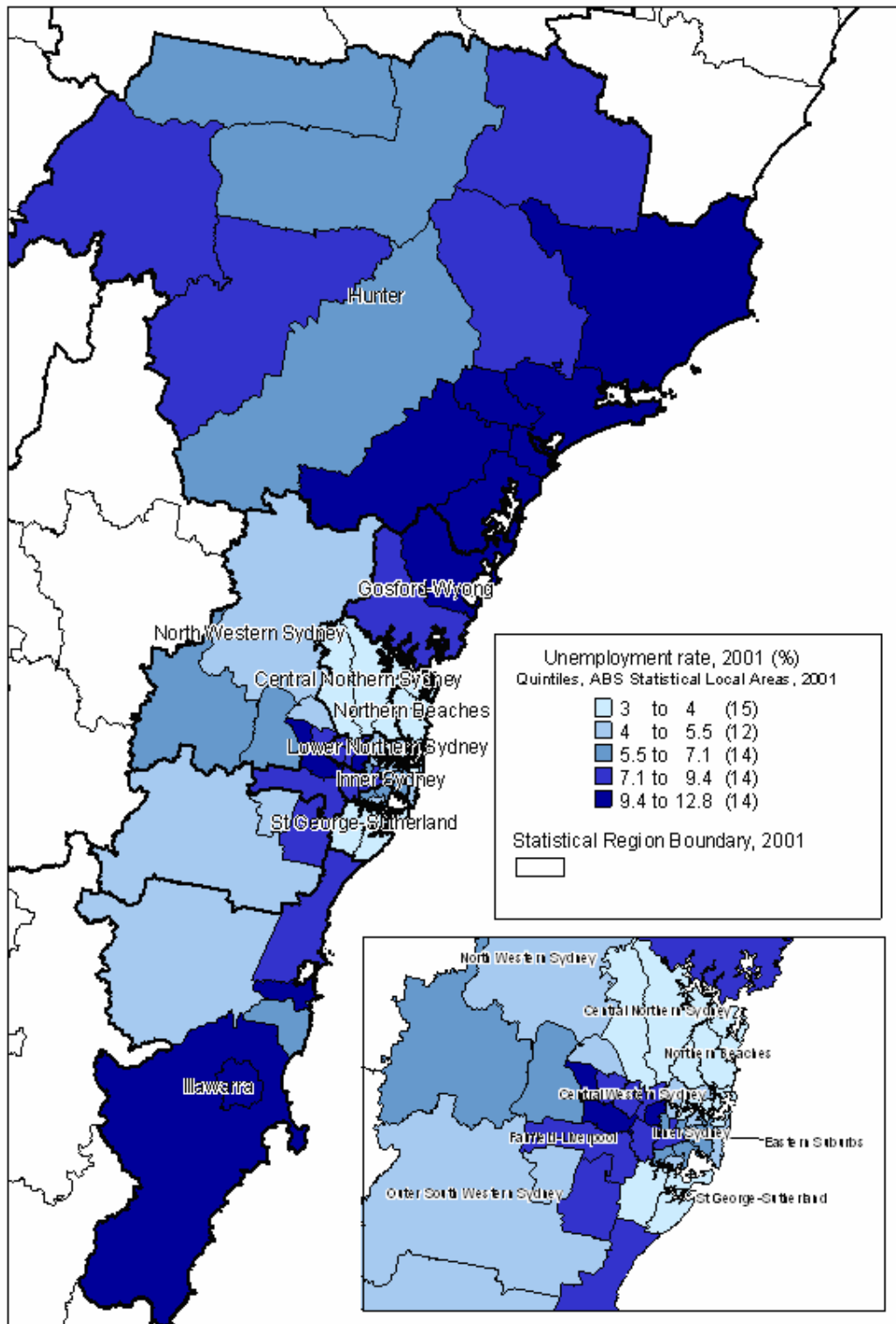
Source: see Figure 1.
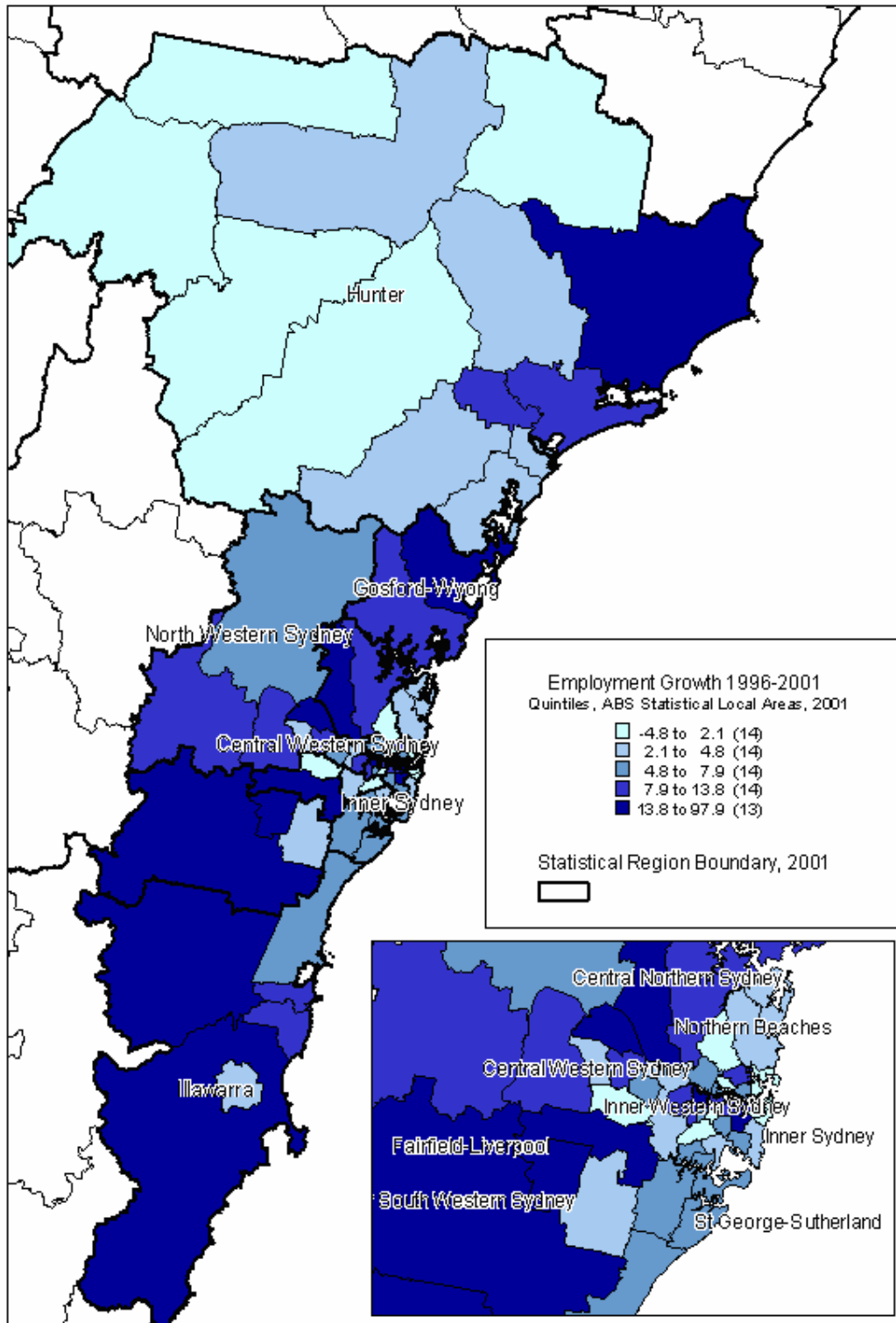
Figure 3.Employment growth for SLAs in Illawarra, Hunter, Sydney and Inner Sydney, 1991 to 2001
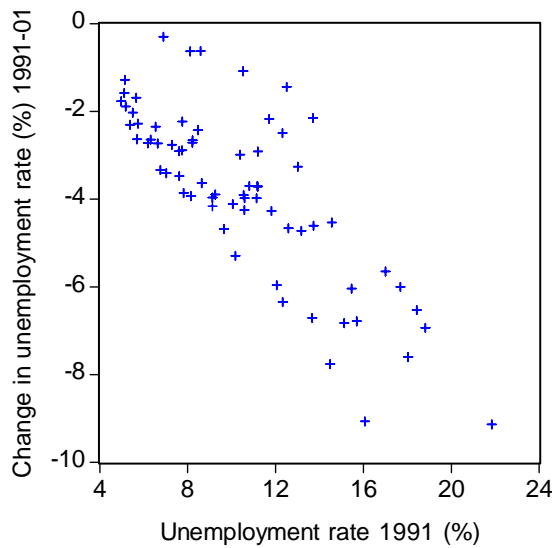

