



Centre of Full Employment and Equity

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**A spatial econometric analysis of the irreversibility of long term
unemployment in Australia**

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1. Introduction

Labour underutilisation in Australia remains a significant economic problem. According to the Centre of Full Employment and Equity hours-based measures around 10 per cent available labour hours are unused in Australia (combining unemployment, underemployment, and hidden unemployment) (CofFEE CLMI, 2005). While the Australian economy has experienced a very long growth cycle since the last major recession in 1991 and national unemployment has steadily fallen there remain regional and demographic pockets of disadvantage characterised by long-term unemployment. The growth has clearly not been sufficient to create full employment and metropolitan labour markets appear to have fared better than non-metropolitan regions (see Mitchell and Carlson, 2003a, 2003b). This heterogeneity across space provides the basis to examine several key hypotheses concerning the way local labour markets operate.

In this paper we use spatial statistical and econometric techniques to investigate the one such hypothesis – we explore whether long-term unemployment has strong irreversibility properties. Orthodox economists have typically considered long-term unemployment to be a (linear) constraint on a person's chances of getting a job. The so-called negative duration effects are meant to play out through loss of search effectiveness or demand side stigmatisation of the long-term unemployed (Layard, Nickell and Jackman – hereafter LNJ, 1991; van den Berg and van Ours, 1996). LNJ (1991: 4, 38) argue that structural shifts in the unemployment-vacancy (UV) relationship are due to a failure of the unemployed to seek work as effectively as before. They explain the outward shift in the European UV relationship by “a fall in the search effectiveness ... among the unemployed.” LNJ (1991: 268) also claim that this shift has been driven by the “rise in long-term unemployment, which reduces search effectiveness ...”

Mitchell (2001) using aggregate level data for Australia to study the rise in long-term unemployment found that outward shifts in the UV relationship largely occurred around recessions. It was difficult to construct them as steady structural shifts driven by behavioural supply-side changes. He also found that the dynamic relationship between long-term unemployment and the aggregate unemployment was very close. Several studies have found that a rising PLTU is not a separate problem from that of the general rise in unemployment (Chapman *et al.*, 1992; EPAC, 1996; Chapman and Kapuscinski, 2000). These results cast doubt on the supply-side policy emphasis that OECD governments have adopted over the last two decades. So while LNJ may claim search effectiveness declines and this contributes to rising unemployment rates, it is highly probable that both are caused by insufficient demand. The policy response is then entirely different. Webster (2003: 2) argues that “there never has been any problem of irreversibility in long-term unemployment and that the policies supposedly required to deal with it are largely a waste of time and money.”

Recently, Dixon and Lim (2004: 501) investigated whether there had “been any long-run increase (or decrease) in the ‘incidence’ of long-term ...” in Australia once the impact of the business cycle is taken into account. They concluded that “once we allow for cyclical factors, the incidence of male long-term unemployment has been neither rising nor falling, while that the incidence of female

long-term unemployment has been rising” (Dixon and Lim, 2004: 512-513). However, their findings do not necessarily support the irreversibility hypothesis.

While most of the previous studies have focused on time-series data, we take a different approach in this paper and attempt to compare the behaviour of short- and long-run unemployment (the latter being unemployment of 12 months or longer) using spatially-dimensioned data for Australia observed at August 2001. A motivation for this approach is that it is possible that the averaging that occurs in aggregate data hides spatial clustering of long-term unemployment which is resistant to employment growth.

In a separate paper (see Bill and Mitchell, 2005) we conduct Exploratory Spatial Data Analysis (ESDA) to determine the extent of global and local spatial dependence in long-term and short-term unemployment data in Australia. The analysis provides detailed information at the Statistical Local Area (SLA) of the way in which regional unemployment rates (short- and long-term) are clustered. We find significant global spatial correlation in both the short-term and long-term unemployment rates. Using Local Indicators of Spatial Autocorrelation (LISA) we find pockets of significant spatial dependence in both short-term and long-term unemployment rates. There does not seem to be major differences between the results for long-term unemployment and short-term unemployment rates.

In this paper, we investigate reduced-form demand and supply effects that allow for spatial dependencies to generate ‘spill-over’ effects across regions. By accounting for spatial dependence, we distinguish our work from previous studies of regional unemployment which have considered each observation in the cross section to be independent.

If there is strong hysteresis operating, we would expect the behaviour of long- and short-term unemployment to be significantly different in particular with respect to demand side variables such as employment growth. A second distinguishing feature of our work is our inclusion of measures of labour demand in cross-sectional explanations of spatial unemployment differentials. This distinguishes our work from previous regional studies that have focused on ‘local’ demographic, industry, occupational and human capital variables and have thus missed this important component of the explanation.

Once we include the demand side, then the interpretation of significant supply side influences changes. We might initially pose the question: how are the unemployed workers in total going to get jobs unless employment growth is faster? In this context, we would expect in times of rationed jobs for supply side factors to operate as screens which serve to sort the labour queue.

Our results show from this perspective, given the evidence available and controlling for spatial spillover effects, that there are no grounds for believing that the regional short-term unemployment rates behave differently to regional long-term unemployment rates. We thus reject the irreversibility hypothesis.

The paper is organised as follows: Section 2 briefly presents some macroeconomic facts concerning the way long-term and short-term unemployment operate over the business cycle in Australia. The overwhelming finding at the macroeconomic level is that the irreversibility effects are not evident in the data. The question then is whether spatial data might reveal substantially different short- and long-term behaviour which is hidden in the aggregated data. Section 3 outlines the data set and its summary

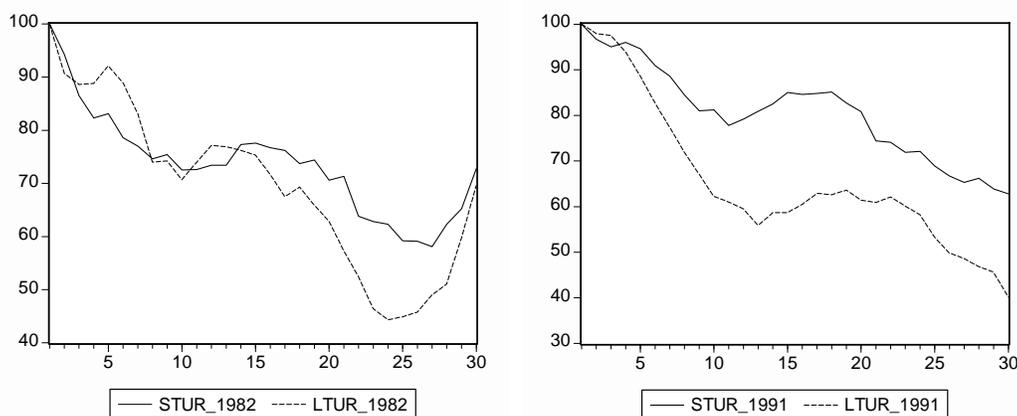
properties. Section 4 introduces the formal spatial econometric modelling structure by class of model and develops the models to be explored. Section 5 presents the results of the spatial econometric modelling. The strong conclusion is that at the spatial level, while unable to model business cycle impacts, there are no obvious differences in behaviour between short- and long-term unemployment. Regional unemployment is strongly inversely related to employment accessibility once we control for a range of local demographic, human capital and structural factors. Concluding remarks follow.

2. Conceptual issues and stylised facts

What is the best way of characterising the relationship between the long-term unemployment (LTU) and other labour force aggregates, given that LTU is a subset of total unemployment? Here we adopt the Australian Bureau of Statistics (ABS) definition of long-term unemployment (LTU) as being a state of 12 months continuous unemployment. It is worth noting that in the early 1970s, LTU was defined as unemployment spells over 13 weeks. In the 1980s, this was redefined to encompass spells over 26 weeks then increased again to 52 weeks. LTU (using the current definition) began to rise sharply in the latter half of the 1970s.

In this study, we choose to study the long-term unemployment rate (LTUR) (long-term unemployment measured as a percentage of the labour force) and the corresponding short-term unemployment rate (STUR). The PLTU variable is problematic because it is affected by the denominator. Webster (2003: 3) notes that PLTU “is not of intrinsic interest since in relation both to policy and to hysteresis-type theories, the issue is the actual amount of long-term unemployment, which is only consistently shown with [long-term unemployment, measured as a percentage of the labour force] ...” While LTU tracks unemployment, PLTU moves in opposite directions at the turning points (see Webster, 2003 who finds similarly in the UK). This occurs because the turning point impacts immediately on short-term unemployment (STU) which ensures that PLTU rises or falls, without altering LTU.

