Neighbourhood inequality – do small area interactions influence economic outcomes?

Anthea Bill
University of Newcastle

ABSTRACT

Over the last 25 years neighbourhood economic outcomes have become increasingly polarised in Australia (Badcock, 1997; Hunter, 2003). The growing spatial dimensions of this inequality have generated discussion about the existence of 'neighbourhood effects', localised externalities and other endogenous processes, leading to underinvestment in education, lower levels of job-creation and economic activity, than might be expected in disadvantaged neighbourhoods. Recently there has been renewed interest in economic models incorporating social interactions, dependence among economic agents and spatial spillovers. In failing to acknowledge the interdependence between neighbouring regions and individuals, traditional economic models ignore an important aspect of space. A range of spatial regression techniques have been developed to measure latent forces of interaction and handle data that violate statistical assumptions of independence.

This paper explores the drivers of changing labour market outcomes within Metropolitan Sydney in 1996 and 2001 (POA level). Moran statistics will be used to determine whether these represent statistically significant clusters of employment and other demographic variables, known as 'hot spots' (high unemployment) and 'cold spots' (low unemployment). Spatial econometric techniques are them employed to ascertain the key drivers of these 'hot' and 'cold' spots; and the extent to which, independent of traditional explanatory factors, location-specific interactions within or between regions might be responsible for any observed polarisation.

INTRODUCTION

In Australia as in the UK labour market outcomes are characterised by distinct geographic patterns that are both uneven and persistent (Gordon, 2003). In Sydney Metropolitan region a clear dichotomy exists between the east and the west, even cursory examination of labour market and wage outcomes, suggest such patterns have persisted despite the strong growth of the 1990s. Outside of traditional macroeconomic explanations of unemployment (ineffective demand, structural or cyclical unemployment) at the small area level - why might non-random spatial clustering of labour market outcomes exist? On the supply-side (relating to worker characteristics) a range of theories provide explanations of residential segregation. One of the most common theories revolves around the idea of residential sorting (see Hunter, 2003 for empirical examination in Australia). That is people with similar educational backgrounds and socio-economic status (SES) locate in similar areas because they share common interests or values, over time these differences may become more pronounced as people sort further along lines of SES and income The housing market of course plays a substantial role in determining how workers of varying 'quality' are distributed across space. On the demand side (relating to firm characteristics) firm location decisions are heavily influenced by the characteristics of areas – not only by skill level of the workforce, but by capital accumulation processes and knowledge externalities flowing from existing markets and firms. Similarly workers may commute to neighbouring labour markets for jobs, generating an obvious economic dependence between regions. Occupational mismatch at the small area level might be a factor, as might spatial mismatch stemming from constraints in employment accessibility because of mismatch between the location of jobs and the location of workers.

Cheshire (2003) argues that it is not surprising that job-accessibility and unemployment vary widely and non-randomly over Census tracts (in the Australian context these tracts are known as Collection Districts, and approximate a street-block). The employed, and particularly those employed in higher paid occupations, tend to have higher incomes, greatly value employment accessibility and therefore are willing and able to outbid the non-employed to access jobs. The higher purchasing power of the employed, ensures the better-paid live in suburbs with better access to jobs, local public goods and amenities. The unemployed are by default likely to be confined to suburbs which rank poorly on such measures. Thus the sorting in the housing and labour market are mutually reinforcing. Housing has fixed geographic attributes and is relatively demand inelastic in the short-run, such a dynamic is likely to have a predictable spatial outcome. Moreover as evidence from the UK's City Challenge programme suggests (Cheshire, 2003:92) programmes which are successful in improving participant's labour market position may induce selective out-migration, as newly employed individuals move to more desirable neighbourhoods. If the nature of housing and amenities in the old neighbourhoods remains unchanged, these residents will be replaced with residents who are as disadvantaged and sometimes more disadvantaged (Cheshire, 2003:92), with the net result that the neighbourhood concentrations of disadvantage have actually increased. Thus in a sense the 'amount' of disadvantage is decided at some aggregate level (like the macro-economy), and it is the housing market that determines how it will be patterned. Where people live does not drive inequality it just determines its geographic location: 'where people live and the incidence of segregation and ultimately of exclusion, mainly reflects the increasing inequality of incomes. So if either the incidence of unemployment rises and/or if the distribution of earnings becomes more unequal then social segregation intensifies…the poor are not poor, isolated and excluded for the reason which makes them poor. They are not poor because of where they live; rather they live where they do because they are poor.' (Cheshire, 2003:84-85)

While the importance of housing in regional concentrations of unemployment cannot be denied, the argument that where you live has no independent or additional effect on the likelihood of being unemployed may be an overstatement. Neighbourhoods are not static units, interactions between individuals and firms are liable to generate outcomes which are independent of the population mix, and which have impacts on property and labour markets outcomes for existing residents. As Martin (2000) notes in contrast to classical models characterising local labour markets in terms of homogeneity and closure, in reality local labour markets are characterised by openness and heterogeneity. Regional interactions on the demand side may mean that local demand effects, spill-over into neighbouring regions, and exacerbate the negative effects of firm closure or structural change. Such regional interactions are most likely to exist in regions tightly linked by interregional migration, commuting and trade (Niehbuhr, 2003), and a region's openness to flows of people and information is likely to increase as its geographic size decreases. In the context of regional labour markets, theoretical explanations of spillovers also relate to capital accumulation processes and knowledge externalities which may create agglomerations influencing firm locational decisions. Local information spillovers (Topa, 2001) ensure the spread of local shocks to neighbouring regions. 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 interrelationships between neighbouring regions will increase the persistence of any regional shock.

On the supply-side strong arguments exist to the counter the idea local concentrations of employment simply reflect the distribution of housing. Social processes may create dependencies in labour market outcomes, for instance where social interactions are facilitated by closeness. The quality and frequency of exchange of information is then dependent on the composition of the suburb a person resides in. This may have significant implications for job-search, which in turn impacts on the overall suburb level of employment and the quality of job information available and so on an so forth. Peer group, role model and contagion effects may also mean that area composition matters: individual decisions (for instance the decision to participate in higher education) are transmitted across neighbourhoods through social mechanisms, leading to sub-optimal outcomes that persist in equilibrium (Durlauf, 2003; Wilson, 1987). Such geographically localised spillovers, are termed neighbourhood effects, and are said to stem from the overall composition of a neighbourhood. They impact on an individual's outcomes independently of their own or family characteristics, most commonly when the behaviour of other residents influences the perceived or real payoffs to decisions (Andrews, 2004). Thus if neighbourhood effects can be said to exist this represents an important case for spatially targeted policy. The concept of a neighbourhood effect has been widely explored in both the US and UK literature. Buck and Gordon (2003) review existing UK literature and conclude that there is strong evidence of links between social exclusion and area characteristics. However they remain unconvinced of neighbourhoood effects on a number of fronts: it is difficult to find conclusive evidence of such effects (partly because of selective out-migration), they are small in magnitude relative to individual and family characteristics, the processes generating them are difficult to isolate and address in a policy context, and the evidence that asymmetries in these effects between poor and affluent areas is weak (p. 251).

A number of Australian studies have explored the notion of neighbourhood effects (see Hunter, 1996; Lewis and Kelly, 2000). 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. 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). Similarly Andrews (2004) examines spatial inequality in the youth labour market using data from the Australian Youth Survey, and finds evidence that youth who reside in disadvantaged areas face a greater likelihood of being unemployed at 18 and 21, even after controlling for personal and family characteristics. Trendle (2005) adopts a spatial econometric approach, and applies this to aggregate data to explicitly capture the impact of regional spillovers on unemployment rates for Statistical Local Areas (SLAs) in the Brisbane Statistical Division. The results indicate the presence of strong spillovers between neighbouring regions, even once demographic and economic factors are controlled for.

This paper aims to apply two relatively new techniques to the study neighbourhood inequality within the Sydney metropolitan region. Firstly Exploratory Spatial Data Analysis (Anselin, 1995) and secondly spatial econometrics to: 1) isolate statistically robust pockets of economic and social segregation and 2) estimate the role of small area interactions in determining the overall spatial pattern of economic outcomes. Indirectly we also aim to assess whether there is a possible independent effect of neighbourhood composition in neighbourhood labour market outcomes across Sydney.

SPATIAL DEPENDENCE AND SPATIAL INEQUALITY IN SYDNEY

The Sydney metropolitan region has reaped the rewards of the strong growth delivered by the 1990s and has emerged as 'Australia's premier global city' (Randolph and Holloway, 2005b). Over the 1990s the population of the Sydney metropolitan region increased by 228,546, and in the Sydney LGA it increased by 24,387. The labour force has increased by 133,187. In 2001 some of Australia's lowest unemployment rates were found in Sydney, in Pittwater, Mosman and Baulkham Hills (but so were some of its highest in Fairfield, Auburn and Blacktown). In 2001 18 per cent of total Australian employment was located in Sydney. The Sydney LGA has also reaped the rewards of shifts to the 'new economy', 47.4 per cent of the labour force were employed as professionals, associate professionals or managers in 2001, compared to 28.9 per cent of NSW labour force. In 2002 20 per cent of the national employment in the financial sector was located in Sydney, and the Sydney basin produced 23 per cent of nations GDP (O'Niell and McGuirk, 2002).