Source: see Figure 1

Figure 4 Employment growth for SLAs in Illawarra, Hunter, Sydney and Inner Sydney, 1996 to 2001

Source: see Figure 1.

Figure 5 Persistence in regional unemployment rates 1991-2001


Source: ABS Census data, 2001.

3.   Spatial autocorrelation: what is it and how is it measured?

3.1   The concept of spatial autocorrelation

Spatial autocorrelation refers to the formal measure of the extent near and distant things are related. Figure 6, using raster representation, depicts the three types of spatial autocorrelation:

1. Positive spatial autocorrelation occurs when features that are similar in location are also similar in attributes;

2. Negative spatial autocorrelation occurs when features that are close together in space are dissimilar in attributes; and

3. Zero autocorrelation occurs when attributes are independent of location.

Figure 6 Stylised patterns of spatial correlation

| (a) positive spatial correlation | (b) negative spatial correlation | (c) zero spatial correlation |
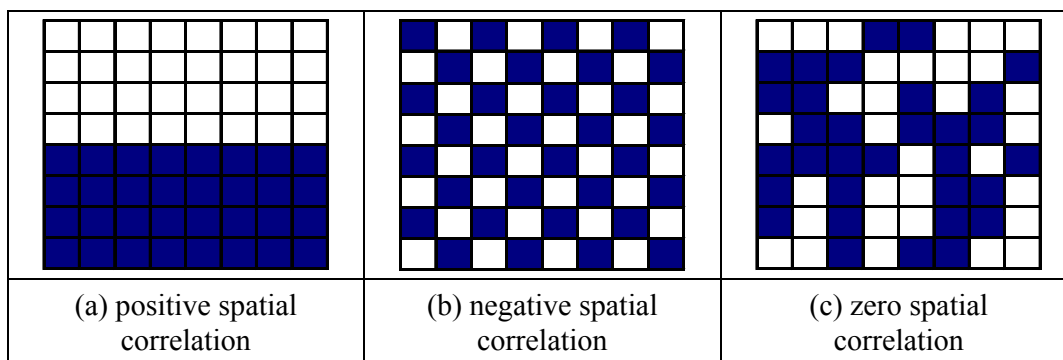
Source: Longley *et al* (2001).

There are two reasons proposed as to why spatial dependence may exist between regions. First, data collected on observations associated with spatial units such as used in the ABS Australian Standard Geographic Classification (of which the SLAs are one unit) may contain measurement error because the administrative boundaries for data collection do not reflect the underlying processes generating the sample data (Anselin, 1988: 11-12). If social or economic

phenomena cross geographic boundaries we would expect to see very similar results amongst neighbouring regions. For example, mobile workers can cross boundaries to find employment in neighbouring areas, and thus labour force or unemployment measures based on where people live could exhibit spatial dependence.

Second, location and distance are important forces at work in human geography and market activity. In the context of this paper, clustering of unemployment rates might occur because of spatial pattern of employment growth (demand) or the distribution of population characteristics such as job skills (supply), and some mismatch between them. Further, housing has clear spatial dimensions which may contribute to the clustering of unemployment rates as disadvantaged workers seek cheaper housing (O'Connor and Healy, 2002; Hulse *et al.*, 2003). Mobility then becomes an important factor in determining the extent of spatial dependence. Neoclassical explanations for regional unemployment differentials revolve around the rigidity of wages and the imperfect mobility of labour resources (Debelle and Vickery, 1999). European empirical evidence points to the strong effects of distance as an obstacle to migration. Migration is significantly reduced as distance increases because the costs of moving rise and the benefits from migration become increasingly unknown (Helliwell, 1998; Tassinopolous and Werner, 1999). Spatial impacts can also occur independently of employment patterns, population characteristics and housing patterns due to the functioning of social networks and neighbourhood effects discussed in the introduction (Borland, 1995; Topa, 2001).

3.2   Representing spatial dependency with spatial weight matrices

Spatial statistics and spatial econometrics analysis require the specification of spatial weight matrices which Stetzer (1982: 571) notes represent "a priori knowledge of the strength of the relationship between all pairs of places in the spatial system." The weights are analogous to lag coefficients in autoregressive-distributed lag time series models. Unlike in time-series data where data points are ordered contemporaneously determining the order of observations in space is difficult as it is multidirectional. A 'spatial order' is typically imposed in a more or less *ad hoc* fashion. Thus, estimation of spatial autocorrelation is sensitive to the weights employed and the weights embody assumptions about the spatial structure (Molho, 1995: 649).

Stetzer (1982: 571) discusses various criteria proposed to guide the specification of the weighting matrices, including "connectivity, contiguity, length of common boundary between political units, and various distance decay functions" (see also Hordijk, 1979; Anselin, 1988). Stetzer (1982: 571) identifies fundamental "spatial attributes of any weighting system which characterises the weights. The first is the size of the effective area or region over which the weights for a particular place are nonzero. The second is the slope of the weights over the effective area." With notions of 'connectivity' or 'contiguity' the 'effective area' is small and distance decay effects are ignored. Alternatively, deriving weights using distance decay functions has the advantage of not constraining the effective area (that is, all weights between regions could be positive) (Cliff and Ord, 1981).

In the context of research that commuting patterns in the Greater Sydney Metropolitan region and its adjacent coastal regions of the Hunter and the Illawarra (our study area) are diverse (Watts, 2004), the distance decay approach is used in this paper. In later research, more comprehensive weight patterns will be explored using Bayesian techniques and nearest-neighbour approaches.

Following Stetzer (1982: 572) two distance-based functions are used to construct the spatial weight matrices:

1. Power function: define $w_{ij} = 1/d_{ij}$ where d_{ij} is the distance between the centroids of regions i and j; for $d_{ij} < D_{max}$; $w_{ij} = 0$ otherwise. Stetzer (1982: 572) that "the value of D_{max} in the distance decay weights must …be defined operationally for the particular study area and units of distance measure." In that regard, two values for D_{max} are used: (a) average distance between first-order contiguous regions (29.3 kilometres); and (b) distance between Newcastle and Sydney given that commuting takes place between the two cities (Watts, 2004).

2. Negative exponential function: define $w_{ij} = \exp(-cd_{ij})$ for $d_{ij} < D_{max}$; $w_{ij} = 0$ otherwise; d_{ij} is the distance between the centres of regions i and j; and c is the distance decay parameter. The elements $w_{ii} = 0$ prevent a region 'predicting itself'.