Figure 1 Long- and short-term unemployment rates, Australia, 30 quarters post trough



(a) 1982 trough plus 30 quarters

(b) 1991 trough plus 30 quarters

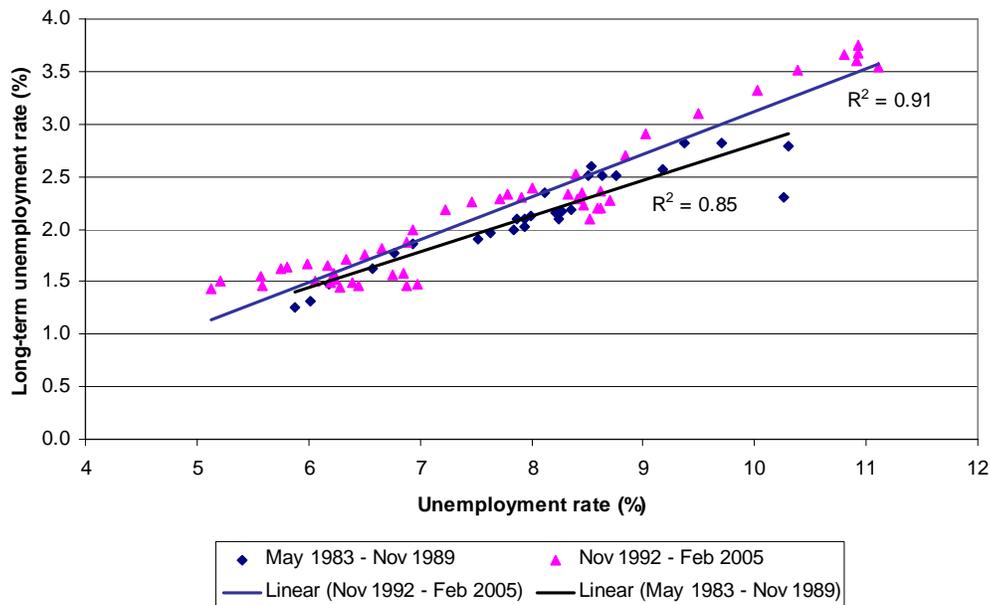
Source: ABS Labour Force Survey and authors’ calculations.

How have the LTUR and STUR behaved over the business cycle? Is there evidence that the LTUR is resistant to growth as is claimed by the irreversibility hypothesis? Figure 1 shows the decline in the LTUR and the STUR from the peaks coinciding with the 1982 and 1991 recessions, respectively. The observations are indexed with

the peak observations being 100. The behaviour is charted for 30 quarters following the peak. The peaks for the short-term unemployment rate precede that of the long-term unemployment, which in turn, lag the related troughs in GDP. The important finding is that the growth phase provides job opportunities for both pools of unemployment. There does not appear to be any sequential accessing of the short-term first, followed by the long-term unemployed, as the irreversibility hypothesis would suggest. Indeed, following the 1991 recession, the long-term unemployment rate fell much more sharply than the short-term rate. Mitchell (2005) has examined the possibility that this could have been due to labour force exit and largely rejects that proposition as an explanation.

Figure 2 compares the relationship between the official unemployment and the long-term unemployment rate for two recovery cycles coinciding with the peak of the official unemployment rate in May 1983 and November 1992 until the respective troughs were reached at the end of the cycle (November 1989 and February 2005, respectively). The lines (and R^2) are simple linear regressions for each of the two sets of (differently notated) pair-wise observations. Figure 2 confirms that the LTUR moves closely with the official rate as the business cycle improves. There does not appear to be any strong indication of hysteresis operating. The two recoveries are also strikingly similar so that the any notion that structural changes (or policy regimes) within the economy have increased hysteresis or that the period of Active Labour Market Programs in the 1990s have decreased it cannot be substantiated by this data.

Figure 2 Unemployment rate and long-term unemployment rate, Australia



Source: ABS Labour Force Survey.

The question this paper addresses is whether the aggregate behaviour, which is inconsistent with the strict irreversibility hypothesis, holds true at the spatial level. The question is approached in a somewhat different way at the spatial level. We capture the idea by conjecturing that the spatial behaviour of short-term and long-term unemployment is similar and responsive to spatially-localised and neighbouring

employment growth, once we control for a host of demographic, structural (industry/occupation), and locational (urban/non-urban, state of region) factors.

3. Data issues and stylised facts

3.1 Data Issues

For the purposes of this analysis we obtained a dataset from Centrelink which provided a snapshot of all New Start and Youth Allowance² recipients unemployed on August 17 2001, for each postcode in Australia. This was further disaggregated by the duration of unemployment into: (a) STU - those who have been unemployed for less than 12 months; and, (b) LTU - those who have been unemployed for 12 months and over.

A number of difficulties arose in attempting to build a regional dataset, which maintained the spatial detail of the Centrelink duration data, but allowed for the addition of demographic and socio-economic characteristics taken from the 1996 and 2001 Censuses. These difficulties were largely owing to well-known anomalies between postcodes and other Australian Standard Geographical Classification (ASGC) used by the ABS in the dissemination of its statistics. The ABS (2001c) states that a postcode is a four digit number used by Australia Post to assist with mail delivery whereas census data are collected on Collection Districts (CDs), which for several reasons are not compatible with postcodes (ABS, 2001c:1). The ABS has developed an ASGC classification known as Postal Areas (POAs) which approximate postcodes by allocating whole CDs to Australia Post postcode areas on a 'best fit' basis.

As postcode boundaries have not been updated since the early 1990s and more recent interpretations have not been endorsed by Australia Post, developing a POA to postcode concordance is not straightforward. A preliminary investigation of the viability of reassigning postcodes to ABS Postal Areas introduced substantial error into the data, especially at lower levels of disaggregation. Aggregation of postcode data to the Statistical Local Area (SLA) level significantly reduces, but does not entirely eliminate, the error generated by boundary differences between POAs and postcodes. For the purposes of converting the unemployment data we obtained a 2001 Postcode to SLA concordance generated by the Small Area Population Unit, within the ABS. This concordance has been derived based on a similar method to that of the Postal Area to SLA 2001 Concordance, but attempts to reflect a postcode geography closer to the Australia Post postcode geography. The ABS does not guarantee the accuracy of this concordance. It also notes that in using this concordance to generate estimates, the estimates' accuracy will be lower if the variable being converted is not distributed across the postcode in the same way that the population (obtained at June 30, 2001) is distributed.

In the course of applying this concordance 80 postcodes were excluded from the Centrelink dataset. These are Australia Post postcodes which are not mappable, such as: post office boxes, mail back competitions, large volume receivers and specialist delivery postcodes. In total the loss of these 80 postcodes resulted in the loss of 280 unemployed from our dataset (121 STU, 159 LTU).³

We then excluded SLAs from our analysis because they do not represent specific geographic areas; have very low population (under 100 persons); have low labour force or have no recorded STU or LTU (see Appendix Table A1).

As a result of the methodological quirks outlined above, after aggregating postcodes to SLAs, the total pool of unemployed given by the 2001 Census, was divided by the proportion of STU and LTU in each SLA. Thus the estimated STU and LTU for each SLA summed to the 2001 Census unemployed, yet still preserved the original Centrelink ratio of STU to LTU. Total estimates revealed 305,231 STU and 354,608 LTU, overall total unemployment of 659,838. Notably, the proportion of LTU to total unemployed in the raw Centrelink dataset differs from that in the ABS Labour Force Survey (LFS). In August, 2001, the LFS reported 645,800 people were unemployed, of these 508,800 were unemployed for less than 12 months and 137,000 were unemployed for 12 months or more (ABS:2005). Thus 78.8 per cent of people in the LFS are STU and 21.2 per cent are LTU. In the Centrelink dataset of 642,312 unemployed persons, 44 per cent of people are STU and 55 per cent are LTU, double the proportion reported by the LFS.

While at the aggregate level there is not a significant difference between the two data sources (0.54 per cent), what could account for the dramatic differences in the share of STU and LTU? One possible explanation is that as the LFS is a sample survey; LTU and STU are only estimates and are subject to sampling and non-sampling error (for example, LTU estimates have a relative error of 3.9 per cent (ABS, 2001a)). The sample for the LFS is designed to ensure that standard errors on key estimates are minimised, within the cost and other constraints imposed. Notably estimates are not benchmarked by duration. Prior to February 2004 the only population benchmarks were: state/territory of usual residence, by part of state of usual residence (capital city, rest of state), by age (ages 15-24 as single years, five-year age groups to age 69, one group for age 70 and over), by sex. (ABS: 2004). In contrast the Centrelink dataset is a headcount of all people in receipt of New Start or Youth Allowance, on the 17 August, 2001.