Much has been written on spatial inequality in Australia, and particularly in Sydney (O'Connor, 2001; O'Neill and Quirk, 2002; Raskall, 2002; Randolph, 2003).The 1990s has brought well-documented shifts in the spatial structure of Australia's economic growth not just in favour of Australia's cities, but within certain suburbs of these cities. In the Sydney metropolitan region, there has been a notable increase in proportion of residents residing within the CBD (Raskall, 2002:286), a reinforcement of the east-west divide (Raskall, 2002:290), and an increase in income disparity between suburbs (Raskall, 2002:290). Raskall (2002) argues that this had been driven in part by spatial sorting - the gentrification of inner city suburbs through in-migration of high income earners. However net of these residential changes, spatial inequality has increased because the earnings of professional occupations relative to other occupations increased sharply over the period and these workers tend to reside in certain suburbs.

Analysing taxation data by postcode for 1996-99, Raskall notes '..the gains from Sydney's economic globalisation have accrued disproportionately in favour of residents residing in Sydney's more affluent suburbs' (2002:293). Moreover as Randolph and Holloway (2005b) argue sharp rises in wealth accumulation (as property prices in certain suburbs sky-rocketed) and inter-generational wealth transfers have exacerbated this inequality (2005b:51). Baum (1997) examined a social polarisation hypothesis for Sydney in the lead up to 1991 and found an important link between "global economic processes, the changing occupational structure within Sydney, and changes in income polarisation" (1997:1891). As well as global drivers, institutional factors and localised factors such as gender and migration (migrants are over-represented in occupations that are lower-skilled and loser-paid) were shown to be important.

The most interesting feature of the spatial impact of the 1990s is that not only has the Sydney LGA experienced strong growth, but suburbs in its immediate hinterlands have experienced the flow-on of increased economic activity via commuting. The key change is that the inner cities are no longer the location of urban disadvantage in Sydney (2005b:52). Instead there has been a 'suburbanisation of disadvantage' (Randolph, 2003) and middle suburbs (suburbs between the east-west divide) are the new locations of relative social and economic decline. Randolph and Holloway (2005b:55) undertake a comparison of LGA unemployment rates relative to the overall Sydney average from 1971-2001 and find the most significant shifts in the location of unemployment have occurred in the middle suburbs. These suburbs (in and around Bankstown, Fairfield and Liverpool) also have aging populations and high levels of immigration. As they are sites of affordable housing, older people are being replaced with 'more mobile renters and lower-income households' (Randolph and Holloway, 2005b:59).A dynamic interaction between inner-city and middle suburbs exacerbates these trends 'older areas losing upwardly mobile populations to the new fringe areas' (Randolph and Holloway, 2005b:59), reinforcing the link between housing and concentrations of disadvantage. Randolph and Holloway (2005a) have also documented in detail the movement of disadvantaged persons (particularly people with children, migrants and those with lower English proficiency) into private rental housing within Melbourne and Sydney, following the gentrification of inner-city suburbs and the reduction in public housing provision.

Much of this analysis confirms the importance of housing in determining spatial concentrations of unemployment and other social pathologies within Sydney's metropolitan region, and relates back to Cheshire's argument: how much is the concentration of labour market disadvantage simply a product of the lower incomes pushing less employable residents into suburbs where housing is affordable? In what sense does this constitute a real problem? If small area interactions occur and can be said to be important, then this makes the polarised nature of housing and labour market outcomes within metropolitan Sydney of additional concern to policy makers.

EXPLORATORY SPATIAL DATA ANALYSIS (ESDA)

Exploratory Spatial Data Analysis (ESDA) is a set of techniques aimed at visualising the spatial distribution of data, identifying 'atypical localisation', detecting patterns of spatial association and suggesting the presence of different spatial regimes, where data provide evidence of heterogeneity (Anselin, 1996). Measures of spatial dependence or spatial autocorrelation are a way of evaluating the amount of clustering or randomness in the data. Unlike standard measures of concentration (Coefficient of Variation, Theil Coefficient and Gini) these measures impose an explicit geographic structure which makes them capable of summarising clustering observed via visual inspection of a map and also capable of testing whether these clusters are significantly non-random.

This section employs uni-variate and bi-variate measures of spatial autocorrelation and compares the geographic pattern of dependence of various socio-economic phenomena within the Sydney Metropolitan labour market. We are interested in whether the pattern is one of segregation (one of distinct pockets of low and high concentrations) or integration (chequered pattern of high and low unemployment side by side) (Frank, 2003).

The Modifiable Areal Unit problem is a well known problem associated with geographic data. As Trendle (2005:2) notes spurious spatial autocorrelation may arise because the geographic area in question is too small to capture distinct economic phenomena, such as the forces of demand and supply in a local labour market. On the other hand the unit chosen is likely to strongly influence the results obtained. The smaller the geographic unit the more homogeneous its population is likely to be, and the homogeneity or heterogeneity of the population will heavily influence the incidence of spatial segregation observed.

To determine if the socio-economic phenomena in the above maps deviate from the pattern that would exist if they were randomly assigned, we need an index of comparison. Global measures of spatial autocorrelation provide evidence of the presence or absence of a stable pattern of dependence across our whole dataset. Upton and Fingleton (1985) defined spatial autocorrelation as a property that mapped data displays whenever it exhibits an organised pattern. Earlier Cliff and Ord (1973) had argued that spatial autocorrelation exists when the distribution of some quality or quantity in a region makes its presence more or less likely in neighbouring regions. The former definition implies that spatial autocorrelation is simply the non-random patterning of data, the latter implies a dependence springing from the proximity of neighbouring regions (after controlling for other factors). The first part of analysis in this paper is largely univariate and bivariate and is closer to the first definition of SA. The second stage of analysis, which explores the driving causes behind the dependence, is closer to the second definition. Most published measures of spatial autocorrelation can be reworked as a cross-product statistic (normalised) that indexes the degree of relation between corresponding observations in two matrices (Sawanda, 2005). The first is a weighting matrix which specifies the degree of interrelatedness ($b_{i,j}$), between a set of n locations or observations. The other reflects a definition of ‘similarity’ – usually correlatedness or concentration ($a_{i,j}$) – between some variable x over n locations (Sawanda, 2005):

$$\tau_{obs} = \sum_{i \neq j} a_{ij} b_{ij} \qquad \textbf{(1)}$$

Thus spatial autocorrelation compares two sets of similarities, similarities in attributes and similarities in location. The relative size of Γobs can be assessed by constructing a p-value, for the index using as a reference the distribution of values under a conjecture of randomness (usually taken to be normal). Common global measures (measures which assess s.a. across a whole dataset) of spatial association include; Moran's I, Geary's C and Global G. The spatial weight matrices (bij) formalises the level of interdependence between all pairs of regions in the system. A 'spatial order' is typically imposed based on some prior assumption and the estimation of spatial autocorrelation is sensitive to this (Molho, 1995: 649). Following LeSage's (2005) comments that the main aim of the weighting matrix is to incorporate some notion of proximity into standard statistical tests, we have opted for the most simple conception of spatial interconnectedness. That is 'first-order contiguity' neighbours defined on the basis of regions whose borders touch[1].

Moran's I is one of the most common indexes of spatial autocorrelation or clustering (see Bill and Mitchell (2005), for a full discussion of Moran I). It is calculated for a range of socio-economic indicators in the Table 1 below. The first point to note is that *Moran's I* is large, positive and significant for virtually all the variables included in this table. All the *Moran I* statistics show that socioeconomic phenomena is not randomly distributed across space within Sydney, and that spatial clustering of high and low values clearly occurs. This provides confirmation that the Sydney Metropolitan Region is spatially segregated in 2001. Areas with high concentrations of advantage and disadvantage tend to be located next-door to areas with similarly high concentrations. The next point is that spatial autocorrelation is strongest amongst residents employed in professional occupations. Areas with very high and low concentrations of professionals in their resident workforce are tightly clustered, and more so than broader measures like income and housing, also included in the Table, would suggest. This is very interesting, and reflects the dramatic impact that the shifts to the 'new economy' have had within the urban structure of Sydney. Strong linkages with the global economy have delivered jobs and income to professionals, but more importantly there is a strong spatial dimension to this change and these workers tend to reside nearby. The flipside is expressed by the relatively strong clustering of areas with high proportions of workers with no qualifications (see Figure 4), these areas are also much more likely to be near-by, than if the distribution was truly random. Similarly there is quite strong clustering amongst areas with high proportions of persons employed in service industries, amongst persons who do not speak English well or at all and amongst persons employed in manufacturing. At the POA level there is moderate, positive and significant co-location of unemployment rates, although this clustering is more pronounced at the Collection District (CD) level. Indigenous residents do not appear to exhibit as significant a clustering as the other characteristics in Table 1. Interestingly the two housing variables included - the mean value of residential buildings approved, 2000-01, and the mean value of total residential buildings approved, 2000-01 – while being positive predictors of spatial association, are not as spatially co-located as some of the other socio-demographic variables modelled here. That is housing values do not cluster as tightly across space as the proportion of persons employed in professional occupations, the proportion of persons employed in services or the proportion of persons with advanced qualifications. The other point is that the smaller the geographic unit employed, generally the greater the spatial dependence observed. For instance the clustering of unemployment rates in CDs is significantly larger than that in POAs or SLAs, and this is likely to reflect the fact CDs naturally do not represent distinct labour markets.