Stetzer (1982: 572) indicates that "for a particular problem, there may be substantive reasons for choosing one … [function] … over another …" Based on the assumption that in practice, the weights are row-standardised to sum to unity over j, Stetzer (1982: 572) says the "appropriate criterion for comparing distance decay functions is their relative magnitude at different distances. On this criterion, the power function weights $1/d$ … are computationally more convenient since they are scale-free; that is, changing the units of measure will not change the relative weights at any two places …[and] …is acceptable for any unit of measure or any size of study area. For the negative exponential weights … the value of the constant … [c] … must be selected with reference to the numerical values of the distance which may be encountered."

To aid interpretation of the empirical results, we follow Bröcker (1989) and use a transformed distance decay parameter γ_e which is defined as:

(1) $\gamma_E = 1 - e^{-c\bar{d}}$ $0 \leq \gamma_E \leq 1$

where d is some relevant distance. Niehbur (2001) uses the average distance between centres of immediately neighbouring regions. The transformed parameter γ_E measures the percentage decrease of spatial effects if distance expands by a given unit of d. We use two values for d as in the power function case. The additional task is in choosing a value of c.

Figure 7 Impact of different assumptions of gamma and distance on weight profiles

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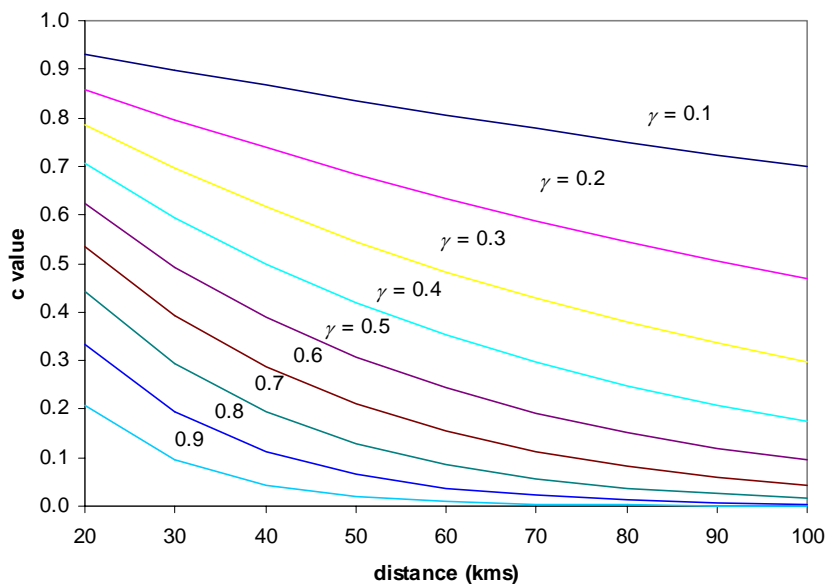
With increasing values of γ_E the distance (geographical) constraints increase in intensity and the decline of spatial dependency rises with increasing distance from any given region. Figure 7 shows different decay profiles for different values of γ and a corresponding c value. Mohlo (1995: 649) says the value c takes determines the "importance of distance in attenuating the spillover effects" between regions. Accordingly, "high values of … [c] …imply short-range interactions only … [and] … low values would allow longer-range interactions" (Mohlo, 1995: 649).

4.   Preliminary statistical analysis

To determine the degree of spatial dependence or concentration of the geographic distribution of unemployment rates over the 1990s, standard measures of concentration (Theil Index) and dispersion (Coefficient of Variation) are employed. Table 1 illustrates that dispersion is higher in 2001 than in the 1991 recession but has fallen from 42.4 per cent in 1996 for the 69 regions. The Thiel Inequality Index compares the distribution across populations by summing, across groups, the weighted natural logarithm of the ratio between each group's unemployment share and that of the population, and is given by the formula below.

$$(2) \qquad T \equiv \sum_{i=1}^{n} w_i \ln\left(\frac{x_i}{\bar{x}}\right)$$

where x_i is the unemployment rate in region i, $\bar{x}$ the average unemployment rate across all regions, and w_i is the share of the ith region's unemployment in total unemployment. If every region has mean unemployment – perfect equality - the Theil Index equals zero. Conversely, a Theil of unity represents a state of perfect inequality (one region has all the unemployment). From Table 1 it is clear that regional inequality has fallen slightly from 1991 to 2001 but it still not close to zero.

Table 1 Concentration and dispersion of regional unemployment rates over the 1990s

	Theil Index	Coefficient of Variation
1991	0.1042	37.6
1996	0.0980	42.4
2001	0.0863	39.8

Source: ABS, Census of Population and Housing, Time Series Profile 1991-2001, authors' calculations

Such traditional measures of dispersion provide no information on whether similar values are found in neighbouring regions. Spatial autocorrelation measures can provide a summary measure of the similarity or dissimilarity of values that are spatially proximate. Moran's I statistic is a well known 'global' measure of spatial autocorrelation and takes the value of zero where no spatial autocorrelation exists. The Moran I statistic is computed as:

$$(3) \qquad I_t = \frac{R \sum_{i=1}^{R} \sum_{j=1}^{R} x_i x_j w_{ij}}{R_b \sum_{i=1}^{R} x_i^2}$$

where R is the number of regions, R_b is the sum of the weights and simplifies to R when the spatial weighting matrix is row-standardised (in our case $R = 69$), x is the unemployment rate in region i (in mean deviations). The Moran I statistic is easily computed from the residuals of a regression on a constant and can be expressed as a standardised normal Z value for inference purposes. At the 5 per cent level of significance we reject the null of no spatial autocorrelation

if the standardised Moran *I* statistic is greater than 1.96. Table 2 presents the standardised Moran *I* statistics and probability values for both distances (29.3 and 153 kms)[4] using the different spatial weight matrices discussed previously.

Based on the Moran *I* statistics, irrespective of the distance metric used, there is evidence that the geographic distribution of unemployment in the study area has become more clustered over the 1990s. These results support Mitchell and Carlson (2003a, 2003b).

Table 2 Spatial autocorrelation of regional unemployment rates in 69 SLAs comprising Greater Sydney, the Illawarra and the Hunter SRs, 1991, 1996 and 2001

Spatial Weighting	D_{max} = 29.3 kms		D_{max} = 153 kms	
	Moran *I*-statistic	Prob Value	Moran *I*-statistic	Prob Value
UR1991				
Power Function	2.03	0.05	2.65	0.01
γ = 0.1	1.86	0.07	0.23	0.39
γ = 0.2	1.90	0.07	0.33	0.38
γ = 0.3	1.95	0.06	0.43	0.36
γ = 0.4	2.01	0.05	0.56	0.34
γ = 0.5	2.08	0.05	0.71	0.31
γ = 0.6	2.17	0.04	0.89	0.27
γ = 0.7	2.27	0.03	1.12	0.21
γ = 0.8	2.43	0.02	1.42	0.14
γ = 0.9	2.68	0.01	1.86	0.07
UR1996				
Power Function	4.27	0.00	4.63	0.00
γ = 0.1	4.62	0.00	2.93	0.01
γ = 0.2	4.65	0.00	3.20	0.00
γ = 0.3	4.70	0.00	3.50	0.00
γ = 0.4	4.75	0.00	3.83	0.00
γ = 0.5	4.80	0.00	4.21	0.00
γ = 0.6	4.87	0.00	4.64	0.00
γ = 0.7	4.95	0.00	5.15	0.00
γ = 0.8	5.06	0.00	5.76	0.00
γ = 0.9	5.21	0.00	6.51	0.00
UR2001				
Power Function	5.03	0.00	5.44	0.00
γ = 0.1	5.34	0.00	4.38	0.00
γ = 0.2	5.38	0.00	4.68	0.00
γ = 0.3	5.43	0.00	5.01	0.00
γ = 0.4	5.48	0.00	5.37	0.00
γ = 0.5	5.54	0.00	5.78	0.00
γ = 0.6	5.60	0.00	6.25	0.00
γ = 0.7	5.68	0.00	6.80	0.00
γ = 0.8	5.78	0.00	7.44	0.00
γ = 0.9	5.91	0.00	8.20	0.00

Note: γ is the adjusted exponential distance decay parameter, Moran's *I* statistic is the standardised Z-value, prob. value is the probability value.