A second reason is that while both definitions of 'unemployed' capture persons 15 years and over, currently in the labour force and not employed. In the LFS, 'employed' follows the standard international definition, which requires a person only to work one hour or more a week (ILO, 1983). Under current New Start payment eligibility criteria a person can be in receipt of unemployment benefits and work one hour or more a week. In a study of the 'Patterns of Economic and Social Participation Among FaCS Customers', Saunders *et al.* (2003: 34) find 25.7 per cent of Newstart Allowees are in some form of paid work. Thus Newstart Allowees who work more than one hour a week (76.6 per cent of the 25.7 per cent do (Saunders *et al.*, 2003: 50)), will not be classified as unemployed using LFS estimates. However, it is unclear whether this group is more likely to be LTU or STU and therefore it is unclear if this explanation may account for the observed discrepancy.

A third explanation is that the intersection of government payments, such as family benefits payments and New Start Allowance, may induce people seeking work to avoid formally registering as unemployed, to avoid adverse impacts on the levels of existing government payments. While it is clear this may drive differences in levels of officially registered and self-reported unemployed (with an understatement occurring in the Centrelink dataset), it is unclear whether such people would be more likely to be STU, and could thus account for the over-estimation of LTU in the Centrelink dataset.

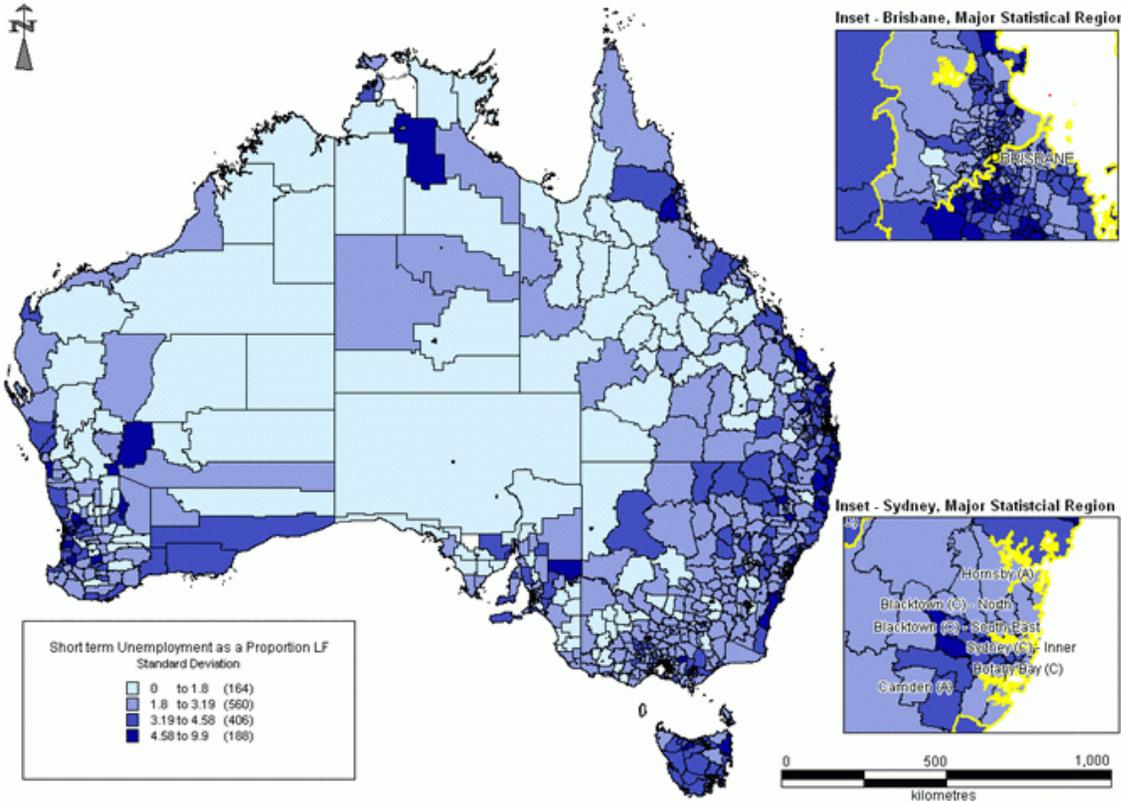
3.2 Stylised facts – long-term and short-term unemployment

In 2001, averaged across Australian SLAs, 3.2 per cent of the labour force experienced unemployment of less than 12 months duration (ST), and 4.0 per cent experienced unemployment whose duration was 12 months or over.

Cursory examination of Figures 3 and 4 which plot standard deviations for SLAs (SLAs plotted in lightest blue are 2 standard deviations below the mean, while those in dark blue are two standard deviations above the mean) reveal that the incidence of LTU exhibits greater deviations above its mean than STU. The highest incidence of LTU is 22 per cent (over 1 in 5 in the labour force experiencing long term unemployment), in Unincorporated Whyalla, South Australia. The lowest incidence is 0.2 per cent in Duntroon, ACT, which might be expected given its status as a military training base. The SLA exhibiting the highest rate of STU is WACOL Queensland (10 per cent) and the lowest rate is exhibited in Duntroon (0.1 per cent).

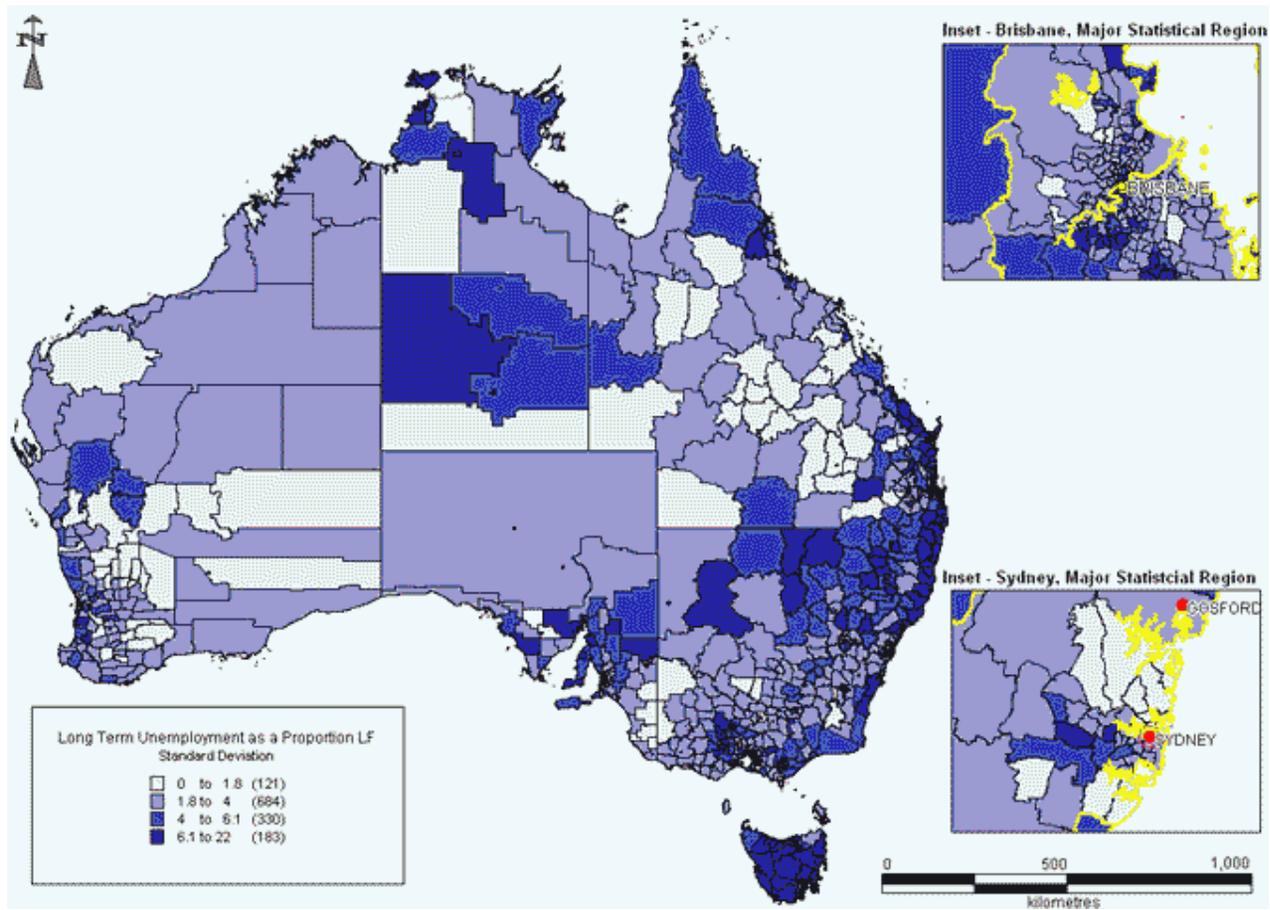
Generally LTURs tend to be lower in metropolitan regions and higher in regional and rural areas, while the trend is somewhat reversed for STU. The average LTUR is 3.8 per cent in metropolitan areas and 4.2 per cent in non-metropolitan areas (with greater variance within the non-metropolitan areas).⁴ Looking at the incidence of LTU and STU in Brisbane and Sydney, shown in the inset, it is clear that STURs are higher than LTURs. For Tasmania, upper regional NSW, regional Victoria (in the central south-west), south-eastern South Australia and the Northern Territory display rates of long-term unemployment significantly above the mean. The incidence of long-term unemployment is also significantly above the mean along the eastern sea-board. Likewise short term unemployment is also well above its mean along the eastern sea-board, with particularly high incidence in SLAs travelling north from northern NSW to Brisbane. The coefficient of variation⁵, a crude measure of dispersion or concentration across SLAs, is 0.45 (short-term unemployment) and 0.56 (long-term unemployment), in 2001. This would suggest there is greater spatial inequality in the incidence of long-term unemployment than short-term unemployment for Australian SLAs, and is consistent with the belief that pockets of labour market disadvantage have persisted throughout the growth period of the 1990s (see Mitchell and Bill, 2004, for more sophisticated measures of clustering).