The global Moran I statistic can be decomposed to provide local measures of spatial association (LISAs), Anselin (1995). These provide more detailed information on the type of spatial association occurring in our dataset and indicate the contribution from each region to the overall spatial association, Trendle (2005:4). These local measures allow the identification of socio-demographic 'hot' and 'cold' spots. If the Sydney metropolitan region is marked by very few 'hot' or 'cold' spots

[1] Previous analysis of Australian-wide data of long-term and short-term unemployment rates (Bill and Mitchell, 2005) revealed that spatial autocorrelation is more pronounced the smaller the geographic unit employed, and the narrower the construction of the weighting matrix. Generally, first order contiguity produces more 'hot' and 'coldspots' than second order contiguity or distance decay weighting matrices. This suggests the technique may benefit from an application to more spatially disaggregated data, such as data at the neighbourhood unit or below, within a confined geographic area, for instance a metropolitan region which in part was the impetus for this paper.

it might be said to be integrated. If the Sydney metropolitan region is marked by prominent ‘hot’ and ‘cold’ spots this may provide evidence to policy-makers that spatial segregation in certain areas is a problem. Most importantly measures of spatial autocorrelation can also evaluate the probability that such concentrations of high and low unemployment might occur by chance, thus the credibility of a purely visual interpretation of clustering is significantly advanced upon (Frank, 2003:160**).**

Table 1 Moran’s I for Selected Socio-Demographic Characteristics in the Sydney Metropolitan Region, CD, POA and SLA, 2001.

Socio-Economic Characteristic	Moran’s I (Collection District), 2001	Moran’s I (POA), 2001	Moran’s I (Statistical Local Area), 2001
Proportion of Employed Workforce who are Professionals	0.837 (0.0001)	0.781 (0.0001)	0.636 (0.0001)
Proportion Population with Low English Language Proficiency – Does Not Speak English Well or at All	0.810 (0.0001)	0.690 (0.0001)	0.560 (0.0001)
Proportion of Employed Workforce in Services	0.531 (0.0001)	0.723 (0.001)	0.754 (0.0001)
Proportion of Employed Workforce in Manufacturing	0.669 (0.0001)	0.768 (0.0001)	0.670 (0.0001)
Proportion of Residents Employed as Manual Workers	0.791 (0.0001)	0.791 (0.0001)	0.643 (0.0001)
Proportion of Residents Indigenous	0.357 (0.0001)	0.425 (0.0001)	0.429 (0.0001)
Proportion of Residents with Advanced Qualifications	0.871 (0.0001)	0.801 (0.0001)	0.738 (0.0001)
Proportion Sole Parents	0.430 (0.0001)	0.41 (0.0001)	0.662 (0.0001)
Unemployment Rate	0.630 (0.0001)	0.239 (0.006)	0.366 (0.0005)
Proportion of Residents Earning less than $300 pw.	0.646 (0.0001)	0.534 (0.0002)	0.617 (0.0001)
Labour Force Participation	0.537 (0.0001)	0.142 (0.006)	0.436 (0.0001)
Personal Income	N/A	N/A	0.221 (0.0001)
Proportion of Residents Renting	0.612 (0.0001)	0.349 (0.0001)	0.662 (0.0001)
Proportion of Residents in State Housing	0.479 (0.0001)	0.233 (0.0001)	0.240 (0.0082)
Value of Approved Residential Buildings	N/A	N/A	0.392 (0.0041)
Value of Approved Total Buildings	N/A	N/A	0.215 (0.01410)

Source: CDATA, 2001; Buildings Approvals; 2000-01 and ABS, Regional Wage and Salary Earner Statistics, 2000-01.

Figures 1 to 6 map these local indicators for a range of variables. Areas plotted in red are statistically significant 'hot spots' - POAs with high (above average) values surrounded by areas with similarly high values. Cold spots are shown in blue are regions with low (below average) values for the variable in question surrounded by similarly low values. Areas plotted in light blue and pink, represent deviations from the overall pattern of positive spatial autocorrelation. Areas in pink have a high value for the variable in question, but are surrounded by low valued areas. Conversely areas in light-blue have a low value for the variable in question but are surrounded by variables with a high value for the variable under examination.

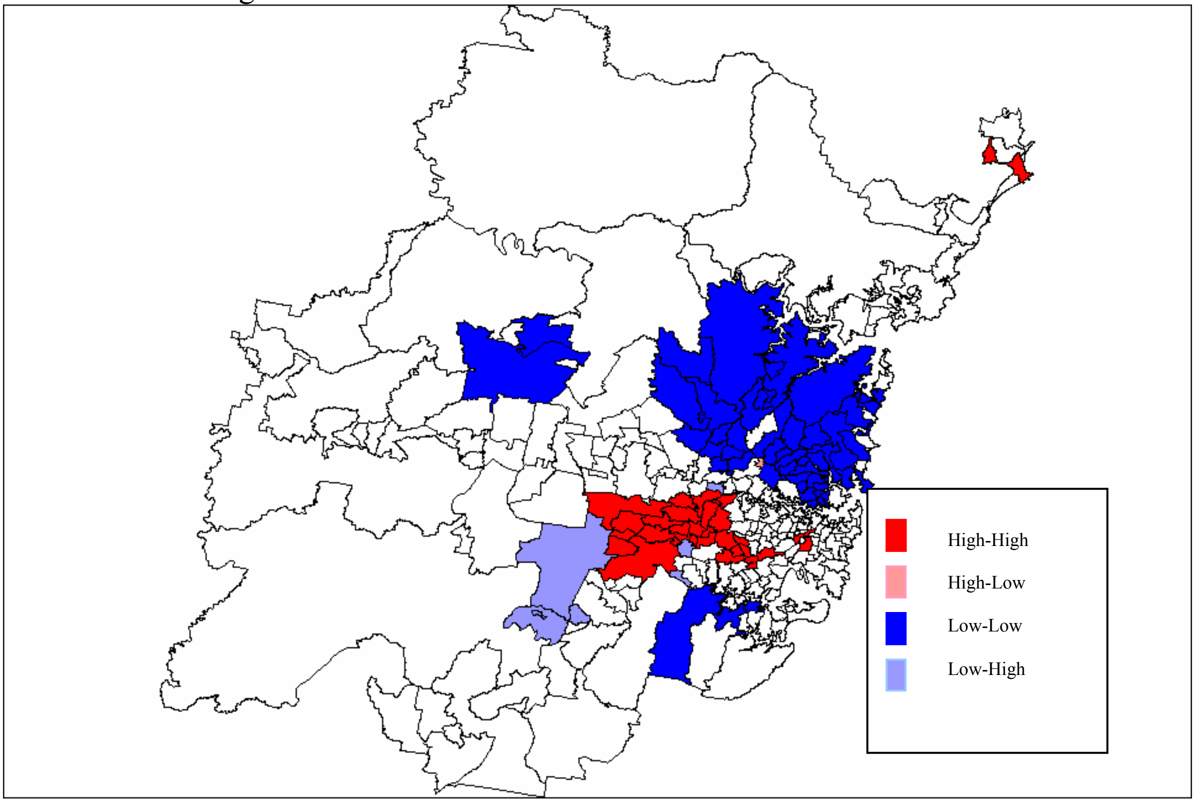

Figure 1 Spatial Dependence in Unemployment Rates, Sydney Metropolitan POAs 1996. Moran's I =0.4502 (0.001). Source: ABS, CLIB, 1996.

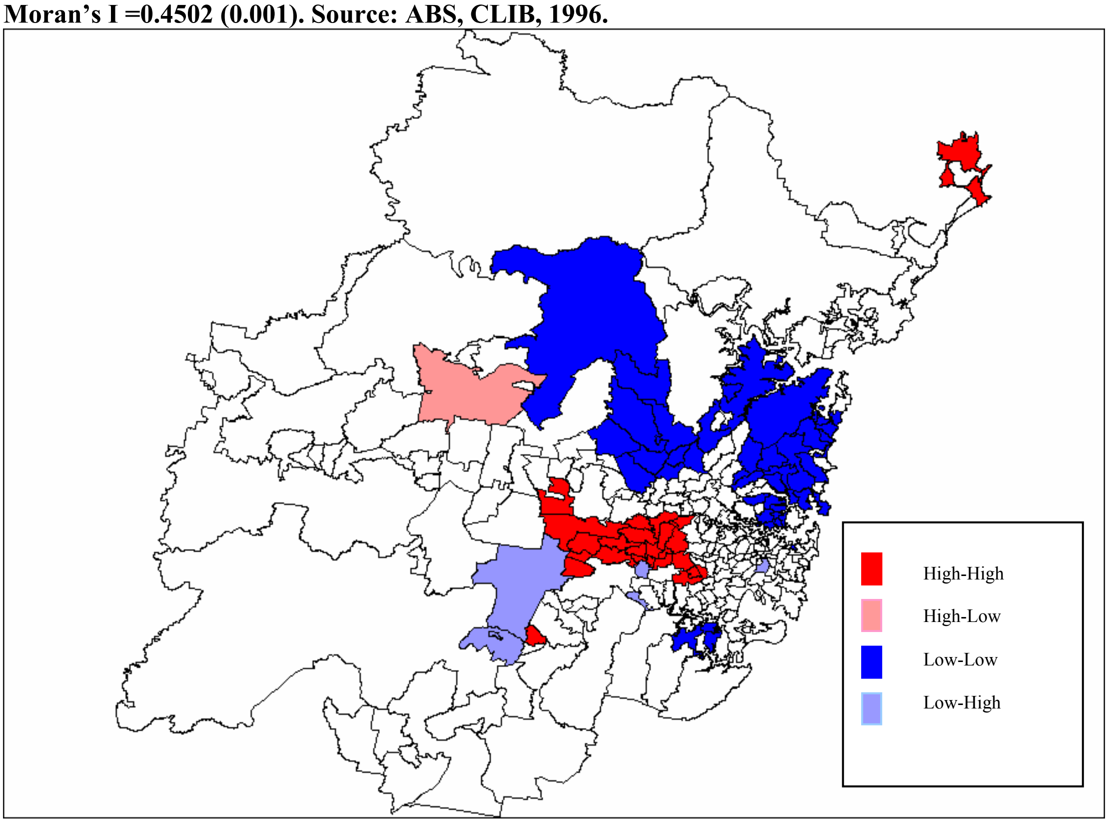

Figure 2 Spatial Dependence in Unemployment Rates, Sydney Metropolitan POAs 2001. Moran's I = 0.4100 (0.001). Source: ABS, CDATA 2001.