Table 2 also reveals that as the exponential decay parameter increases the First-order spatial autoregressive (FAR) model's fit improves (see Section 5), indicating that in our data interactions are localised and decline sharply with distance (distance is simply the distance between centroids of SLAs). To validate this finding using available data on the pattern of real world interactions, we draw on journey to work data from the 2001 census, by SLA. While not exhaustive, commuting is an obvious form of interaction between regions (it is also in some ways more closely related to the concept of measurement error than local spillovers, see also Watts, 2004). In 2001, for our study area, 2,183,995 people were employed part-time or full-time. Of these, 1,954,825 responded to the question on journey to work[5] and 1,216,593 actually commuted to work, that is travelled outside their own SLA. Figure 8 shows the frequency of interactions, proxied by commuters moving from place of residence to work, as distance increases. The average distance travelled by those who commute is 41 km (14 km if you include those who do not travel outside their own SLA for work). The number of commuters increases from 0-20 kilometres and thereafter falls, indicating when residents do commute they are more likely to do so for 20 kilometres than 10 kilometres, but thereafter the number of commuters decline with distance. The pattern confirms the results of our grid search (Table 2), it shows very sharp decline in the number of commuters as distance increases beyond 20 kilometres – and closely resembles the exponential decay pattern shown in Figure 7, for small values of c. The optimal model is one associated with relatively high distance decay $\gamma = 0.9$ (see Table 2), according to this distance decay, the intensity of spatial effects declines quickly, by approximately 50 per cent between 20-30 kilometres (where D_{max} = 29.3 kilometres). Journey to work data reveals the proportion of commuters declines by approximately 50 per cent over 20-35 kilometres, although the decay in commuters is not necessarily a smooth downward function of distance.

Figure 8 Total commuters by distance commuted, 2001 – SLAs in Illawarra, Hunter, Sydney and Inner Sydney SRs.
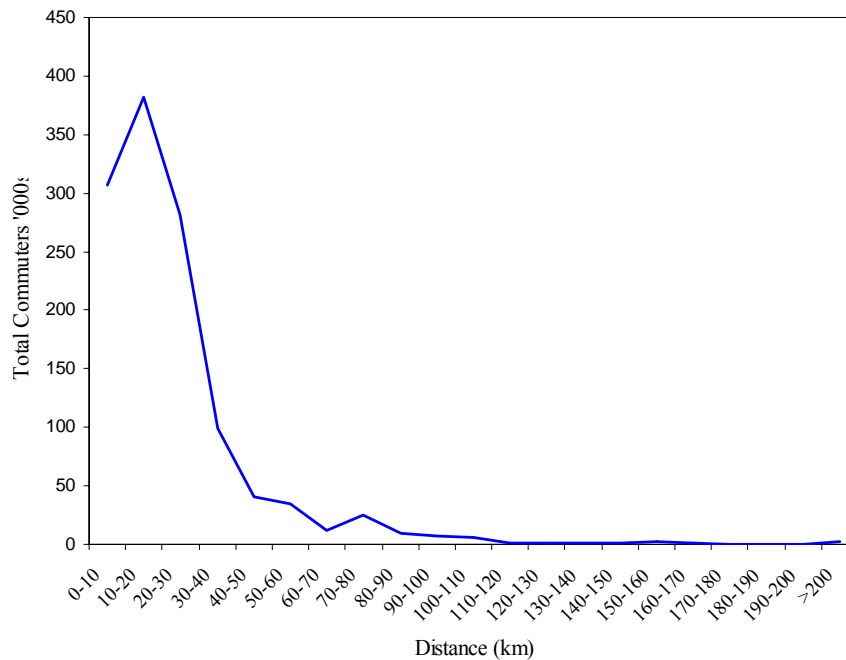
Source: ABS, Custom Table, 2001 Census of Population and Housing.

The presence of spatial interaction in data samples suggests the need to quantify and model the nature of the spatial dependence. In the next section we outline the taxonomy of spatial econometric models that can more formally explore the spatial interaction between unemployment rates in the 69 regions. In a later paper we will report the results of 'local' Moran analysis which allows the nature of the spatial dependencies to be expressed in terms of spatial clusters with positive or negative spatial autocorrelation and spatial outliers.

5.   A taxonomy of spatial econometric models

5.1   Introduction

Anselin (2003) attempts to extent the earlier work on spatial dependence which was characterised by the "standard taxonomy of *spatial autoregressive lag* and *error* models commonly applied in spatial econometrics" (Anselin, 2002: 2; Anselin 1988). He notes that this taxonomy "is perhaps too simplistic and leaves out other interesting possibilities for mechanisms through which phenomena or actions at a given location affect actors and properties at other locations." In this extension, he makes a distinction between 'global' and 'local range' spatial dependencies which have implications for the econometric specification of spatially lagged dependent variables (**Wy**), spatially lagged explanatory variables (**WX**) and spatially lagged error terms (**Wu**) (here the **W** matrix is a weighting scheme designed to capture the spatial dependencies).

Anselin (1988: 34) introduced the general spatial model specification which applies to "situations where observations are available for a cross-section of spatial units, at one point in time." The approach begins with a general specification which can then be simplified by imposing specific parameter restrictions that reflect different spatial hypotheses. In this section we describe the general and specific spatial econometric models that we estimate in this paper (we follow Anselin, 1988 and LeSage, 1999 in terminology and syntax).

5.2   The general spatial autoregressive econometric model

The general spatial autoregressive model is:

(4) $\mathbf{y} = \rho \mathbf{W_1 y} + \mathbf{X\beta} + \mathbf{u}$

$\mathbf{u} = \lambda \mathbf{W_2 u} + \mathbf{\varepsilon}$

$\mathbf{\varepsilon} \sim N(0, \sigma^2 \mathbf{I})$

where **y** is a *n* x 1 vector of observations for the dependent variable, **X** is a *n* x *k* matrix of observations on the explanatory variables (including a constant) with an associated *k* x 1 vector of unknown parameters **β**, and **ε** is a *n* x 1 vector of random terms. The error variance matrix $\sigma^2 \mathbf{I}$ could be further generalised to capture the standard problem of heteroscedasticity by appropriate re-specification of its diagonal elements.

The *n* x *n* spatial weight matrices $\mathbf{W_1}$ and $\mathbf{W_2}$ can be standardised (row elements sum to unity) or non-standardised and are, respectively, associated with a 'spatial autoregressive process in the dependent variable" (Anselin: 1988: 35) and in the error term. The spatial weight matrices are usually specified in terms of first-order continuity relations or as functions of distance (LeSage, 1998: 30). So $\mathbf{W}_{ij}$ is the spatial weight of region *i* in terms of region *j* (typically scaled to sum to one over *j*) and are discussed at length in Section 3.