Figure 3 Short-term unemployment as a proportion of the Labour Force, Statistical Local Areas, Australia, August 2001



Source: Centrelink, 2001 and CDATE, 2001

Figure 4 Long-term unemployment as a proportion Labour Force, Statistical Local Areas, Australia, August 2001.



Source: Centrelink, 2001 and CDATEA, 2001

4. Spatial weighting and spillovers

Following Stetzer (1982: 572) we employ a distance-based function to construct the spatial weight matrices, \mathbf{W} . We prefer this approach to the contiguity and/or nearest neighbours approach because of the extreme differences in size of the Australian spatial units being analysed. In this regard, we employ negative exponential functions (see Mitchell and Bill, 2004 for an application of the inverse distant power function in a spatial econometric analysis unemployment in the Sydney MSR and adjacent Hunter and Illawarra regions). Accordingly, we define:

$$(1) \quad w_{ij} = \exp(-cd_{ij}) \text{ for } d_{ij} < D_{max};$$
$$w_{ij} = 0 \text{ otherwise;}$$

where d_{ij} is the distance between the centres of regions i and j ; and c is the distance decay parameter (taking values between 0 and 1). The elements $w_{ii} = 0$ prevent a region ‘predicting itself’.

Mohlo (1995) weights Equation (1) by employment in the j^{th} region and row standardises so that the weights sum to unity over j . However, this raises questions concerning the endogeneity of the spatial weight matrix. The purpose of the spatial weight matrix is to capture the pattern of dependence across the observational space and the resulting regression results are clearly dependent on the choice of spatial weights. This issue can be seen in terms of the ‘identification problem’ in econometric analysis. When spatial dependence is present in the cross-sectional data, the spatial weight matrix has to be exogenously imposed because the variance matrix has too many parameters. To identify the decay parameter, c and the variance-covariance matrix we require the spatial weights to be exogenous to the model being considered (Anselin and Bera, 1998). This is also an issue given our use of the explanatory variable, employment accessibility (to be discussed).

Equation 1 creates a spatial weight matrix such that the spillovers between region i and region j decrease exponentially with distance between the two regions. If the decay parameter, c is high (close to 1) then regional interactions are very proximate and close to the contiguity weighting case. Low values of c suggest the regional interactions are more spread out in area. Figures 3 and 4 show plots of the non-zero elements in the 1318 by 1318 spatial weight matrixes generated via the exponential decay and simple first-order contiguity, respectively. The figures were generated using the MATLAB spy function which operates on sparse matrices. In the contiguity case, there are 7878 non-zero weights (denoted by nz) whereas in the distance decay approach we get 138,244 non-zero weights (for a decay parameter $c = 0.2$).

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 c (from 0.1 in 0.1 increments to 0.9) and the best model was chosen on the basis of its R^2 (Mohlo, 1995).

Figure 3 Spatial weight matrix using an negative exponential function, $c = 0.2$

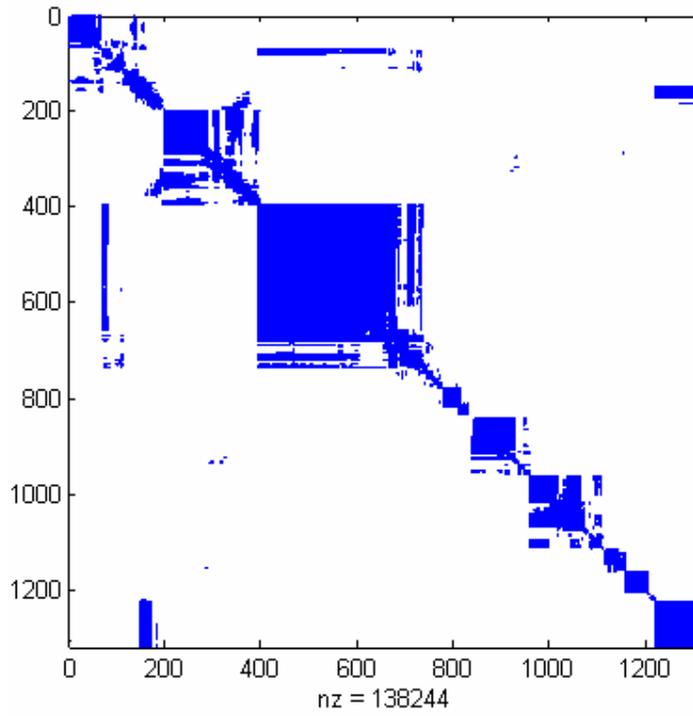
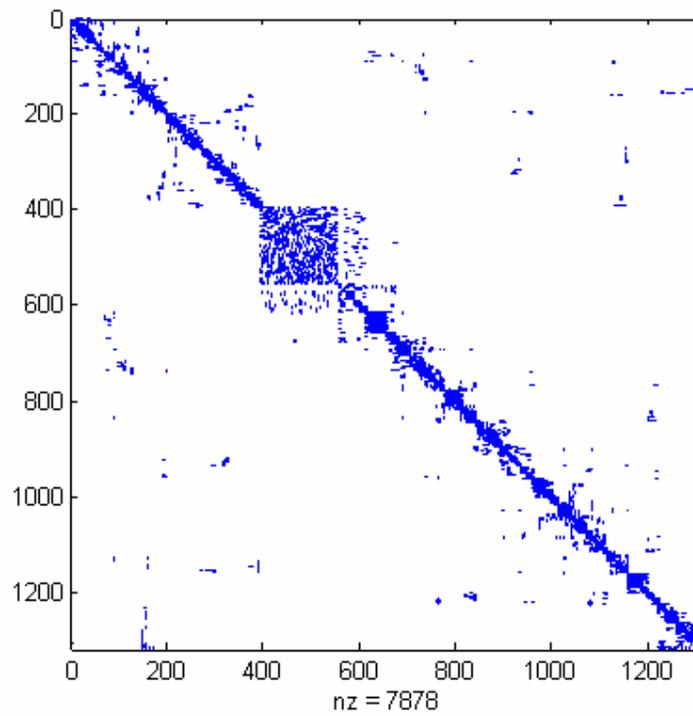


Figure 4 Spatial weight matrix based on first-order contiguity



5. The class of spatial econometric models

5.1 A taxonomy of spatial econometric models

Mitchell and Bill (2004) describe the spatial econometric models that are used in this section (see also Anselin, 1988). The general spatial autoregressive econometric model is the starting point:

$$(2) \quad \begin{aligned} \mathbf{y} &= \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \mathbf{u} \\ \mathbf{u} &= \lambda \mathbf{W}_2 \mathbf{u} + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon} &\sim N(0, \sigma^2 \mathbf{I}) \end{aligned}$$

where \mathbf{y} is a $n \times 1$ dependent variable vector, \mathbf{X} is a $n \times k$ explanatory variables matrix (including a constant) with an associated $k \times 1$ vector of parameters $\boldsymbol{\beta}$, and $\boldsymbol{\varepsilon}$ is a $n \times 1$ random errors vector. \mathbf{W}_1 and \mathbf{W}_2 are $n \times n$ spatial weight matrices and \mathbf{W}_{ij} is the spatial weight of region i in terms of region j . Table 1 outlines the family of spatial models that can be derived by imposing various restrictions on Equation (2).