Figures 1 and 2 map the unemployment rate in 2001 and 1996 for Sydney POAs, strong clustering can be observed. In 1996 a clearly demarcated unemployment hotspot was present in inner-western Sydney around the suburbs of Fairfield. Holroyd, Parramatta, Liverpool, and extending down to Canterbury, and across to Auburn. Pockets of high-high concentration were also present in South Sydney and Marrickville. A 'coldspot' is present across suburbs of the North shore: Lane Cove, Willoughby, North Sydney, Hunter's Hill, Ryde, Manly, Baulkham Hills, Warringah and extending up to Ku-ring-gai, Hornsby and Pittwater. Interestingly Penrith and Hawkesbury also emerge as areas of statistically significant low-low concentrations, as does the Sutherland shire. Areas with unusually low concentrations of unemployment surrounded by areas with high unemployment are found in Liverpool, Camden and Campbelltown.

In 2001 the picture has changed somewhat and overall level of clustering as shown by the Moran I statistic has decreased. The 'coldspot' in the Sutherland shire has been dramatically reduced and the 'coldspot' in Baulkham Hills has moved north towards Hornsby. However low-low concentrations of unemployment are no longer as pronounced along the North shore, suburbs around Ku-ring-gai, Lane Cove and Ryde are no longer statistically significant. The hotspot in Western Sydney has shifted west, commensurate with the arguments of Randolph (2003) and Raskall (2002), away from Canterbury and Bankstown, and creeping up towards south-west Blacktown. Penrith formally an unemployment 'coldspot' now represents an area of high-low association, that is it has unusually high concentrations of unemployment compared to the low concentrations of unemployment observed amongst its neighbours.

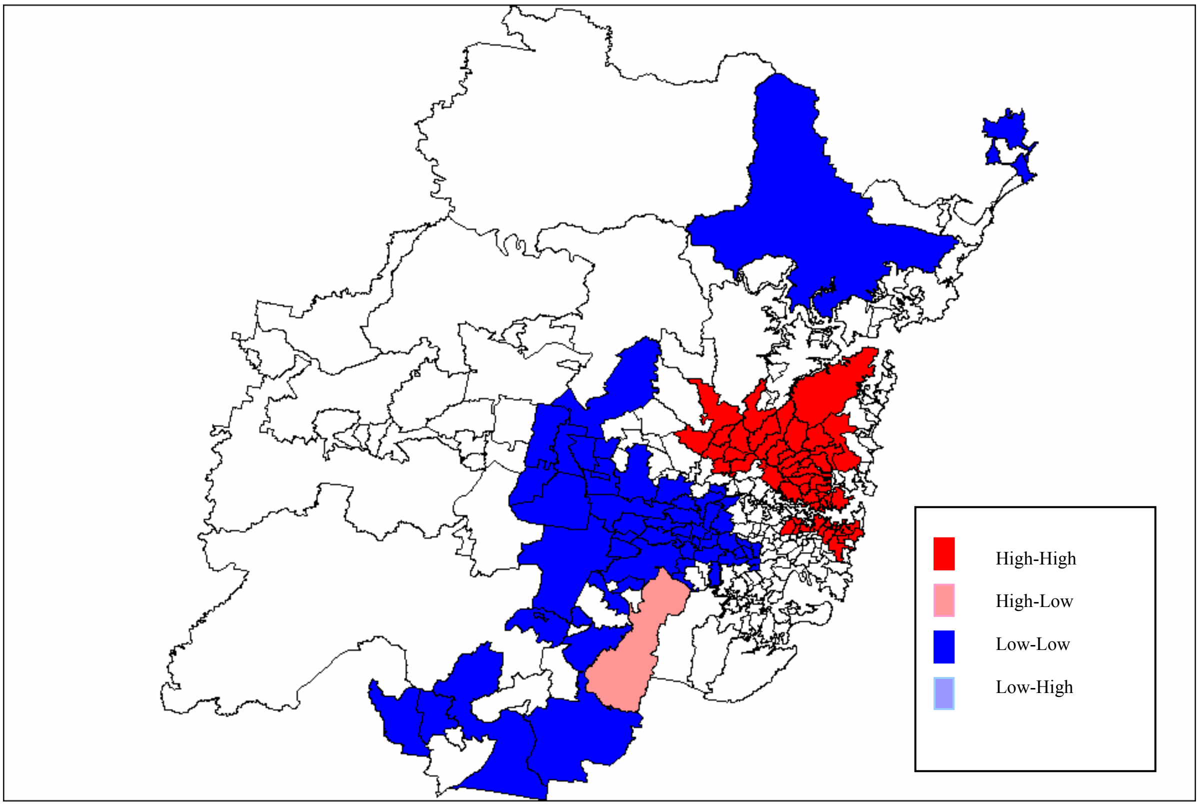

Figure 3 Spatial Dependence in ABS SEIFA Index of Relative Socio-Economic Disadvantage, Sydney Metropolitan POAs, 2001
Moran's I = 0.7407 (0.0001). Source: ABS, CDATA 2001.

Figure 3 uses the summary measure of socioeconomic disadvantage, the ABS Index of Relative Socio-economic Disadvantage (IRSED), to examine spatial clustering, and the pattern more or less reaffirms the familiar inner-north and outer-west divide, which is driving much of the overall spatial dependence observed in the Sydney metropolitan region. A high score represents relative advantage and a low score represents relative disadvantage. Hot spots of relative advantage spread towards

Pittwater and out to Baulkham Hills, also toward Leichhardt and Waverly. Gosford, Western Sydney (north to Blacktown and Fairfield) emerge as cold spots or areas of relative disadvantage, along with the inner and outer west. Sutherland Shire. Wollondilly in the far south also experiences a statistically significant clustering of disadvantage. Figure 4 plots LISA estimates for persons with

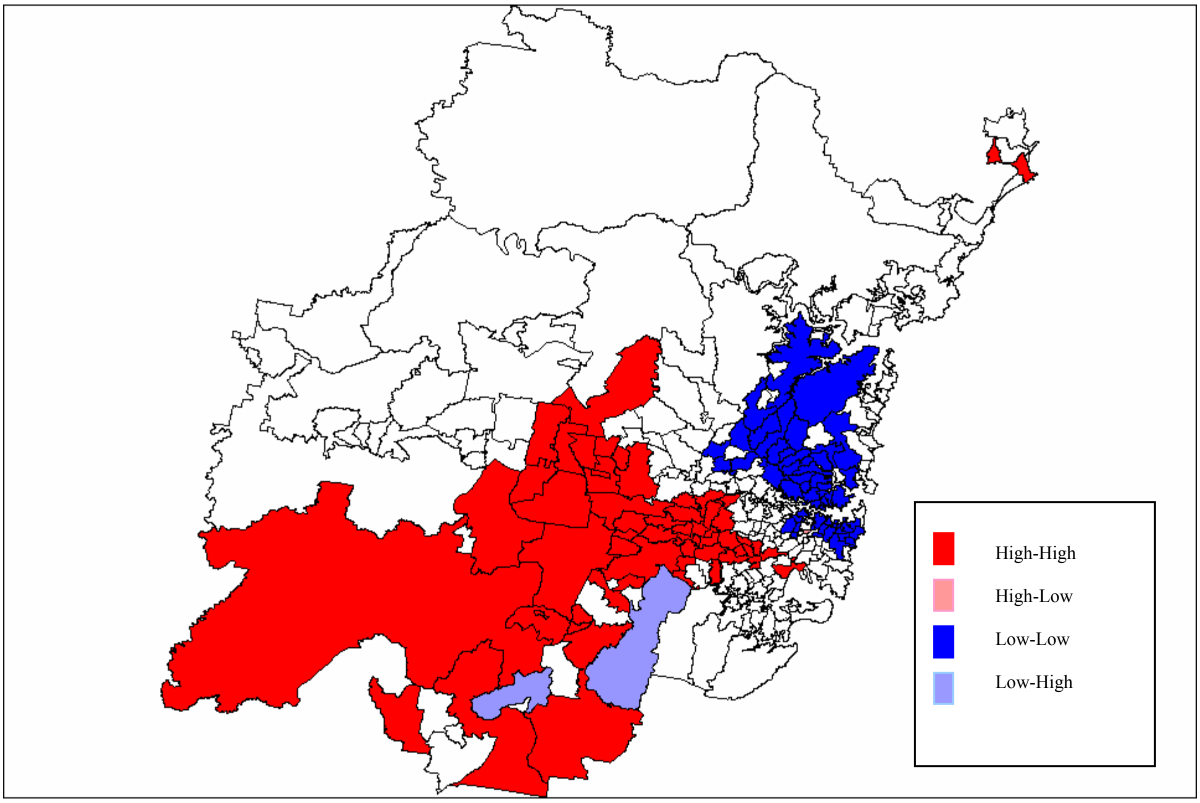

Figure 4 Spatial Dependence in the Proportion of Residents with No Qualifications, Sydney Metropolitan POAs 2001.
Moran's I = 0.7049. (0.001). Source: ABS, CDATA, 2001.