5.3   Simple linear model with no spatial effects

The introduction of spatial elements into the econometric specification reflects the fact that if substantive spatial effects exist, a standard OLS specification linking specification linking **y**

and $\mathbf{X}$ will produce biased estimates. However, it is clear that the standard linear regression model is obtained by imposing $\mathbf{W}_1 = \mathbf{0}$ and $\mathbf{W}_2 = \mathbf{0}$ on the Equation (4):

(5) $\quad \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$

$\quad\quad \boldsymbol{\varepsilon} \sim N(0, \sigma^2 \mathbf{I}_n)$

5.4 First-order spatial autoregressive (FAR) model

The FAR model is obtained by imposing $\mathbf{X} = \mathbf{0}$ and $\mathbf{W}_2 = \mathbf{0}$ on Equation (4) such that the restricted model is:

(6) $\quad \mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \boldsymbol{\varepsilon}$

$\quad\quad \boldsymbol{\varepsilon} \sim N(0, \sigma^2 \mathbf{I}_n)$

The FAR model indicates that variation in $\mathbf{y}$ is explained by a "linear combination of contiguous or neighbouring units with no other explanatory variables" (LeSage, 1999: 44).

5.5 Mixed autoregressive-spatial autoregressive (SAR) model

The SAR model is obtained by imposing $\mathbf{W}_2 = \mathbf{0}$ on Equation (4) such that the restricted model is:

(7) $\quad \mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$

$\quad\quad \boldsymbol{\varepsilon} \sim N(0, \sigma^2 \boldsymbol{I})$

This model is called a mixed regressive-spatial autoregressive model (Anselin, 1998) because it combines the standard regression model with a spatially lagged dependent variable. Anselin's (1988) called this the 'spatial error model' and LeSage (1999: 44) notes that "this model is analogous to the lagged dependent variable model in time series." The parameter ρ measures the degree of spatial dependence inherent in the data. In this paper, it will measure the average influence of the unemployment rates in neighbouring regions on the unemployment rate in our region of interest.

5.6 Spatial autocorrelation (SEM) model

The SEM model is found by imposing $\mathbf{W}_1 = \mathbf{0}$ on Equation (4) and the resulting equation is a standard regression model with spatial autocorrelation in the error term:

(8) $\quad \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$

$\quad\quad \mathbf{u} = \lambda \mathbf{W}_2 \mathbf{u} + \boldsymbol{\varepsilon}$

$\quad\quad \boldsymbol{\varepsilon} \sim N(0, \sigma^2 \boldsymbol{I})$

The presence of spatial autocorrelation may be due to measurement problems (rather than endogenous effects occurring between neighbours).

5.7 Spatial Durbin (SDM) model

The SDM model is found by adding a spatially weighted term to the FAR model such that:

(9) $\quad \mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X}\boldsymbol{\beta}_1 + \mathbf{W}_1 \mathbf{X}\boldsymbol{\beta}_2 + \boldsymbol{\varepsilon}$

$\quad\quad \boldsymbol{\varepsilon} \sim N(0, \sigma^2 \boldsymbol{I})$

Equation (9) includes a 'spatial lag' of the dependent variable in addition to a 'spatial lag' of the explanatory variables matrix. One or more of the $\mathbf{X}$ variables can be spatially lagged.

5.8   Spatial autocorrelation diagnostic tests

We employ the standard spatial diagnostic tests to test for spatial autocorrelation in the residuals from the OLS regression and the SAR models. These tests are outlined in LeSage (1999) and are summarised as follows:

<u>Moran *I*-statistic</u> (Cliff and Ord, 1972, 1973, 1981) is written as:

$$(10) \quad \mathbf{I} = \mathbf{e}'\mathbf{W}\mathbf{e} / \mathbf{e}'\mathbf{e}$$

where **e** is the regression residuals. The ***I*** statistic has an asymptotic distribution that corresponds to the standard normal distribution after subtracting the mean and dividing by the standard deviation of the statistic (Anselin, 1988: 102). We thus interpret the standardised version as rejecting the null of no spatial autocorrelation if its value exceeds 1.96 (at the 5 per cent level).

<u>Likelihood ratio test</u> compares the LR from the OLS model to the LR from the SEM model and this statistic is asymptotically distributed as $\chi^2(1)$. We reject the null of no spatial autocorrelation if the test statistic exceeds 3.84 (at the 5 per cent level) and 6.635 (at the 1 per cent level).

<u>Wald test</u> (Anselin, 1988: 104) is asymptotically distributed as $\chi^2(1)$. We reject the null of no spatial autocorrelation if the test statistic exceeds 3.84 (at the 5 per cent level) and 6.635 (at the 1 per cent level).

Lagrange Multiplier (LM) test (Anselin, 1988: 104) uses the OLS residuals **e** and the spatial weight matrix **W**, and is computed as:

$$(11) \quad LM = (1/T)\left[(\mathbf{e}'\mathbf{W}\mathbf{e})/\sigma^2\right]^2 \sim \chi^2(1)$$

$$T = tr(\mathbf{W} + \mathbf{W}')\mathbf{W}$$

<u>Spatial error residuals LM test</u> (Anselin, 1988: 106) is based on the residuals of the SAR model to determine "whether inclusion of the spatial lag term eliminates spatial dependence in the residuals of the model" (LeSage, 1999: 75). The test requires the spatial lag parameter *r* is non-zero in the model. The test produces a LM statistic which is asymptotically distributed as $\chi^2(1)$. As before, we reject the null of no spatial autocorrelation if the test statistic exceeds 3.84 (at the 5 per cent level) and 6.635 (at the 1 per cent level).

6.   Results and analysis

6.1   Estimation model

The general model we will use to explore the evolution of the regional unemployment rates between 1991 and 2001 is:

$$(12) \quad \Delta\mathbf{ur} = \rho\mathbf{W}\mathbf{ur} + \boldsymbol{\alpha}\Delta\mathbf{e} + \gamma\mathbf{W}\Delta\mathbf{e} + \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

This includes the spatial lag term for the change in the unemployment rate $\Delta\mathbf{ur}$, where ρ measures the average influence of the change in unemployment rates in neighbouring regions on the change in the unemployment rate in region *i*; the spatial Durbin term where γ is the coefficient on the spatial lagged employment growth rate $\Delta\mathbf{e}$; and **X** is a matrix of control variables outlined below. The coefficient on the spatially lagged regional employment growth, allows us to test whether a region's unemployment rate is a function (expected to be negative) of its neighbour's employment growth. Accordingly, job loss/growth in one area generates job

loss/growth in neighbouring areas, even when the neighbouring areas job loss/growth is held constant (and after controlling for other regional characteristics in **X**).

Our main focus is to seek evidence of spatial dependence between regional unemployment rates and also to determine whether regional employment growth exhibits spill-over effects on regional unemployment rates.

6.2   Control variables

In addition to including the demand-side influence of employment growth (measured as the log ratio of employment between two census years), we control for other factors including:

1. Population Density (averaged over the period 1991 to 2001) to capture the density of local labour markets. One hypothesis is the matching efficiency improves with increases in density and thus unemployment rates should be lower (Elhorst, 2000). Alternatively, dense markets may attract displaced job-seekers from other regions and the supply effects may increase the unemployment rate in that region.

2. Labour force participation rate – which may measure supply or demand factors.

3. Human capital variables – including the Percentage no-post school qualifications (skill proxy); the Percentage of 15-24 year olds in region's population; the proportion of indigenous residents in each region; the proportion of residents born overseas.

4. Industrial composition variables including proportion of manufacturing employment in region's total employment (to model deindustrialisation processes) and the proportion of non-government service employment (embracing ANZSIC divisions Retail Trade; Accommodation, Cafes and Restaurants; Finance and Insurance; Property and Business Services; Cultural and Recreational Services and Personal and Other Services).