The interpretation of the parameters in $\boldsymbol{\beta}$ has similarities with the interpretation of coefficients in a dynamic ARDL time series model, where we distinguish between short-run and long-run effects. In the spatial case, the analogy is captured by the concept of the spatial multiplier. We can rewrite the reduced form mean equation as:

$$(3) \quad \mathbf{y} = (\mathbf{I} - \rho \mathbf{W})^{-1} [\boldsymbol{\beta} \mathbf{x} + \boldsymbol{\varepsilon}]$$

where for simplicity we assume well-behaved errors. The marginal effect of an increase in one of the columns of \mathbf{X} is thus:

$$(4) \quad \frac{\partial \mathbf{y}}{\partial \mathbf{x}} = (\mathbf{I} - \rho \mathbf{W})^{-1} \boldsymbol{\beta}$$

The term $(\mathbf{I} - \rho \mathbf{W})^{-1}$ is the spatial multiplier (see Anselin, 2002).

We can think about this term as spreading the effects of any shocks to the dependent variable across (in this context) space to neighbouring regions. There are thus two effects embedded in the spatial multiplier. If we decompose the spatial multiplier (by geometric expansion, given $|\rho| < 1$) we get:

$$(5) \quad \frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \mathbf{I} \boldsymbol{\beta} + \rho \mathbf{W} \boldsymbol{\beta} + \rho^2 \mathbf{W}^2 \boldsymbol{\beta} + \dots$$

So the first term ($\mathbf{I} \boldsymbol{\beta}$) is termed the direct effect of a marginal change of \mathbf{x} on \mathbf{y} (operating via the main diagonal). The second term is a matrix with zero values on the main diagonal and the off-diagonal elements capture the local indirect or spillover effects arising from the direct shocks. The third term (and all subsequent higher order terms) capture the induced effects which spillover into the neighbouring regions (see Abreu *et al.*, 2004).

In other words, the spatial lag model is a way of capturing interdependency between the data points across space (or across any cross sectional data set where the observations are not independent).

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Table 1 Taxonomy of spatial econometric models

| Model | Specification | Restrictions | Comments |
|---|---|---|---|
| Ordinary Least Squares | $\mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \boldsymbol{\varepsilon}$ $\boldsymbol{\varepsilon} \sim N(0, \sigma^2 \mathbf{I}_n)$ | $\mathbf{W}_1 = \mathbf{0}$ $\mathbf{W}_2 = \mathbf{0}$ | No spatial effects |
| First-order spatial autoregressive (FAR) model | $\mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \boldsymbol{\varepsilon}$ $\boldsymbol{\varepsilon} \sim N(0, \sigma^2 \mathbf{I}_n)$ | $\mathbf{X} = \mathbf{0}$ $\mathbf{W}_2 = \mathbf{0}$ | |
| Mixed autoregressive-spatial autoregressive (SAR) model | $\mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ $\boldsymbol{\varepsilon} \sim N(0, \sigma^2 \mathbf{I})$ | $\mathbf{W}_2 = \mathbf{0}$ | <p>ρ measures the degree of spatial dependence.</p> <p>In this study it is the average influence of unemployment rates in neighbouring regions on the unemployment rate in region i.</p> |
| Spatial autocorrelation (SEM) model | $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$ $\mathbf{u} = \lambda \mathbf{W}_2 \mathbf{u} + \boldsymbol{\varepsilon}$ $\boldsymbol{\varepsilon} \sim N(0, \sigma^2 \mathbf{I})$ | $\mathbf{W}_1 = \mathbf{0}$ | Spatial autocorrelation may be due to measurement problems (rather than endogenous effects occurring between regions). |
| Spatial Durbin (SDM) model | $\mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X}\boldsymbol{\beta}_1 + \mathbf{W}_1 \mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\varepsilon}$ $\boldsymbol{\varepsilon} \sim N(0, \sigma^2 \mathbf{I})$ | $\mathbf{W}_2 = \mathbf{0}$ | Spatially weighted term added to the FAR model. The parameters ρ and γ measure the strength of the spill-over effects. One or more \mathbf{X} variables can be spatially lagged. |
| General spatial model (SAC) | $\mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$ $\mathbf{u} = \lambda \mathbf{W}_2 \mathbf{u} + \boldsymbol{\varepsilon}$ $\boldsymbol{\varepsilon} \sim N(0, \sigma^2 \mathbf{I})$ | | Combines the SAR and SEM models. λ measures the degree of spatial residual correlation. |

Source: Anselin, 1988.

5.2 Model selection methods

The issue of model selection techniques (specification strategies) remains contentious in the spatial econometric literature although some consensus is emerging. One viewpoint is that the researcher should not engage in a specification search but rather pre-filter the data, netting out any inherent spatial dependence (for example, Getis, 1995). The spatially-filtered data can then be approached using conventional OLS estimation.

The alternative approach to ‘filtering’ can be cast, once again, in the broader debate common among time series econometricians. Two options appear possible. First, should we proceed with a specific-to-general approach (the so-called ‘classical approach’), which begins with the most simple OLS regression and then uses appropriate LM tests to test a range of ‘added variables’ including the presence of spatial dependence? In this case, the specification search is less transparent and the researcher would ultimately choose the model with some highest test value. For example, Anselin (1992) suggests that LM tests could provide the basis for the choice between the SEM and the SAR model. We can test whether $\lambda = 0$ in the SEM model and whether $\rho = 0$ in the SAR model. The model with the largest test statistic would be rejected.

Second, as an alternative, we might follow the Hendry general-to-specific approach, where the researcher deliberately sets out with an over-parameterised model, which in this context would be include all the spatial effects, and then ‘test down’ using valid simplifying restrictions to the parsimonious form. Florax *et al.*, (2003) used Monte Carlo simulation to demonstrate that the classical approach provides for better inference than the Hendry approach.

Other issues regarding parsimony of the spatial weights matrix also arise – in the sense, that the asymptotic properties of the estimators are unclear after a certain number of non-zero elements is included (Anselin, 2001). As a consequence, when using distance decay type approaches to specification some truncation has to be introduced. In our case it is set at 130 kilometres (noting the average distance between the centroids of our dataset is 67 kilometres). Mitchell and Bill (2004) used 130 kilometres based on known commuting patterns between Newcastle and Sydney which seemed to be exhausted by that radius.

A further specification issue is the choice of decay (the value of c). While commuting and migratory patterns clearly help us to define plausible values of c , in practice, an empirical solution is used. We adopt a grid search method such that we produce spatial weight matrices for values of c from 0.1 to 0.9 in 0.1 steps. In the ESDA, we produce test statistics for each. However, in the regression modelling we choose the value of c which maximise the R^2 or using pair-wise LR tests. In this paper, we used the maximum R^2 as our criteria. The alternative is to employ Bayesian methods which is the topic of another paper (see Le Sage, 1997).

5.3 Spatial autocorrelation diagnostic tests

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

Moran I -statistic (Cliff and Ord, 1981) is written as:

$$(7) \quad \mathbf{I} = \mathbf{e}'\mathbf{W}\mathbf{e}/\mathbf{e}'\mathbf{e}$$

where \mathbf{e} is the regression residuals. The \mathbf{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).

Likelihood ratio test 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).

Wald test (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 \mathbf{e} and the spatial weight matrix \mathbf{W} , and is computed as:

$$(8) \quad LM = (1/T) [(\mathbf{e}'\mathbf{W}\mathbf{e})/\sigma^2]^2 \sim \chi^2(1)$$

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

Spatial error residuals LM test (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. The empirical spatial model

To explore the behaviour of the LTUR and the STUR we propose to estimate a spatial lag model that incorporates local labour market conditions emanating from national employment growth, demographic factors, structural labour market characteristics, and regional characteristics. The models are a reduced-form function of labour demand and labour supply influences:

$$(9) \quad \mathbf{ur}_{L,S} = \rho \mathbf{W}\mathbf{ur} + \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

where L, S refer to the long- and short-run unemployment, respectively. \mathbf{X} is a matrix of control variables detailed below. The model includes the spatial lag term for the change in the unemployment rate \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 .

Our main focus is to determine whether there are different patterns of behaviour for long-run and short-run unemployment. An interesting hypothesis to explore is whether there is a higher degree of spatial dependence between regional long-term unemployment rates and than there is for regional short-term unemployment.

Employment growth variables

We consider employment growth to be the primary determinant of the robustness in labour demand. The irreversibility hypothesis would suggest that employment growth impacts differentially on long-term and short-term unemployment, with the former being resistant to growth.

Employment growth may not however reduce a specific region's unemployment rate. It is possible that an increasing dispersion in employment growth across regions contributes to higher unemployment rates. Further, if a region's industrial composition of employment is enjoying favourable circumstances, then its employment growth will be faster than the national average. However, this may not necessarily reduce the region's unemployment rate. Blanchard and Katz (1992) show that it is possible that in-migration could absorb all the jobs created given that the long-term unemployed may be considered inferior. The irreversibility hypothesis certainly considers the long-term unemployed to be both ill-equipped to compete for jobs on a skills basis and of suspect motivation in terms of search effectiveness (LNU, 1991).