'no qualifications'. The pattern of disadvantage is somewhat different. Once again the North Shore and inner-city suburbs emerge as areas with statistically significant clustering of low proportions of people with 'no qualifications', however hotspots which contain high concentrations of persons with 'no qualifications' are spread over a large portion of south-western Sydney. Such suburbs include Baulkham Hills, Penrith, Campbelltown and Liverpool and south to parts of Wollondilly. Parts of Campbelltown and the closely situated Wollondilly POA 2568, emerge as areas of unusually low concentrations of disadvantage (high-low associations).

Spatial clustering in the proportion of persons employed in services (Figure 5) is very sharply divided between high-high and low-low association. High concentrations are present in the inner-eastern and northern suburbs – particularly around Ku-ring-gai, North Shore and Mosman. A very large 'coldspot' is present in most of outer Sydney (north towards Hawkesbury, Gosford and south in Penrith, Camden, Blue Mountains and Wollondilly). Figure 6, is not surprisingly an inversion of the pattern shown in Figure 4, with high concentrations of persons employed in professional occupations emerging in the inner-north and eastern suburbs, and a professional employment 'coldspot' stemming in Blacktown and running south to Wollondilly and east into the inner West (very few atypical high-low and low-high POAs are observed). The final map, Figure 7 illustrates the spatial clustering in NESB residents across Sydney Metropolitan POAs, in 2001. The demarcation is once again dramatic and illustrates migrant preferences for residence in inner-west and inner-city regions with high accessibility to jobs and services, and perhaps rental accommodation. Significant 'hot spots' occur in the inner-west, and spread out to Fairfield and Liverpool in south-western Sydney. The outer ring of Sydney emerges as a significant 'coldspot', running from Gosford, Hawkesbury, the Blue Mountains and south to Wollondilly, have experienced very low levels of persons with low English proficiency.

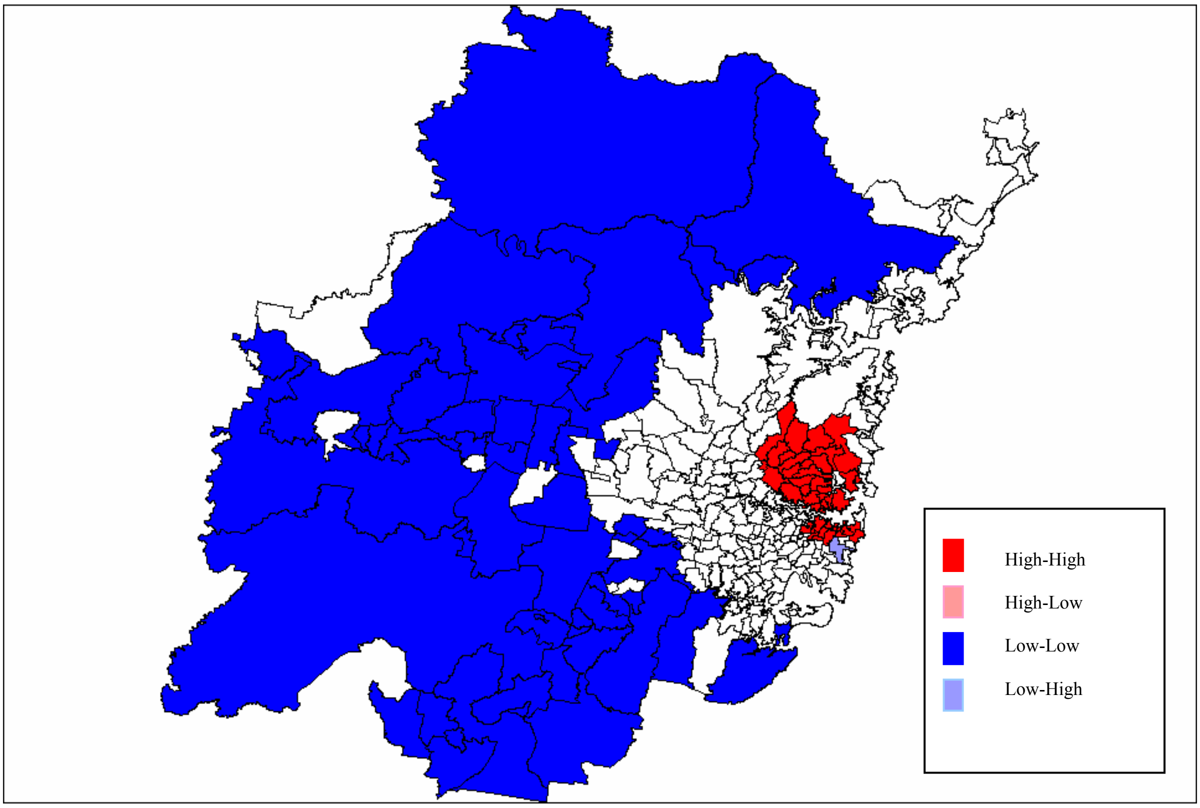

Figure 5Spatial Dependence Proportion Employed in Services, Sydney Metropolitan POAs 2001. Moran's I=0.723 (0.0001). Source: ABS, CDATA, 2001.

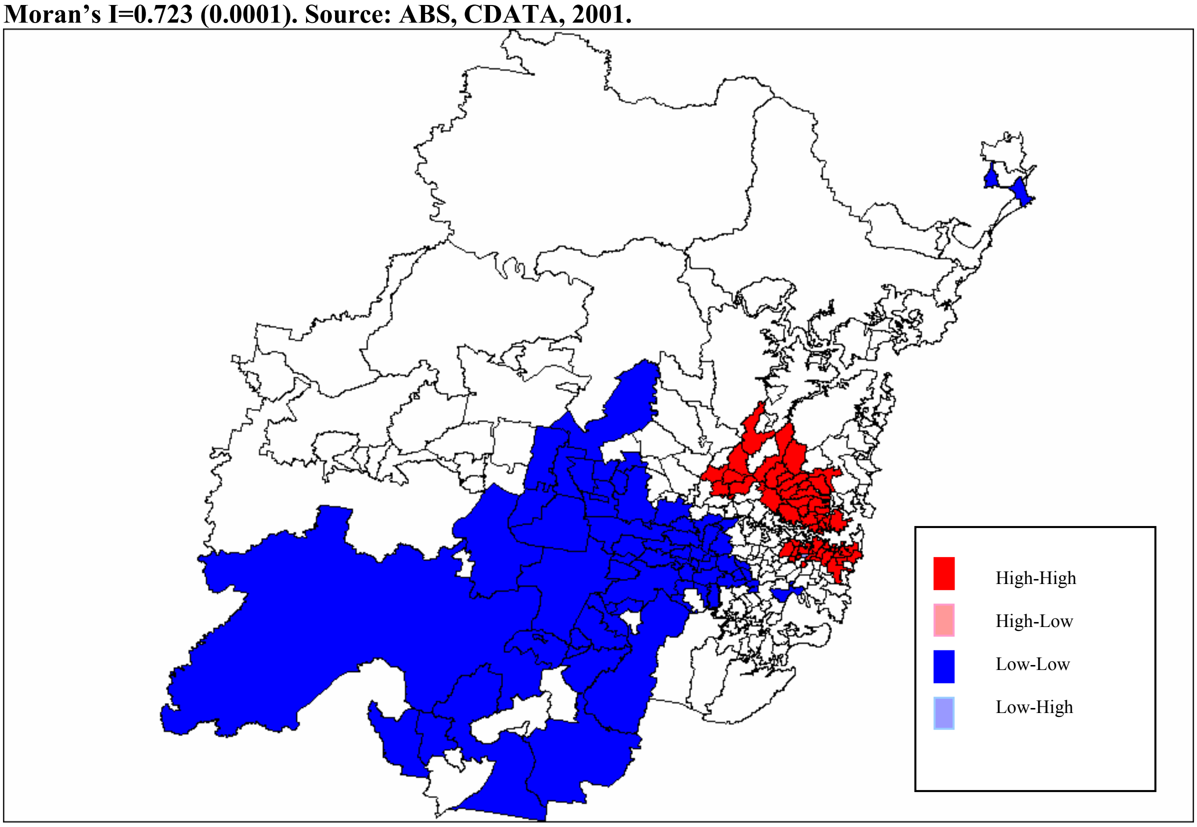

Figure 6 Spatial Dependence in Proportion of Residents Employed as Professionals, Sydney Metropolitan POAs 2001.
Moran's I=0.781 (0.0001). Source: ABS, CDATA, 2001.