5. Industrial diversity index – a modified Herfindahl index (based on Lawson and Dwyer (2002) application of Duranton and Puga (1999)):

$$(8) \quad RDI_i = \frac{1}{\sum_j \left| S_{ij} - S_j \right|}$$

    RDI is the industrial diversity of region *i* in 2001, which is the inverse of the share of regional employment in industry *j* minus national share of employment in industry *j* summed over all 1-digit ANZSIC industries present in a region in 2001.

6. Other indicators including the proportion changed address in the last year (as some measure of mobility) and the proportion using the Internet (as some measure of network skills).

7. Proportion of part-time employment to full-time employment.

All spatial weight matrices were row-standardised and the Matlab sparse matrix handling capacity was used in all estimation. A grid search methodology was used whereby exponential decay spatial weight matrices were constructed for each value of γ (from 0.1 in 0.1 increments to 0.9) and the best model was chosen on the basis of its statistical veracity (Mohlo, 1995).

6.3   Results and analysis

This is preliminary work and no attempt is made at this stage to delve into the structure or causal relations that might be driving the spatial interactions. Given the evidence gleaned from this study, our future work will devise behavioural models of social network interaction.

Table 3 reports the various regression results using Matlab Maximum Likelihood functions programmed for spatial analysis (LeSage, 1999). The reported results are for the preferred spatial weight function $1/d$ where D_{max} = 29.3 kms. We do not present the results where D_{max} = 153. The preliminary results are not dissimilar to the SAC estimates presented in 4.3 although there is residual spatial autocorrelation remaining. This requires further exploration, but as specified in Equation 1 if we allow a larger distance truncation the spatial dependency increases.

We first explored the specification for the 1991-2001 change and found that there was no evidence of spatial autocorrelation in the OLS model which was consistent with the evidence presented in Table 2, the Moran I statistic indicate an increasing level of spatial dependency in the unemployment rates over the 3 observation periods: 1991, 1996 and 2001. We thus turned our attention to modelling the dependent variable log ($ur2001/ur1996$) for the period between 1996 and 2001. We include the level of the log of the unemployment rate for 1996 to capture persistence or regression to the mean. All other variables are in logs. The results reported are after several control variables were deleted due to statistical insignificance.[6]

In Table 3, the column denoted 3.1 reports the OLS regression results using the Newey-West correction to produce consistent estimates of the covariance matrix (given the cross-section contained regions of vastly different population sizes) for the change in unemployment rate and the employment growth rate corresponding to observations taken from the 1996 and 2001 censuses. The proportion of 15 to 25 year olds in the region (P1525) is highly significant and has the largest coefficient. It suggests that there will be larger changes in the unemployment rate (in percentage points) where this ratio is higher. We interpret the negative sign on the Proportion Born Overseas (PBOS) as being a mobility factor – the newer Australians will seek out better regional employment opportunities. The proportion of part-time employment to total employment (PPTEMP) is significantly negative which we interpret as indicating regions that have experienced higher part-time employment growth will have decreases or relatively small increases in their unemployment rate. Finally, the statistically significant negative labour force participation rate (LFPR) effect may be capturing a combination of mobile labour supply and/or added workers effects both which would be consistent with that region having decreases or relatively small increases in its unemployment rates. The signs and significance of these control variables are relatively robust across the various specifications. Not surprisingly, a region's employment growth has a stronger negative effect on unemployment change, once spill-overs from near-by regions' unemployment rates are controlled for (SAR). A region's labour force participation rate has less of a negative effect on the growth in unemployment, after controlling for unemployment spill-overs (SAR) and employment (SAC) in near-by regions.

The spatial autocorrelation tests confirm that the OLS model (3.1) reveals significant residual spatial autocorrelation in the residuals. We then tested the SAR specification shown in column 3.2 by including a spatially lagged dependent variable. The ρ parameter is highly significant and positive and indicates that there is significant spatial dependence between closely proximate regional unemployment rates such that a higher rate in region i will tend to push up the rate in region j. This impact declines inversely with the distance and given the spatial weight matrix (inverse distance) shown the decay is fairly rapid. So in this context, the spillovers appear to be very localised. The spatial autocorrelation tests on 3.2 were also significant and so we decided to estimate a SEM with a spatially weighted employment growth term added (so a mixture of the SAR-SEM-SDM which is referred to as the SAC model).

The positive coefficient on the spatially-lagged employment growth term in 3.3 is not intuitive. We might have expected a negative coefficient which would have been consistent with the notion that increased employment in region j also leads to reductions in the unemployment rate in neighbouring region i perhaps because of labour mobility. In this case, the result suggests that the change in the unemployment rate in region i is larger the stronger the employment growth in neighbouring regions. It suggests that labour mobility is low and this may help explain the persistence in regional unemployment disparities. It could also be that employment growth in the neighbouring region is inducing an increase in labour supply which has not been offset by the increase in employment in the region itself, thus leading to a rise in the unemployment rate - in the SAC model LFP still has a negative sign, although it's magnitude has decreased. The exact causal processes operating require further exploration.

The significance of the parameter ρ (the spatially lagged dependent variable) indicates that there are strong spillover effects between regions that decline inversely with distance. This result helps explain the clusters of high unemployment and low unemployment that casual observation in Figures 1 and 2 reveal. If region i experiences a rising unemployment rate this will spill over significantly into neighbouring regions until the distance decay is exhausted.

Finally, in the SAC model 3.3 we see evidence of spatial errors which may be due to measurement errors or omitted variables. Again they signal that more work is required to get beneath the superficial knowledge that the regressions provide. It is clear from this example that the SAC model doesn't collapse to a SEM or a SAR model given the significance of all spatially-weighted coefficients.

Table 3 Regression results, change in unemployment rate, 1996 to 2001, 69 regions

Variable	3.1	3.2	3.3
	ΔUR01_96	ΔUR01_96	ΔUR01_96
	OLS	SAR	SAC
Constant	4.49	3.06	2.87
	(8.96)	(2.90)	(3.36)
EMPG01_96	-0.17	-0.22	-0.24
	(3.07)	(2.65)	(2.86)
UR1996	-0.29	-0.19	-0.19
	(13.0)	(4.17)	(4.77)
P1525	0.40	0.36	0.32
	(7.81)	(4.47)	(4.69)
PBOS	-0.08	-0.07	-0.06
	(4.74)	(3.21)	(4.06)
PPTEMP	-0.24	-0.18	-0.13
	(3.10)	(1.85)	(2.00)
LFPR	-0.96	-0.69	-0.66
	(10.6)	(3.46)	(3.84)
ρ		0.508	0.81
		(3.90)	(7.65)
λ			-0.64
			(2.12)
γ			0.38
			(1.91)
R^2	0.63	0.37	0.61
s.e.	0.067	0.005	0.004
LLR	93.01	103.91	145.8

Diagnostic tests for spatial autocorrelation

Moran I statistic	3.11	4.71	0.39
LM error prob value	0.01	0.00	0.97
Wald prob value	0.02	0.00	0.98
LR prob value	0.01	0.00	0.98

Note: t-statistics in parentheses. DINV was chosen as the preferred spatial weight function. The OLS regressions contained other insignificant control variables. Prob value refers to probability value. All variables in logs.

7. Conclusion

Visual inspection of ABS census data from 1991 to 2001 reveals increasing spatial concentration of unemployment rates in the Sydney, Hunter and Illawarra regions. The incidence of higher unemployment spreads southwards across SLAs of the Hunter, while the incidence shrinks in SLAs of outer Western Sydney and Illawarra. The incidence of high employment growth declines in the Upper Hunter relative to the study area as a whole, and increases in Illawarra and Central Sydney.