We use shift-share techniques (see Mitchell and Carlson, 2003b for a detailed discussion; see also Partridge and Rickman, 1998 for specific discussion) to decompose a region's employment growth into two components which are net of national employment growth: (a) the industry mix employment growth effect; and (b) the region-specific employment growth effect.

The industry mix employment growth effect is defined as:

$$(10) \quad IM_i = \frac{\sum g_{in} E_{it-1k}}{E_{it-1}} - g_n$$

where g_{in} is the national growth rate in industry i , g_n is the national employment growth rate (between 1996 and 2001), E_{it-1k} is employment in region i in industry k in time period $t-1$ (1996), and E_{it-1} is overall employment in region i in $t-1$.

The IM variable captures the share of regional employment growth that can be attributed to the local industry mix and reflects the degree to which the region specialises in industries that are either growing fast or slow nationally. A region with a lot of industries that are growing fast nationally will have a positive IM whereas a region with a concentration of industries that are growing slowly (or declining) nationally will have a negative IM .

The region-specific employment effect is defined as:

$$(11) \quad RS_i = \left(\frac{E_{it}}{E_{it-1}} - 1 \right) - IM_i - g_n$$

where the components are as previously defined. RS is the difference between the region's employment growth net of the IM and national growth effects. It captures the change in regional employment due to differences between the local industry employment growth (decline) rate and the industry's national employment growth rate rather than reflecting industry composition influence. This component indicates growth or decline in industry employment due to local factors.

The impact these two growth components have on local unemployment rates is influenced by a number of factors (Partridge and Rickman, 1995). The degree of

worker mobility across industries relative to worker mobility across regions is important (see Partridge and Rickman, 1998: 200). Poor mobility across industries will stifle migration where the local industry mix is unfavourable. Alternatively, negative region-specific shocks are not driven by a national industry downturn and workers may have motivation to chase jobs elsewhere leaving the local unemployment rate relatively stable. In general, region-specific growth would probably be more attractive to in-migrants than industry-mix growth. In this regard, if the long-term unemployed are seen as ‘lemons’ then region-specific growth will be less advantageous to them relative to the short-term unemployed. The latter group may be considered more competitive with the new arrivals.

Employment accessibility

Employment accessibility, which refers to the density of employment in neighbouring regions, is an important indicator of the strength of local labour demand. We conjecture that the higher employment accessibility is for a region the lower will be its unemployment rate, other things equal. This should impact negatively on both the long-term and short-term unemployment. If demand conditions reduce the number of jobs available in the area around a region then the short-term unemployment rate will be higher and if this demand constraint has been persistent, we would also expect duration to be higher.

Following Mohlo (1994) we constructed an employment accessibility measure as:

$$(12) \quad A = \sum_{i \neq j} E_j \exp(-cD_{ij})$$

In the regressions, we expressed the region’s employment accessibility as a percentage share of total national employment. Mohlo (1995: 653) says that it “measures the proximity of each area to other employment centers in the system.” Mohlo (1994: 124) construes the variable as capturing “the interaction between distance deterrence and cumulative inertia.” The idea is that economic adjustment which would otherwise eliminate disequilibrium spatial disparities in unemployment may be constrained by distance and tensions arising from the nature of social settlement. Distance deterrence occurs because mobility over longer distances is costly (involving relocation etc.). Distance also introduces informational frictions which restrict knowledge of broader labour market opportunities. The cumulative inertia relates to slow adjustment by the social settlement to economic shocks. Specifically, labour inflows and outflows to any given region may be unequal if social factors (attachment to location, family relationships etc.) outweigh economic forces.

Wage mix variable

In the absence of specific regional earnings data, we follow Partridge and Rickman (1998) and use a real wage mix (Wage Mix) variable which is constructed by assuming that each industry in each region pays the national average wage rate:

$$(13) \quad WageMix_i = \sum w_{itk} W_{ntk}$$

where w_{itk} is the employment share of industry k in region i at time t (2001) and W_{ntk} is the national n average ordinary time earnings in industry k at time t . The rates were expressed in real terms using the CPI (all capitals) index as at August 2001.

The impact on the unemployment rates is ambiguous. Clearly, variations in high and low wage mix regions are then determined by the regional distribution of industry. Regions with proportionately more high-wage industries may attract migrants who

take push the unemployment rate up. Additionally, workers who lose their jobs in these regions may not have an incentive to seek work in other regions. The impact could be negative if demand effects via higher earnings are multiplied within the specific region.

Other control variables

In addition to the employment variables, we control for other factors that may impact on the long- and short-term unemployment and which are typically included in other studies. These include:

- % population under 15 years;
- % population between 15-25 years;
- % population over 65 years;
- % population did not finish year 10;
- % population with Degree/Diploma
- % population who are classified in trade occupations;
- % households who are sole parents;
- % population who are divorced;
- % of new arrivals in last two years;
- Part-time employment share;
- Manufacturing employment share;
- % population who are born overseas;
- % population who are new arrivals from overseas;
- % housing classified as state rental housing;
- Dummy variable for non metropolitan (1, otherwise 0);
- State dummies (NSW, VIC, QLD, SA, WA and TAS).

Various other industrial composition variables, occupational variables, employment diversity (a modified Herfindahl index), and the proportion using the Internet (as some measure of information and network skills) were tried but not reported.

7. Results and analysis

Table 2 reports the regression results using Matlab Maximum Likelihood functions (LeSage, 1999). Extra code was written to create the spatial weight matrixes and the spatial field summaries (Table 4). Columns (2) and (3) report the OLS results for LTUR and STUR, respectively. Columns (4) and (5) report the results for the SAR models (which incorporate the spatial lag variable with coefficient ρ) for LTUR and STUR, respectively. There was no remaining spatial error correlation in the SAR models for both the LTUR and STUR. The figures below the coefficients in parentheses are *t*-statistics. The results are presented for an exponential decay parameter in the spatial weight matrix (*c*) of 0.4 and 0.05 for the employment accessibility variable. While these parameters maximised the R^2 in a grid search, the overall results are not very sensitive (qualitatively or quantitatively) to the range of *c* values between 0.2 and 0.4 for the spatial weight matrix and 0.05 and 0.10 for the employment accessibility variable.

Table 2 Spatial regression results, Australia, 1318 SLAs, 2001, *t*-stats in brackets

| Variable | OLS LTUR | OLS STUR | SAR LTUR | SAR STUR |
|------------------------------------|------------------|------------------|------------------|------------------|
| Employment Accessibility | -0.139 (2.72) | -0.093 (2.88) | -0.095 (2.03) | -0.071 (2.33) |
| Employment Accessibility non-metro | -0.754 (4.43) | -0.062 (0.58) | -0.679 (4.38) | -0.158 (1.58) |
| Industry mix growth | -0.011 (0.21) | 0.114 (3.40) | 0.006 (0.12) | 0.125 (4.10) |
| Industry mix growth non-metro | 0.048 (0.85) | -0.064 (1.79) | -0.019 (0.38) | -0.090 (2.73) |
| Region-specific growth | 0.001 (0.86) | -0.000 (0.07) | 0.000 (0.56) | -0.000 (0.37) |
| Region-specific growth non-metro | -0.015 (3.53) | -0.010 (3.64) | -0.012 (3.23) | -0.008 (3.28) |
| % 15-25 years | 0.058 (3.79) | 0.057 (5.97) | 0.052 (3.99) | 0.054 (6.57) |
| % over 65 years | -0.013 (0.97) | 0.018 (2.24) | -0.013 (1.26) | 0.017 (2.65) |
| % Born Overseas | 0.051 (5.67) | 0.044 (7.86) | 0.043 (5.27) | 0.039 (7.37) |
| % New Arrivals | 0.109 (2.55) | 0.082 (3.03) | 0.115 (2.90) | 0.089 (3.50) |
| % Divorced | 0.374 (12.23) | 0.213 (11.06) | 0.320 (12.09) | 0.192 (11.21) |
| % Sole Parents | 0.038 (2.67) | 0.032 (3.65) | 0.043 (3.46) | 0.033 (4.16) |
| % State Housing | 0.043 (4.41) | 0.024 (3.80) | 0.048 (5.26) | 0.027 (4.54) |
| % Did not finish year 10 | 0.084 (8.71) | 0.003 (0.49) | 0.078 (8.85) | 0.005 (0.97) |
| % Degree/Diploma | -0.048 (5.28) | -0.051 (8.86) | -0.035 (4.16) | -0.044 (8.07) |
| % Trade Occupations | -0.074 (7.09) | -0.032 (4.90) | -0.050 (5.32) | -0.020 (3.27) |
| % Part-time employment share | 0.110 (12.26) | 0.050 (8.87) | 0.101 (12.38) | 0.045 (8.59) |
| % Manufacturing employment share | 0.061 (5.69) | 0.048 (7.02) | 0.046 (4.67) | 0.038 (6.05) |
| Wage Mix | 0.315 (1.70) | 0.044 (0.37) | 0.169 (2.16) | 0.079 (1.50) |
| NSW | 0.632 (2.28) | 0.304 (1.74) | 0.371 (1.46) | 0.155 (0.94) |
| VIC | -0.000 (0.00) | -0.081 (0.45) | -0.120 (0.45) | -0.123 (0.72) |
| QLD | 0.481 (1.98) | 0.550 (3.60) | 0.308 (1.38) | 0.367 (2.54) |
| SA | 0.191 (0.72) | -0.405 (2.40) | -0.085 (0.35) | -0.442 (2.77) |
| WA | -0.377 (1.46) | 0.389 (2.38) | -0.333 (1.39) | 0.261 (1.69) |
| TAS | 2.594 (9.33) | 0.678 (3.87) | 0.956 (7.83) | 0.555 (3.37) |
| Non-urban dummy | 1.112 (4.87) | 0.274 (1.90) | 0.964 (4.64) | 0.326 (2.43) |
| ρ (spatial lag) | | | 0.251 (12.84) | 0.207 (13.01) |
| R-squared variance | 0.629 1.79 | 0.635 0.71 | 0.648 1.53 | 0.651 0.64 |