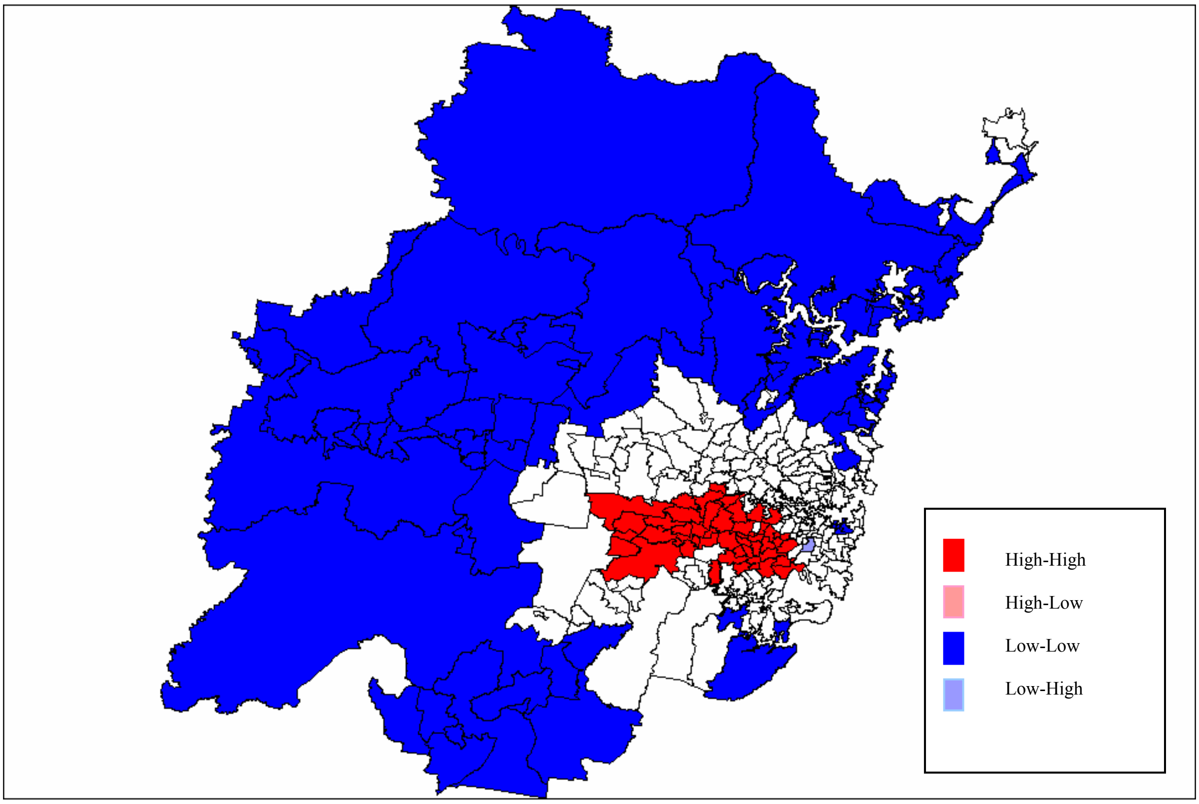

Figure 7 Spatial Dependence in Low English Language Proficiency, Sydney Metropolitan POAs 2001. Moran's I = 0.4676 (0.001). Source: ABS, CDATA, 2001.

SPATIAL ECONOMETRIC ANALYSIS OF LABOUR MARKET OUTCOMES, 1996-2001

While the above figures, particularly Figures 1 and 2, provide significant evidence of clustering in labour market outcomes it is difficult to determine what may be driving this clustering, and whether in fact interactions between regions, either through neighbourhood effects or through small area spillovers are a plausible explanation of such segregation. Spatial econometric models provide a means to ascertain the role of small area interactions in determining regional outcomes, for instance small area unemployment rates, independent of other driving factors in the region itself. Furthermore when employing data collected across various geographic points, it may not be appropriate to view it as conceptually identical to cross-sectional data on individuals or businesses at a single location. Spatially adjacent observations are likely to exhibit spatial interdependence, owing to dynamics which accompany proximity. This reflects 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).

A number of spatial econometric models have been developed, to overcome such problems and capture regional interdependence, these are estimated using maximum likelihood techniques.

The *General Spatial Auto-regressive (SAC) Model* is:

$$y = \rho W_1 y + X\beta + \mu \qquad (2)$$

$$\mu = \lambda W_2 u + \varepsilon$$

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

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 $\sigma^2 I$ 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 $\mathbf{W_1}$[2] and $\mathbf{W_2}$ are standardised (row elements sum to unity) and capture a 'spatial autoregressive process in the dependent variable', in other words the degree of inter-relatedness between regions. The idea of row-standardisation is to give equal aggregate weight to each region regardless of the number of neighbours or bordering regions. That is, a region with 5 immediate neighbours is given the same aggregate weighting as a region with 10 neighbours - if the weight matrix is not row-standardised the latter would receive double the weight

The below model Equation (5) is the second-order *Spatial Auto-Regressive* model (SAR) obtained by imposing the restriction W2 =0 on the first model:

$$\mathbf{y = \rho W_1 y + W_1 X\beta_2 + \varepsilon} \qquad (3)$$

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

This model is called a mixed regressive spatial model (Anselin, 1988) because it combines the standard regression model with a spatially lagged dependent variable. The parameter *p* measures the degree of spatial dependence inherent in the data. For example the average influence of the change in unemployment rates in a region's neighbours, on the unemployment rate that has occurred in the region in question.

The *Spatial Durbin Model* below Equation (6) adds further spatially weighted terms to the FAR model, by including a spatial lag of the dependent variables, one or more of the X variables can be spatially lagged.

$$\mathbf{y = \rho W_1 y + X\beta + W_1 X\beta_2 + \varepsilon} \qquad (4)$$

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

The simple linear model (one which we would test if we did not believe that spatial effects exist) is as follows:

$$\mathbf{\mathit{y} = X\beta + \varepsilon} \qquad (5)$$

It is obtained by imposing two constraints on Equation (4) W_1=0 and W_2=0.

The simple OLS linear model is estimated first and tested for residual spatial dependence. That is it is tested as to whether neighbouring values are more similar values than might be expected. There are a number of asymptotic approaches for testing whether spatial correlation is present in the residuals from a least-squares regression model. Some of these are the: *a)* Moran I test *b)* Likelihood Ratio Test *c)* Wald test *d)* Lagrange Multiplier test – all of which are based on the maximum likelihood estimation of the SEM model (LeSage, 1999). If spatial dependence is present in the residuals, the FAR, SAR and Spatial Durbin models are next estimated to ascertain the role of small area interactions in labour market outcomes in the period, 1996 to 2001. Results for the OLS and maximum likelihood models, run across Metropolitan Sydney POAs[3], are reported in Tables 2 and 3.

Examining the unemployment rate in 2001 in the Sydney Metropolitan region, some interesting results emerge. The proportion of part-time employment as a share of total employment is a strong predictor of the 2001 unemployment rate, perhaps reflecting the higher turnover and lack of job-

2 These weights link a region to its immediate neighbours using *Delaunay* triangles, with each region receiving an equal overall weight (row-standardisation).

3 In creating growth rates in employment, labour force and unemployment rates over 1996 to 2001, a number of POAs had to be combined because new postcodes were created in 2001 or 1996 postcodes did not exist. In 1996 postcode '2091' and '2092' were combined. POAs '2128' and '2130', and POAs '2260' and '2261' were combined in 2001. In 1996 '2139' and '2140' were also combined, as were POAs '2259', '2260' and '2261' in 1996. Also deleted are '2757' and '2755' because population, employment and labour force totals differ incommensurately between the periods which suggest that boundary changes may have occurred.

security afforded in industries which have a heavy part-time share of employment. The percentage of sole parents is also a strong predictor of the unemployment rate capturing an adverse employment history, or some other latent variable not controlled for in the model. Also a strong predictor of unemployment is the proportion of people employed in manufacturing, which reflects the deindustrialisation of the past 20 years and high unemployment rates associated with these industries. Not surprisingly the proportion of residents with low English language proficiency, emerges as a strong predictor of unemployment within the Sydney Metropolitan region

Table 2: Unemployment Rate 2001, Spatial Econometric Results.

	OLS (Dependent Variable= Unemployment Rate, 2001)		SAC (Dependent Variable= Unemployment Rate, 2001)		Spatial Durbin(Dependent Variable= Unemployment Rate, 2001)	
	Coefficient	Significance	Coefficient	Significance	Coefficient	Significance
Constant	-17.65	*	-14.47	*	-25.24	*
Part-Time Employment as a Proportion of Total Employment	0.257	*	0.218	*	0.183	*
Percentage Sole Parent	0.323	*	0.278	*	0.242	*
Percentage of Residents with Low English Language Proficiency	0.141	*	0.165	**	0.201	*
Percentage Professionals	0.083	*	0.057	*	0.067	*
Percentage Manufacturing	0.282	*	0.265	*	0.251	
Employment Per Sq km - Density	-0.0008		-0.00009		0.000025	
Percentage Indigenous	0.197	*	0.189	*	0.188	*
No Vehicle	-0.610	*	-0.517	*	-0.468	*
State Housing	0.028		0.044	**	0.0605	*
Persons Aged 15-24 years	-0.044	*	-0.001		0.040	*
Persons Aged 65 plus	-0.117	*	-0.09	*	-0.095	*
No Qualifications	0.098	*	0.07	*	0.080	**
Percentage Change Employment, 1996-01	0.007	**	0.008	**	0.007	**
Rho			0.01		0.278	*
Lambda			0.406	*		
Lagged Proportion NESB					-0.167	*
Lagged Proportion Professionals					0.107	**
Lagged Proportion 15-24 Years					-0.176	*
R2	0.8572		0.8781		0.885	
Adjusted R2	0.8491		0.8712		0.871	
Durbin-Watson						
Variance	1.609		1.2950		1.156	
Breusch-Pagan LM	25.9234		18.287			
Log Likelihood			-158.15		-282.615	
Moran I Statistic for Spatial Residuals	4.27					
LM test	12.20		20.13			
Number Observations	245		245		245	

Source: ABS, CDATA, 2001.
Note : * significant at the 1% level; ** significant at the 5% level.

other factors held constant. This is likely to reflect the lower skills and employability of recent migrants, or perhaps employer perceptions of their competencies. The higher an area's proportion of Indigenous residents, the higher the unemployment rate. This can be explained in terms of the significant labour market disadvantage experienced by this group. Likewise, the higher the proportion of an area's residents with 'no qualifications', the higher the 2001 unemployment rate. Human capital theory would predict such an outcome because education raises a person's productivity in the labour market, although it could equally be argued education is a screen for employers to determine a person's innate ability.