Traditional measures of dispersion (given by Thiel Index and Coefficient of Variation) indicate that regional inequality has fallen slightly from 1991 to 1996 and again from 1996 to 2001 but is still not close to zero. However using the Moran I measure of spatial autocorrelation, we find, irrespective of the distance metric, that the geographic distribution of unemployment rates has become more clustered. That is a non-random patterning of unemployment has become more pronounced in the latter half of the 1990s, exhibiting the expected relationship given the presence of spatial dependence (Tobler's Law, 1970).

Ordinary Least Squares (OLS) regressions of the change in the unemployment rate between 1996 and 2001, with controls for demand and supply side variables, reveal significant spatial autocorrelation in the residuals. One explanation for the more pronounced clustering found in the late 1990s is that given the early 1990s recession most SLA's start the study period with high unemployment, growth processes only emerge by the mid-1990s and operate to make spatial interdependencies more pronounced. Controlling for demand and supply characteristics but incorporating spatially lagged unemployment rates and employment growth, we conclude positive spatial effects exist - that is a change in one region's unemployment or employment growth rate impacts positively on proximate regions unemployment rates. The effect is slightly stronger for unemployment rates, and both effects decline with distance. Thus we might conclude that significant interactions are occurring between the neighbouring regions, leading to more similar outcomes than we might expect from a truly random distribution. This is the case even after controlling for the underlying similarities in population composition, rates of economic growth and labour force participation between near-by regions. If spatial dependence does point to the presence of interactions between spatially proximate regions (keeping in mind sensitivities to model misspecification and the weighting structure employed), spillovers between regions will magnify local responses to national economic phenomena. This provides a possible explanation for the divergent behaviour of regions witnessed in the late 1990s. While the exact nature of this spatial dependence requires further exploration, initial application of spatial econometric techniques to Australian data demonstrate their usefulness in understanding changing patterns of regional labour market outcomes.

References

ABARE (2001) *Country Australia: Influences on Employment and Population Growth*, AGPS, Canberra.

Akerlof, G. (1997) 'Social Distance and Social Decisions', *Econometrica*, 65(5), 1005-1007.

Anselin, L. (1988) *Spatial Econometrics: Methods and Models*, Kluwer Academic Publishers, Dordrecht, The Netherlands.

Anselin, L. (2002) 'Spatial Externalities, Spatial Multipliers and Spatial Econometrics', *mimeo*, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

Anselin, L. (1999) 'Spatial Econometrics', *mimeo*, Brunto Centre, School of Social Sciences, University of Dallas, Texas.

Audretsch, B. and Feldman, M.P (1996) 'R&D spillovers and the geography of innovation and production'. *American Economic Review* 86, 630-39.

Australian Bureau of Statistics (ABS), (2001) *Census Dictionary*, Catalogue No. 2901.0, AGPS, Canberra.

Australian Local Government Association (ALGA) (2002) *The State of the Regions*, October 2002.

Banerjee, A.V. (1992) 'A Simple Model of Herd Behavior', *Quarterly Journal of Economics* 107(3), 797-818.

Barkley, D., Henry, M. and Bao, S. (1996) 'Identifying "Spread" versus "Backwash" Effects in Regional Economic Areas: A Density Functions Approach', *Land Economics*, 72 (3), 336-57.

Beer, A., Maude, A. and Pritchard, B. (2003) *Developing Australia's Regions – theory and practice*, University of New South Wales Press, Sydney.

Blanchard, O.J and Katz, L.F. (1992) 'Regional Evolutions', *Brookings Papers on Economic Activity* 1, 1-73.

Borland, J. (1995) 'Employment and income in Australia – Does the neighbourhood dimension matter?', *Australian Bulletin of Labour*, 21, 281-293.

Borland, J. (2000) 'Disagregated Models of Unemployment in Australia', *Melbourne Institute Working Pape*r No. 16/00, The University of Melbourne.

Bröcker, J. (1989) 'Determinanten des regionalen Wachstums im sekundären und tertiären Sektor der Bundesrepublik Deutschland 1970 bis 1982', *Schriften des Instituts für Regionalforschung der Universität Kiel*, München.

Cashin, P. and Strappazzon, L. (1998) 'Disparities in Australian Regional Incomes: Are They Widening or Narrowing?', *The Australian Economic Review*, 31(1), 3-26.

Clark, T.E. (1998) 'Employment fluctuations in US regions and industries: the roles of national, region-specific and industry-specific shocks', *Journal of Labour Economics* 16, 202-299.

Cliff, A. and Ord, J. (1981) *Spatial Processes: Models and Applications*, Pion, London.

Debelle, G. and Vickery, J. (1999) 'Labour Market Adjustment: Evidence on interstate labour mobility', *Australian Economic Record,* 77(238), September, 252-269.

De Luna, X. and Genton, M.G. (2004) 'Spatio-temporal autoregressive models for US unemployment rate', in J.P. LeSage and R.K. Pace (eds.), *Advances in Econometrics: Spatial and Spatiotemporal Econometrics*, Elsevier, Volume 8, 283-298.

Duranton, G. and Puga, D. (1999) 'Diversity and Specialisation in Cities: Why, where and when does it matter?', *Centre for Economic Performance,* Discussion Paper No. 433.

Durlauf, S. (2003) 'Neighborhood Effects', *mimeo*, Department of Economics, University of Wisconsin.

Elhorst, J. (2003) 'The Mystery of Regional Unemployment Differentials: Theoretical and Empirical Explanations', *Journal of Economic Surveys*, 17(5), 709-748.

Glaeser, E., Sacerdote, B. and Sheinkman, J. (1996) 'Crime and Social Interactions', *The Quarterly Journal of Economics*, 111(2), 507-548.

Glaeser, E. Sacerdote, B. and Sheinkman, J. (2002) 'The Social Multiplier', *Working Paper 9153, National Bureau of Economic Research* (NBER), Cambridge.

Goodchild, M., Anselin, L., Applebaum, R. and Herr Harthorn, B. (2000) 'Toward Spatially Integrated Social Science', *International Regional Science Review*, 23(2), 139-159.

Gregory, R.G. and Hunter, B. (1995) 'The macro-economy and the growth of ghettos and urban poverty in Australia', *Discussion Paper No. 325*, *Centre for Economic Policy Research*, Australian National University, Canberra.

Heath, A. (1999) 'Job-search Methods, Neighbourhood Effects and the Youth Labour Market', *Reserve Bank Discussion Paper, RDP1999-01*, Economic Group, Reserve Bank of Australia

Helliwell, J.F. (1998) *How Much Do National Borders Matter?,* Brookings, Washington DC.

Hordijk, L. (1979) 'Problems in Estimating Econometric Relations in Space', *Papers of the Regional Science Association*, 42, 99-115.

Hulse, K., Randolph, B., Toohey, M., Beer, G. and Lee, R. (2003) 'Understanding the Roles of Housing Costs and Housing Assistance in Creating Employment Disincentives', *Positioning Paper*, Australian Housing and Urban Research Institute.

Hunter, B. (1996) 'Explaining Changes in the Social Structure of Employment: the Importance of Geography', *Social Policy Research Centre (SPRC), University of New South Wales, Discussion Paper No. 67*, July.

Islam, S. (2003) 'Distance Decay in Employment and Spatial Spillovers of Highwyas in Appalachia', *Research Paper 2003-4,* Paper presented to the Annual Meeting of the North American Regional Science Association, Philadelphia, November 20-22.

Jensen, B. and Harris, M. (2003) 'Neighbourhood Measures: Quantifying the Effects of Neighbourhood Externalities', *Melbourne Institute Working Paper* No. 4/03, University of Melbourne.