Note: constant not shown.

The spatial diagnostic tests on the OLS regressions were all highly significant with zero probability values. They indicate that there is significant spatial dependence in the data and while most of the coefficients are relatively stable between the OLS and the SAR models there are key exceptions (Employment Accessibility, Manufacturing Share and the Wage Mix). The NSW and TAS State dummies also lose significance once spatial association is accounted for in the SAR model. Further, the non-urban impacts are over-estimated under OLS which suggests that spatial dependence is more pronounced in non-urban areas.

Given the significant spatial dependence in the data, we estimated the SAR model shown in Columns (4) and (5). By accounting for spatial dependence, we distinguish our work from previous studies of regional unemployment which have considered each observation in the cross section to be independent. Further, our results confirm the necessity of including measures of labour demand in cross-sectional explanations of spatial unemployment differentials. This finding also distinguishes our work from previous regional studies that have focused on 'local' demographic, industry, occupational and human capital variables and have thus missed this important component of the explanation.

The employment accessibility variable (with $c = 0.05$) is highly significant and has the expected negative impact on both LTUR and STURs, the former impact being higher in magnitude. The importance of employment accessibility for non-metro (less dense) labour markets is clear with the size and significance of the coefficients on the interactive variable (Employment Accessibility non-metro) substantially increasing for both pools of unemployment (although the non-metro effect is only marginally significant for the STUR). The importance of the spatial density of employment in surrounding regions in reducing unemployment is well established by these results. There is no evidence that the LTUR is less sensitive than the STUR in terms of enjoying the benefits of employment accessibility.

The employment accessibility impact can be considered in relation to the summary statistics for LTUR and STUR. The means of LTUR and STUR are 4.0 (range 0 to 22) and 3.2 (range 0 to 9.9) respectively, over the sample. The employment accessibility variable varies from 0 to 9.1 over the sample with a mean of 1.6. The span between the maximum and minimum employment accessibility values in the sample constitutes a 0.9 per cent difference in the LTUR and a 0.6 per cent difference in the STUR for metropolitan areas and an extra 6.2 per cent (LTUR) and 1.4 per cent (STUR) for non-metropolitan areas before we account for the spatial lag effect. This is hardly small given their average values. The more remote the region (less employment being accessible in the surrounding areas) is, the higher the unemployment rate (both short- and long-term) will be, other things equal.

The spatial lag term (ρ) is positive and significant in both the LTUR and STUR SAC regressions. The coefficient is slightly higher for the LTUR (0.251) compared to 0.207 for the STUR. The result indicates that if we start from an equilibrium position (which may be consistent with sharp disparities in regional unemployment rates), then a negative shock will not only increase the LTUR and STUR of the specific region, but then 'ripple' out (spillover) to neighbouring regions according to the distance decay function. The spatial dispersal impacts are larger the higher is the spatial weight pertaining to the neighbouring region. Reversals in the unemployment rates will also ripple out favourably. The spillover effect is stronger for LTUR than STUR, implying that clusters (or 'hot spots') of regions with high long-term unemployment can easily

form and reinforce each other. Taken together, the results suggest that steps to increase employment accessibility (for example, via job creation programs) will generate reductions in unemployment generally in the region of focus but then favourably spillover to neighbouring regions independent of the demographics of the regions.

Table 3 presents a summary of the percentage of spatial weight effects by discrete distance bins to assist in our understanding of the explicit spatial variables: employment accessibility and the spatially weighted dependent variable. These ‘spatial fields’ (see Mohlo, 1995: 652) show the distance spans that the spillover effects operate based upon the data used.

For $c = 0.4$, 49 per cent of the spatial spillovers occur within 10 kilometres and 70 per cent occur within 25 kilometres, which is consistent with the concentration of commuting patterns (see Watts, 2004; Mohlo, 1995). The average distance between the SLAs was computed (centroid-to-centroid) to be 67 kilometres. The $c = 0.05$ decay function (applicable to employment accessibility) generates a flatter profile and the spillover effects thus occur over a broader spatial field. Around 73 per cent of the interactions occur within 50 kilometres compared to 89 per cent when $c = 0.4$ (applicable to the spatial lag term). In either case, nothing much happens above 75 kilometres.

Table 3 Spatial weight fields by distance

| Distance range (kilometres) | $c = 0.4$ % Spatial weights | $c = 0.05$ % Spatial weights |
|--------------------------------|--------------------------------|---------------------------------|
| 0-10 | 48.8 | 21.2 |
| >10 <= 25 | 22.0 | 28.8 |
| >25 <= 50 | 18.6 | 23.3 |
| >50 <= 75 | 6.1 | 14.2 |
| >75 <= 100 | 2.1 | 7.0 |
| > 100 <= 130 | 2.4 | 5.5 |
| | 100.0 | 100.0 |

See Mohlo (1995). The Table elements were computed in four steps: (a) allocate all the regions in the distance matrix (D_{ij}) into distance range bins defined in column (1) of the Table, such that a pair of regions 6 kms apart (using centroids) would be in the first bin; (b) extract from the relevant negative exponential spatial weight matrix (for values of c) the weights corresponding to the regional pairs in each distance bin; (c) for each distance bin aggregate the weights (recalling that they are row-standardised so the grand total will equal the total number of regions unless there are regions that have no weighted relationship with any other region). Given the remoteness of some areas of Australia there were 45 such regions; and (d) express the frequencies for each bin as a percentage of the total.

Table 4 summarise the shift-share employment growth effects for the statistically significant variables (at 5 per cent level) in the LTUR and STUR regressions. Note that these effects are net of national employment growth effects which are inversely related to regional unemployment rates (see Mitchell and Carlson, 2003b). For the LTUR, the industry mix effects are not significant. Contrary to expectation, the industry mix growth effects impact positively on STURs in both metropolitan and non-metropolitan labour markets. Intuitively, if the regional industry mix is favourable then employment growth should be stronger than regions with a heavy reliance on declining industries. However, a favourable industry mix may not reduce

its unemployment rate if in-migration takes the new jobs (Blanchard and Katz, 1992; Partridge and Rickman, 1998). Employers may prefer the newcomers to the existing stock of unemployed workers (particularly the long-term unemployed). This industry mix effect is much lower in non-metro areas which would imply that migration flows are lower in these areas.

The region-specific effect (sometimes called the local competition effect) is clearly negative for both the LTUR and STUR in non-metropolitan regions being statistically insignificant overall. So an industry in a region which is expanding much faster than the national average may not be able to attract workers from other regions quickly enough and thus draw on their local long-term (and short-term) unemployed workers.

Taken together these results suggest that local demand initiatives (particularly in non-metropolitan areas) rather than nationally focused demand policy initiatives will be more effective in reducing chronic pools of long-term unemployed. This policy strategy lies at the foundation of what Mitchell and Carlson (2003b) referred to as the development of a ‘Spatial Keynesian’ approach to macroeconomic policy.