A small area's unemployment rate is inversely related to the proportion of person's aged 15 to 24 years and the proportion of persons aged 65 plus years (the latter reflects lower rates of labour force participation of the aged). Employment change from 1996 to 2001 is also a significant predictor of the 2001 unemployment rate, but is positive contrary to expectations, and is not as strong a predictor as some of the demographic variables. An explanation for the weak effect of employment growth is that, as already discussed, the dynamics observed depend very much on the unit chosen. POAs are relatively small geographic units, not likely to be large enough to capture the effects of labour demand and supply that operate in standard labour market models. One explanation for the positive sign is that, perhaps in the Sydney Metropolitan region, high levels of in-migration and increased in-commuting have accompanied employment growth, with the implication that unemployment rates have been sustained (see Mitchell and Bill, 2005b, and Bill, Mitchell and Watts, 2005). The OLS model is tested for hetroskedasticity using the Bruesch-Pagan test which is rejected at the 1% level.

Following the confirmation of spatial autocorrelation in the OLS residuals, we now run models which incorporate spatially weighted variables – that is we test whether the values of a neighbouring region influences the region in question. Lambda emerges as significant in the SAC model indicating the presence of some 'unspecified' inter-relationships between neighbouring regions. For the spatial Durbin model, where all explanatory variables are lagged as well as the dependent variable, *rho* is now significant and positive. This means that independent of other factors the higher the unemployment rate in the neighbouring regions the higher the region's own unemployment rate, which confirms the presence of economic spill-overs in our dataset. Additionally a number of explanatory variables, also exhibit significant spatial effects. POAs which are surrounded by regions with a high proportion of NESB residents have lower unemployment rates, other factors held constant; perhaps this represents a positive spillover from cultural or social networks in terms of improved job search. Regions surrounded by residents aged 15-24 years are also likely to experience lower unemployment rates. Surprisingly being closely located to high levels of professional employment is negatively related to a region's unemployment rate, other factors held constant.

Table 3 examines the drivers of employment growth within the Sydney metropolitan region over the 1990s. The proportion of total employment which is part-time emerges as a negative predictor of growth. While the proportion of residents who are of Non-English Speaking Background (NESB) emerges as a positive predictor, holding other factors constant. This is curious given that the proportion of NESB residents are also linked to higher unemployment rates, although both high employment growth and high unemployment rates may be occurring in rapidly growing areas (which are attractive to migrants) within Sydney, so this is not implausible. Similarly the higher the proportion of residents employed in manufacturing the lower the POAs employment growth over the period, reflecting the poor performance of this sector during the 1990s. The proportion of residents employed in service sector is negatively related to employment growth as is the percentage of manual workers, other things held constant. Interesting the higher the proportion of residents who 'moved 5 years' ago the larger the employment growth of an area, and this effect is large and significant. The causation of this variable is likely to be multi-directional. On the one hand movers may have higher skills and greater labour market attachment, and thus contribute to a region's economic growth. However on the other hand workers may be moving in response to the growth that is occurring within these labour markets. For this reason a 'moved 5 years ago' variable was chosen, although if the same labour markets that experienced growth in 1996-2001 experienced growth in 1991-1996, this may not entirely control for the two-way causation. State housing is strongly positively related to employment growth and in part reflects the fact that much of the remaining stock of state housing is in high growth inner-city areas, now undergoing gentrification.

The higher a regions proportion of rented dwellings the lower the regions employment growth, other things held constant. This is interesting, and confirms that housing matters in the determination of small area economic outcomes. It also ties in with research by Randolph and Halloway (2005a) that indicates a growing concentration of disadvantage within private rentals in the Sydney region. Again, the OLS model is tested for hetroskedasticity using the Bruesch-Pagan test, and it is rejected at the 1% level.

The least-squares residuals are examined for spatial autocorrelation and a SAC model is estimated. In the SAC model a person's marital status emerges as significant, and the higher the proportion of married residents the higher the employment growth of an area and the effect is large and significant. While the spatially lagged employment growth term is not significant in the SAC

Table 3: Percentage Growth in Employment, 1996-2001, Spatial Econometric Results.

	OLS (Dependent Variable=Percentage Change Employment, 1996-2001)		SAC (Dependent Variable=Percentage Change Employment, 1996-2001)		Spatial Durbin (Dependent Variable=Percentage Change Employment, 1996-2001)	
	Coefficient	**Significance**	**Coefficient**	**Significance**	**Coefficient**	**Significance**
Constant	-40.75		-35.348		-60.011	
Part-Time Employment as a Proportion of Total Employment	-1.26	*	-1.331	*	-0.727	
Percentage Sole Parent	-0.962		-1.300	*	0.078	
Percentage of Residents with Low English Language Proficiency	1.646	*	1.665	*	1.418	*
Percentage Indigenous	2.248		2.564		1.964	
Percentage Manufacturing	-1.280	**	-1.491	*	-1.016	
Percentage Dwellings State Housing	1.278	*	1.305	*	1.054	*
Percentage Employed in Services	-0.614	**	-0.755	*	-0.156	
Percentage Employed in Manual	-0.604	*	-0.621		-0.319	
Percentage Did Not Finish Year 10	0.129		-0.025		0.546	
Trade Certificate	1.266	*	1.319	*	0.818	
Percentage Married	0.397		0.466	*	0.599	**
No Qualifications	0.457		0.601		-0.421	
Moved 5 years ago	2.560	*	2.471	*	2.564	*
Proportion of dwellings rented	-1.310	*	-1.148	*	-1.428	*
Rho			**0.04**		**-0.373**	*
Lambda			**-0.428**	*		
Lagged Sole Parents					-3.42	*
R^2	0.5251		0.5578		0.5668	
Adjusted R^2	0.4962		0.5065		0.5107	
Durbin-Watson						
Variance	276.81		241.957		224.381	
Bruesch-Pagan LM	132.16					
Log Likelihood			-798.622		-928.699	
Moran I Statistic for Spatial Residuals	3.47					
LM test	6.69		9.97			
Number Observations	245		245		245	

Source: ABS, CDATA, 2001.
Note : * significant at the 1% level; ** significant at the 5% level.

model, lambda is significant, negative and large, which suggests the presence of some residual ‘unspecified’ spatial dependence between neighbouring regions. In the spatial Durbin-model all explanatory variables are spatially lagged along with the dependent variable. Only the spatially lagged sole parent variable emerges as significant (the others are not reported). This is very interesting, independent of other demographic variables in the model, the higher the proportion of sole parents amongst a region’s immediate neighbours the lower the employment growth in the region itself. This indicates the presence of a ‘neighbourhood effect’, perhaps through attitudinal, role model or social network type linkages, creating spill-overs with adverse impacts for a neighbouring regions economic activity. In this model *Rho* emerges as significant, but negative, which means that the higher a neighbouring region’s employment growth the lower the employment growth in the region itself. This possibly reflects job competition between immediately neighbouring small areas, net of other factors.

CONCLUSION

This paper confirms the presence of significant spatial clustering across metropolitan Sydney. Moran statistics illustrate that socio-demographic, occupational and economic variables are strongly and positively related across space. Thus the pattern is one of moderate spatial segregation - high values of advantage or disadvantage tend to congregate with high values of socio-economic advantage or disadvantage to form ‘hot’ and ‘cold’ spots (keeping in mind that Australian cities are significantly more heterogeneous than US cities with fewer concentrations of extreme disadvantage (Vinson, 1999)). While globally unemployment rates have become slightly less clustered within the Sydney metropolitan region over the period 1996 to 2001, local measures show that divisions between east and west Sydney have remained, although there has been some shift south-west, and a scaling back of low-low associations within outer northern Sydney. Spatial clustering is most pronounced amongst persons employed in professional occupations, persons employed in service industries and persons with advanced qualifications. Interestingly housing values do not appear to be as clustered as occupational, industry and educational variables, at the SLA level. Moreover looking at unemployment rates in 2001, spatial dependence holds even once demographic and other socio- economic variables, thought to influence labour market outcomes, have been controlled for. This suggests, independent of population mix and housing (allowing for the fact housing controls only capture the proportion of renters and persons in state housing, and admittedly may not fully capture housing market constraints), unemployment rates in neighbouring directly influence each other. While a number of factors may explain such an interrelationship - commuting, trade spillovers and migration - the interrelationship between areas as small as POAs indicates that neighbourhood effects may be present. In the model of employment growth, the spatial error term emerges as significant and negative, which indicates the presence of some ‘unspecified’ variable causing employment growth in neighbouring POAs to be more different than might otherwise be expected.