Kettunen, J. (2001) 'Labour Mobility of Unemployed Workers', *Regional Science and Urban Economics*, 32(2002), 359-380.

Krugman, P. (1991) *Geography and Trade*, MIT Press, Cambridge.

Lall, S. and Yilmaz, S. (2000) *Regional Economic Convergence: Do Policy Instruments Make a Difference?*, The World Bank, Washington, D.C.

Lawson, J. and Dwyer, J. (2002) 'Labour Market Adjustment in Regional Australia', *Research Discussion Paper, 2002-04*, Economic Group, Reserve Bank of Australia.

LeSage, J.P. (1999) *Spatial Econometrics*, University of Toledo, available at http://www.rri.wvu.edu/WebBook/LeSage/spatial/spatial.html.

Lloyd, R., Yap, M. and Harding, A. (2004) 'A Spatial Divide? Trends in the incomes and socioeconomic characteristics of regions between 1996 and 2001', Paper presented to the *28th Australian and New Zealand Regional Science Association International Annual Conference*, Wollongong, September 28-October 1, 2004.

Longley P., Goodchild, M., Maguire, D. and Rhind, D. (2001) *Geographic Information Systems and Science*, John Wiley & Sons, New York.

Lucas, R. (1988) 'On the Mechanics of Economic Development', *Journal of Monetary Economics*, 22, 3-42.

Maierhofer, E. and Fischer, M. (2001) 'The Tyranny of Regional Unemployment Rates – conceptual, measurement and data quality problems', Paper presented to the *41st Congress of the European Regional Science Association*, Zagreb.

Manski, C. (1993) 'Identification of endogenous social effects: the reflexion problem', *Review of Economic Studies*, 60, 53-542.

Mitchell, W.F. (2001) 'The Unemployed Cannot Find Jobs That Are Not There', in W.F. Mitchell and E. Carlson (eds.), *Unemployment: The Tip of the Iceberg*, Centre for Applied Economic Research, UNSW Press, Sydney, 85-115.

Mitchell, W.F. and Carlson, E. (2003a) 'Regional employment growth and the persistence of regional unemployment disparities', *Working Paper No. 03-07*, Centre of Full Employment and Equity, The University of Newcastle.

Mitchell, W.F. and Carlson, E. (2003b) 'Why do disparities in employment growth across metropolitan and regional space occur?' in Carlson, E. (ed.) *The Full Employment Imperative, Proceedings of the 5th Path to Full Employment Conference/10th National Conference on Unemployment*, University of Newcastle, December 10-12, 121-152.

Molho, I. (1995) 'Spatial Autocorrelation in British Unemployment', *Journal of Regional Science*, 35(4), 641-658.

Monchuk, D. and Miranowski, J. (2004) 'Spatial Labour Markets and Technology Spillovers – analysis from the US Mid-West', *mimeo*, Department of Economics, Iowa State University.

Niebuhr, A. (2001) 'Convergence and the Effects of Spatial Interaction', *HWWA Discussion Paper 110*, Hamburg Institute of International Economics, Hamburg.

O'Connor, K. and Healy, E. (2002) 'The Links Between Labour Markets and Housing Markets in Melbourne', Australian Housing and Urban Research Institute, Swinburne-Monash Research Centre.

O'Connor, K., Stimson, R. and Daly, M. (2001) *Australia's Changing Economic Geography: A Society Dividing*, Oxford University Press, Sydney.

Overman, H. and Puga, D. (2002) 'Regional Unemployment Clusters', *Economic Policy*, CEPR, DES, MSH.

Petrucci, A., Salvati, N and Segheri, C., (2003) 'The Application of a Spatial Regression Model to the Analysis of Poverty', *Environment and Natural Resources Series No. 7*, Rome.

Pisati, M. (2001) 'Tools for Spatial Data Analysis', *Stata Technical Bulletin*, 60.

Productivity Commission (1999) *Impact of Competition Reforms on Rural and Regional Australia*, AGPS, Canberra.

Puga, D. (1999) 'The Rise and Fall of Regional Inequalities', *European Economic Review*, 43(2), 303-334.

Quah, D. (1997) 'Empirics for growth and distribution: Stratification, polarization and convergence clubs', *Journal of Economic Growth*, 2(1), 27-59.

Ramirez, M. and Loboguerrero, A. (2002) 'Spatial Dependence and Economic Growth: Evidence from a panel of countries', *Banco de la Republica, Columbia*. http://www.banrep.gov.co/docum/ftp/borra206.pdf.

Ramakrishnan, U. and Cerisola, M. (2004) 'Regional Economic Disparities in Australia', *Working Paper WP/04/144*, Asia and Pacific Department, International Monetary Fund.

Randolph, B. and Hulse, K. (2003) 'Housing &Unemployment—Role of Housing Assistance', Paper presented to the *National Housing Conference*, November, Adelaide.

Rey, S and Montouri, B. (1999) 'Convergence or divergence? Types of Regional Responses to Socioeconomic Change', *Journal of Economic and Social Geography*, 90, 363-378.

Romer, P.M. (1986) 'Increasing Returns and Long-Run Growth', *Journal of Political Economy*, 94, 1002-1037.

Shields, M. and Wooden, M. (2003) 'Investigating the Role of Neighbourhood Characteristics in Determining Life Satisfaction', *Melbourne Institute Working Paper*, No. 24/03, The University of Melbourne.

Stetzer, F. (1982) 'Specifying Weights in Spatial Forecasting Models: The Results of Some Experiments', *Environment and Planning*, 14, 571-584.

Tassinopoulos, A. and Werner, H. (1999) 'To Move or Not to Move. Migration in the European Union', *IAB Labour Market Research Topics 35*, IAB, Nurenberg.

Tobler, W. (1979) 'Cellular geography', in S. Gale and G. Olsson (eds), *Philosophy in Geography*, Reidel, Dordrecht, 379 -386.

Tobler, W. (1970) 'A computer movie simulating urban growth in the Detroit region', *Economic Geography*, 46, 234-40.

Topa, G. (2001) 'Social Interactions, Local Spillovers and Unemployment', *Review of Economic Studies*, 68, 261-295.

Watts, M. (2004) 'Local Labour Markets in NSW: Fact or Fiction?', in E. Carlson (ed.), *A Future that Works: Proceedings of the 6th Path to Full Employment and the 11th National Unemployment Conference*, Centre of Full Employment and Equity, The University of Newcastle.

Wilson, W. J. (1987) *The Truly Disadvantaged*, University of Chicago Press, Chicago.

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[2] Durlaf, (2003: 74) notes "The literature has identified deep identification problems that exist due to Manski's (1993) reflection problem between endogenous and contextual effects… [and while] … the estimation problems that exist because of self-selection and other types of unobserved heterogeneity are relatively well understood", these empirical issues are largely yet to be resolved.

[3] All data from the three censuses are mapped using 2001 SLA boundaries. Small boundary changes occur between censuses, with the result that actual geographic areas for which the data was collected may be marginally different to those boundaries mapped for 1991 and 1996.

[4] The average distance commuted by residents for work in 2001 is 41 kilometres; this is very close to the average distance between first-order contiguous regions of 29.3 kilometres, which we have taken to be the 'relative distance' in the exponential decay function.

[5] After assembling the 2001 JTW database Sydney (undefined) was deleted. Persons who are not enumerated in a work study area, unemployed persons looking for either full-time or part-time work, persons not in the labour force, persons whose labour force status is not stated and persons under 15 years are excluded. Persons who did not state their occupation are also excluded.

[6] This perhaps suggests the presence of multicolinearity in our control variables.