Table 4 Industry mix growth and region-specific growth effects, urban and non-urban

| | LTUR | | STUR | |
|---------------------------------|-------|-----------|-------|-----------|
| | Metro | Non-metro | Metro | Non-metro |
| Industry mix growth effects | | | 0.125 | -0.090 |
| Region-specific growth effects | | -0.012 | | -0.008 |
| Total employment growth effects | | -0.012 | 0.125 | -0.098 |

Source: Table 2 and authors’ calculations. Metro refers to SLAs classified within the Major Statistic Division for each State/Territory. The non-metro category then captures all other SLAs outside the MSD.

How do we interpret the other impacts from the control variables? Clearly there is a significant difference in the metro/non-metro regions, particularly in terms of the LTUR. The highly significant non-urban dummy (independent of the interactive metro/non-metro effects) confirms the view that long-term unemployment is a plight of non-metropolitan Australia, other things equal. Pockets of persistent long-term unemployment exist in the regions. In part, this may be a consequence of information being ‘cheaper’ to access in urban areas (Aragon *et al.*, 2003).

Often regional dummies (such as our state dummies) are used as a proxy for spatial effects. In our case, once we explicitly model the spatial dependence, the role for the state dummies diminishes (compare the OLS to the SAR coefficients for size and statistical significance). The remaining significant state dummy effects highlight the particular problem for the long-term unemployed in Tasmania and also show that STURs are substantially higher in South Australia and Tasmania and Queensland. Mitchell and Carlson (2003a, 2003b) previously noted that the higher unemployment rates in Queensland were largely supply-side outcomes (strong in-migration and rising labour force participation) whereas for the other states they indicated demand-deficiencies (inadequate employment growth and declining participation rates).

Migration from poor labour markets to stronger labour markets is a fundamental equilibrating force (Mohlo, 1994). There was no evidence that regions with higher proportions of their population under 15 have lower LTURs and STURs. At the other end of the age spectrum, regions with high proportions of residents who are over 65

seem to suffer no impact on their LTURs and only a small negative impact on STURS. The interesting and statistically robust result is that regions with higher proportion of 15-25 year olds suffer higher LTURs and STURS with the coefficients on each pool being nearly identical. We would interpret this as capturing the chronic lack of job and training opportunities for youth across Australia.

The human capital variables generate predictable outcomes and can also be interpreted in a migration flows context. Highly educated workers have better access to information about job opportunities and may be less reluctant to relocate to search for new employment. Many will have already 'migrated' to another region to study at a higher education institution (see Aragon *et al.*, 2003). However, the human capital effect cannot be entirely interpreted in the context of ease of migration. In job-rationed regions, particularly those facing industrial retrenchment, lower skilled workers will be rationed out of employment first. In this light, the failure to complete secondary education is strongly positively associated with regional LTURs (but not STURs). Similarly, regions with high proportions of tertiary graduates have lower unemployment rates.

Regions with higher proportions of the population born overseas also have higher LTURs and STURs (the impact is similar on both), other things equal. This probably reflects their relative disadvantage in the rationed labour market. The migration flow proxy (% New Arrivals) is highly significant and positively impacts on both the LTUR and the STUR. There are two opposing forces operating. First, new migrants stimulate demand which generates employment and should, other things equal, reduce the LTUR and the STUR. Second, if these migrants are in competition with lower-skilled local workers for the scarce jobs then the LTUR and STUR may increase. We interpret this result as the latter impact overwhelming the demand stimulus.

The sole parent and state housing and divorced impacts are also predictable and suggest that segregation in housing is an important rigidity across regions. Housing is a significant cost factor militating against mobility. In regions with high economic growth, housing and land prices are also likely to be inflating and this reduces the incentive to migrate. Regions with higher proportions of low cost housing may attract disadvantaged workers who cannot afford the high cost areas. These workers may commute longer distances while employed but once they become unemployed (or are sole parents) they cannot afford to pursue employment in expanding (and inflating) areas. Further, the ability to invest in human capital may be limited in terms of opportunity (time and other resources) for a sole parent.

The one-digit ANZSIC manufacturing employment share is strongly significant and positive in both the LTUR and STUR regressions. We interpret this result as indicating longer-term disadvantage faced by regions as a result of the deindustrialisation processes set in train by the national decline in manufacturing. Unemployment rates are also significantly higher in regions where part-time as a proportion of total employment is high. CoffEE (2005) finds an increasing incidence of underemployment in Australia. The two points are related. One sign of a demand-constrained region is that the employment growth that does occur will tend to ration hours. We would be less confident about this conclusion if underemployment had not been increasing over the last decade in Australia. The significance of the part-time share variable suggests that while the jobs are low skilled and accessible to those who are most likely to be long-term unemployed, there are not enough jobs overall to generate full employment. Occupational impacts were tested and regional

unemployment rates were found to be negatively related to the proportion of tradespersons in total occupational employment. The growing shortage of skilled tradespersons may explain this – they are likely to be at the top of the queue as employment grows.

The wage mix variable is significant for the LTUR but not the STUR. The positive coefficient suggests that regions with an industry composition that generates higher wages than average experience higher long-term unemployment perhaps due to ‘more attractive’ workers being induced to the region by the higher wages. It may also be interpreted as evidence of wait unemployment but we must temper that by the strong results relating to employment accessibility.

8. Conclusion

In this paper we set out to explore whether the behaviour observed at the aggregate level with respect to long-term unemployment was consistent with the spatial behaviour. We used Centrelink data on long-term unemployment at the spatial level of the Australian postcode and via a concordance technique combined this with Census data from available from the ABS at the spatial level of a postal area to create a consistent integrated dataset at the SLA level. This provided a cross-sectional dataset containing employment growth variables (between Censuses) and other demographic and industry factors control variables.

The results support our contention that there is no irreversibility in the long-term unemployment rate in Australia, which brings into question the reliance on active labour market programs and the welfare-to-work emphasis as a strategy to deal with persistent regional unemployment and spatial spillover effects. The evidence appears to support the view that employment growth has not been strong enough in areas that have persistent long-term unemployment.

Our overall finding is that there is no evidence to support the irreversibility hypothesis. Consistent with the macroeconomic evidence, the results suggest that the usual demographic and human capital suspects are clearly present in regions with high long-term unemployment rates. However, our interpretation is, given the strong finding that employment growth and employment accessibility matter (and generate spatial spillovers in confined spatial fields), the ‘supply side’ variables then sort the rationed labour queue. In this regard, the less skilled, lowly educated workers will be the residents who face long-term unemployment. There is evidence of migratory behaviour but also of segregation based on housing.

9. Appendix

Table A1 Excluded SLAs

| SLA CODE | SLA NAME |
|-----------|--------------------------------------|
| 185019779 | Off-Shore Areas & Migratory |
| 215058469 | Lady Julia Percy Island |
| 255208529 | French Island |
| 255208649 | Bass Strait Islands |
| 285019779 | Off-Shore Areas & Migratory |
| 305051143 | City – Inner |
| 305051394 | Moreton Island |
| 350052066 | Cairns (C) – City |
| 355058809 | Unincorp. Islands |
| 385019779 | Off-Shore Areas & Migratory |
| 405108899 | Unincorp. Western |
| 415058969 | Unincorp. Yorke |
| 420109109 | Unincorp. Murray Mallee |
| 430059179 | Unincorp. Lincoln |
| 485019779 | Off-Shore Areas & Migratory |
| 505057081 | Perth (C) – Inner |
| 585019779 | Off-Shore Areas & Migratory |
| 685019779 | Off-Shore Areas & Migratory |
| 710153309 | South Alligator |
| 785019779 | Off-Shore Areas & Migratory |
| 805055049 | Kowen |
| 805057479 | Russell |
| 805100549 | Belconnen - SSD Bal |
| 805207839 | Stromlo |
| 805208829 | Weston Creek-Stromlo - SSD Bal |
| 805258189 | Tuggeranong - SSD Bal |
| 805352979 | Fyshwick |
| 805354329 | Hume |
| 805354589 | Jerrabomberra |
| 805356759 | Parkes |
| 805403529 | Gungahlin-Hall – SSD Bal |
| 805406039 | Mitchell |
| 910051009 | Jervis Bay Territory |
| 910052009 | Territory of Christmas Island |
| 910053009 | Territory of Cocos (Keeling) Islands |

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2 Youth Allowance recipients who are full-time students were excluded; Youth Allowees retained in our dataset were validated counts of non-fulltime students for the fortnight ending 17 August 2001 (FaCS, 2001:20)

3 Persons with an 'invalid Postcode' in the Centrelink Duration dataset were immediately excluded, this represented 2,501 customers; 750 (STU) and 1750 (LTU).

4 The average STU rate is 3.3 per cent in metropolitan areas and 3.1 per cent in non-metropolitan areas, so there is very little difference.

5 This is computed simply as the standard deviation divided by the mean.