It should be noted that demographic variables remain key drivers of economic outcomes within Metropolitan Sydney, these include: the proportion of persons who have low English speaking proficiency, the proportion of sole parents, the proportion of movers, the proportion of persons with a trade certificate and the proportion of residents who are Indigenous. The level of state housing and the proportion of rented dwellings are also significant variables in virtually all the models estimated. Thus housing remains a very important sorting mechanism across space. Interestingly independent of other factors, the higher the proportion of sole parents in the neighbouring POA, the lower a region’s employment growth, net of other factors. This may suggest the presence of adverse ‘neighbourhood effects’, stemming from the disadvantage commonly associated with sole parenthood. In such communities the quality and frequency of the exchange of information about job openings or the perceived benefits of returns to education may be under-estimated with adverse consequences for an individual’s future employability.

Thus this paper provides evidence of regional interactions at the small area level, operating across unemployment rates and a few notable socio-demographic variables. These may be contributing to the persistent regional clustering of high levels of unemployment, and low levels of employment growth, in the face of strong overall economic performance of Sydney over the 1990s.

REFERENCES

Andrews, D. Green, C. and Mangan, J. (2004), 'Spatial Inequality in the Australian Youth Labour Market: The Role of Neighbourhood Composition', *Regional Studies*, vol. 38, 1, 15-25

Anselin, L., Syabri, I. and Smirnov, O., (2002), *Visualizing Multivariate Spatial Correlation with Dynamically Linked Windows*, Regional Economics Applications Laboratory (REAL), University of Illinois, Urbana-Champiagn, Urbana.

Anselin, L. (1995), Local Indicators of Spatial Association - LISA, *Geographical Analysis*, 27, 92-115.

Anselin, L. (1996), 'The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association'. pp. 111–125 in Fischer, M. M., Scholten, H.J. and Unwin, D. (eds) *Spatial Analytical Perspectives on GIS*, Taylor & Francis, London.

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

Australian Bureau of Statistics, (ABS) (2002), *Census of Population and Housing Basic Community Profile 2001*, Catalogue No. 2001.0, Government Publishing Service, Canberra.

Australian Bureau of Statistics (ABS) (2001), *Buildings Approvals, Australia*, Catalogue Number 8731.0, Government Publishing Service, Canberra.

Australian Bureau of Statistics (ABS), (2003), *Regional Wage and Salary Earner Statistics*, Australia – Electronic Publication:

http://www.abs.gov.au/Ausstats/abs@.nsf/lookupresponses/701ff26e20367345ca256e01000213a7?opendocument (accessed 13/10/05)

Badcock, B. (1997), 'Recently Observed Polarising Tendencies in Australian Cities', *Australian Geographical Studies*, 35(3): 243-259.

Baum, S. (1997), 'Sydney, Australia: A Global City? Testing the Social Polarisation Thesis', *Urban Studies*, vol. 34, No. 11, 1881-1901.

Bill, A., Mitchell, W. and Watts, M. (2005), 'Examining the Relationship Between Commuting Patterns, Employment Growth and Unemployment in the Sydney Major Statistical Region', Working Paper 10-05, *Centre of Full-Employment and Equity*, University of Newcastle., Australia.

Bill, A. and Mitchell, W. F. (2005), 'Local Spatial Analysis of Unemployment in Australia', Working Paper 06-05, Centre of Full-Employment and Equity, University of Newcastle., Australia.

Buck, N. and Gordon, I. (2004), 'Does Spatial Concentration of Disadvantage Contribute to Social Exclusion?' in *City Matters: Competitiveness, Cohesion and Urban Governance*, Boddy, M. and Parkinson, M. (eds) , The Policy Press, University of Bristol, Bristol.

Cheshire, P., Monastiriotis, V. and Sheppard, S. (2003), 'Income Inequality and Residential Segregation: Labour Market Sorting and the Demand for Positional Goods' in *Geographies of Labour Market Inequality*, Martin, R. and Morrison, P.S. (eds), Routledge, London.

Cliff, A.D. and Ord, J.K. (1973), *Spatial Autocorrelation,* Pion, London.

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

Elhorst, P.J. (2003), 'The Mystery of Regional Unemployment Differentials: Theoretical and Empirical Explanations', Journal of Economic Surveys, vol. 17, No. 5, Malden.

Frank, A. (2003), ‘Using Measures of Spatial Autocorrelation to Describe Socio-economic and Racial Patterns in US Urban Areas’, in Kidner, D., Higgs, G. and White, S (eds), *Socio-Economic Applications of Geographic Information Science*, Taylor & Francis, London.

Gordon, I. R. and Monastiriotis, V. (2004) 'Using Aggregate Evidence to test for Neighbourhood Effects on Social Exclusion', LSE Research *Papers in Environment and Spatial Analysis* (forthcoming), London School of Economics and Political Science.

Gregory, R. and Hunter, B. (1995), ‘The Macro-Economy and the Growth of Ghettos in Urban Poverty in Australia’, Discussion Paper No. 325, Economics Program Research School of Social Sciences, Australian National University.

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.

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

Hunter, B. (2003), ‘Trends in Neighbourhood Inequality of Australian, Canadian and United States of America Cities Since the 1970s’, *Australian Economic History Review*, vol. 43 no.1, 22-44.

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

Kelly, R. and Lewis, P.E.T, (2000a), ‘Neighbourhoods, Families and Youth Employment Outcomes, A study of Metropolitan Melbourne’, *The Centre of Labour Market Research*, Discussion Paper Series, No. 00/04.

Le, A.T. & Miller, P.W. (1999), ‘Occasional Paper: A Risk Index Approach to Unemployment - An Application Using the Survey of Employment and Unemployment Patterns’, cat. no. 6293.0.00.001, ABS, Canberra.

Le Sage, J. (1999), *The Theory and Practice of Spatial Econometrics*, *mimeo*, Department of Economics, University of Toledo, Toledo.

Le Sage, J. (2005), ‘Using the Spatial Econometrics Toolbox for Estimation of Spatial Regression : Models and Mapping in MATLAB’, Keynote Address to ARCNISS Workshop – Methodology, Tools and Techniques Paradigm Forum, 15-17 June, University of Newcastle.

Martin, R.L. (2000), ‘Local Labour Markets: their nature, performance and regulation’, ch 23., in Clark, G.L., Feldman, M. and Gertler, M. (eds), *Handbook of Economic Geography*, 455-476.

Mitchell, W.F. and Bill, A. (2005), ‘Who Benefits from Growth? Disadvantaged Workers in Growing Regions’, Paper presented to *Australian and New Zealand Economic and Regional Development Conference*, 27-30 September, Manukau City, Auckland.

Mitchell, W.F. and Bill, A, (2004) ‘Spatial dependence in regional unemployment in Australia’, in Carlson E. (ed) A Future that works: economics, employment and the environment, Proceedings of the 6th Path to Full Employment Conference and the11th National Conference on Unemployment, 312-326.

Mitchell, W.F. and Bill, A, (2005), A Spatial Econometric Analysis of the Irreversibility of Long Term Unemployment in Australia, Working Paper No. 05-05, Centre of Full Employment and Equity, Newcastle.

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

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

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

O’Neill, P. and McGuirk, P. (2002), Prosperity along Australia’s Eastern Seaboard: Sydney and the Geopolitics of Urban and Economic Change, *Australian Geographer*, Vol. 33, No. 3, pp. 241-261.

O'Regan, K.M and Quigley, J.M., ‘Spatial Effects in Employment Outcomes: The Case of New Jersey Teenagers’ (1996) Federal Reserve Bank of Boston, 41-64.

Raskall, P. (2002), ‘Equity Issues in the “New Prosperity” of the 1990s: the case of Sydney’, *Australian Geographer*, Vol. 33, 281-299.

Randolph, B. (2003), Overview: Changing Spatial Structure, *State of Australian Cities National Conference*, Carlton Hotel, Parramatta, 3-5 December 2003.

Randolph, B. and Holloway, D. (2005a), ‘Social Disadvantage, Tenure and Location: An Analysis of Sydney and Melbourne’, *Urban Policy and Research*, vol. 23 (2), 173-201.

Randolph, B. and Holloway, D. (2005b), 'The Surburbanization of Disadvantage in Sydney: New Problems, New Policies', Opolis : An International Journal of Suburban and Metropolitan Studies, vol. 1, Issue 1, Article 6, ,49-64.

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

Sawanda, M., (2005), ‘Global Spatial Autocorrelation – Moran’s I, Geary’s C and the General Cross-Product Statistic’, (mimeo), University of Ottawa, Ottawa. http://www.1pc.uottawa.ca/publications/moransi/moran.htm (21/06/2005).

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* (2001) 68, 261-295.Conely, T and Topa, G. (2002), Dynamic Properties of Local Interaction Models, mimeo, Department of Economics, New York University.

Trendle, B. (2005), ‘Unemployment Variation in Metropolitan Brisbane – the Role of Geographic Location and Demographic Composition’, Presented to the *Australian and New Zealand Economic and Regional Development Conference*, 27-30 September, Manukau City, Auckland.

Upton, G.J. and Fingleton, B. (1985), *Spatial Data Analysis by Example, Volume 1: Point Pattern and Quantitative Data*, Wiley, Toronto.

Vinson, T., (1999), *Unequal in Life: the Distribution of Social Disadvantage in Victoria and New South Wales*, Jesuit Social Service, Melbourne.

Wilson, W. (1987), *The Truly Disadvantaged: The Inner City, the Underclass and Public Policy*, University of Chicago Press, Chicago.