Modelling the Determinants of Spatial Differentials in Endogenous Regional Employment Growth and Decline across Regional Australia, 1996-2006

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Abstract

A spatially weighted regression approach is used to model the determinants of spatial differentials in endogenous regional employment growth and decline across non-metropolitan Local Government Areas in Australia over the decade 1996-2006. The differential or regional component derived from a shift-share analysis of employment change across industry sectors, standardised by size of the regional labour force, is used as the dependent variable. Independent or explanatory variables used n the modelling are surrogate measures – both static and dynamic - relating to a region's industrial and occupational structure and industry specialisation, population size and growth, human capital characteristics, social capital, creative capital, and a set of locational proxies. Implications of the findings for regional policy are discussed.

Key words: Endogenous growth; regional economic development; regional performance.

Introduction

Traditional approaches to regional economic development theories were embedded in neo-classical economic *exogenous* growth theory, based largely on the Solow (1956; 2000) model. But the subsequent evolution of theory and of regional economic development planning strategy has seen an increasing emphasis being placed on the importance of *endogenous* factors (see, for example, Johansson, Karlsson and Stough 2001; Stimson, Stough and Roberts 2006; Stimson and Stough, in press, 2008). That has been associated with the so-called 'new growth theory' (see Arthur 1994; Barro 1990; Grossman and Helpman 1991; Lucas 1995, 1988; Norton and Rees 1975; Rees 1979, 2001; Rebelo 1991; Romer 1986, 1990).

However, as discussed elsewhere (see Stimson, Stough and Salazar 2005; Stimson, Robson and Shyy forthcoming, 2008) there is neither a standard definition of endogenous growth, nor the specification of a standard operational model incorporating those factors that are hypothesised to be determinants of spatial variations in endogenous regional growth performance. In fact, there is not even a universally accepted measure of endogenous regional growth. And in addition, there are few instances of operational models in which researchers have investigated the degree to which differentials in endogenous regional growth (and decline) might be explained by those factors that have been discussed in the literature referred to above and have been hypothesised as being important determinants of endogenous regional development.

A notable recent exception is a new model framework proposed by Stimson, Stough and Salazar (2005) and elaborated in Stimson and Stough (forthcoming, 2008), and the attempts to operationalize that model framework in Australia by Stimson, Robson and Shyy (forthcoming, 2008) and in the U.S. by Stough, Song, Wang and Qian (2007). The aim of those research efforts was to develop and apply exploratory models to measure variations in endogenous regional growth (and decline) and to ascertain the explanatory power of sets of variables relating variables factors such as industrial structure, levels of income and human capital, population size and growth, entrepreneurship, leadership and institutional arrangements.

This paper reports a more recent application of that modelling approach in an investigation of spatial patterns of endogenous regional employment growth (and decline) performance across non-metropolitan regions in Australia over the decade 1996 to 2006. In addition, it tests the degree to which those differentials are explained by a set of variables that are operational measures of factors that are hypothesised as likely to account for differences in regional performance.

Data and methodology

The reported in this paper research builds on previous work by the authors in which they developed an operational model to investigate endogenous regional growth across non-metropolitan regions – the spatial units being Local Government Areas (LGAs) - of Australia over the decade 1991 to 2001 (Stimson, Robson and Shyy forthcoming, 2008). In that previous study the separate models were run for each of the five mainland states, namely New South Wales, Victoria, Queensland, South Australia and Western Australia. However, for the study reported here, where the focus is on change over the decade 1996 to 2006, the modelling is applied to an analysis of all the non-metropolitan LGAs across the whole of Australia. Most importantly, that modelling incorporates spatially weighted regression approaches.

Unfortunately, available national data sets do not include variables from which it is possible to derive operational surrogate measures for some of the endogenous factors that had d been proposed in Stimson, Stough and Salazar (2005) model framework. That is particularly the case for the leadership, entrepreneurship and institutional factors. Those omissions are regrettable and reduce the potential explanatory power of the operational model applied in the study reported here.

Using data derived from the Census of Population and Housing

In this study we are restricted to secondary data analysis using information available in the five yearly Census of Population and Housing conducted by the Australian Bureau of Statistics.

Typically in using data from the census, the researcher is restricted to use categories of the demographic and socio-economic attributes of people as defined by the Australian Statistician. Often those categories may only be used to identify an adequate surrogate or proxy measures as a variable depicting a dynamic outcome state that represents endogenous regional growth (or decline) - that is, the *dependent variable* - across specified geographic regions. It might involve the use of a surrogate or a proxy measure derived as a summative combination of a number of categories for an attribute or across a number of attributes in order to develop a set of model operational variables that relate to factors that have been hypothesised in the literature as being potential *independent variables* that might explain spatial differentials in endogenous regional growth performance. Researchers might also select a battery of variables derived from range of census data that attribute categories which relate to constructs which are hypothesised to influence the outcome state. Those variables represent the *explanatory variables* which may be used in a model - such as a multiple regression model - to investigate the relationship between the dependent variable and the explanatory variables.

The level of geography used in the analysis reported in this paper is non-metropolitan Local Government Areas (LGAs), which may be Statistical Local Areas (SLAs) or aggregations of SLAs. There is a considerable range of information available at this level of spatial scale in the form of time series data derived from the three last three Censuses of Population and Housing, namely 1996, 2001 and 2006. Thus, it is possible to derive variables that are either cross-sectional for the beginning or end point of the time series or that are dynamic measuring change over time.

Ideally the spatial unit of analysis for this the type of modelling attempted here would use functional labour market areas that are characterised by a high degree of self-containment in terms of where people work and where they live. But unfortunately there is no such regional demarcation available as yet in Australia.

Using the LGA as the spatial unit for analysis

The modelling focuses on LGAs outside the metropolitan areas of Sydney, Melbourne, Brisbane, Adelaide and Perth. This is in order that we will have an explicitly 'rural and regional Australia' perspective for the analysis of endogenous regional growth (and decline). The LGA is used because of the administrative importance of this spatial unit as the third tier of government in Australia. Across much of regional Australia the LGA contains a major urban centre - sometimes more than one - plus rural areas and smaller urban settlements. In many - or even most - instances there is a high or at least a significant degree of employment self-containment within LGAs.

Often LGAs are also a Statistical Local Area (SLA) or comprises two or more SLA. The SLA is the spatial unit for which time-series data are available across a decade period for spatial unit that has the end point common bounded area. However, it needs to be realised that the data in the Census of Population and Housing for SLAs relates to persons recorded as being located within that spatial unit on census night and not place of work location.

However, for various technical reasons - and in particularly to facilitate spatial autocorrelation analysis - it has been necessary to actually use three different units of geography. This is because there is a problem with using LGAs in some parts of Australia (particularly in Queensland and the Northern Territory) because a few LGAs are non-contiguous. Those tend to be Indigenous communities. To solve that problem, those LGAs in Queensland were removed from the modelling. In the Northern Territory, the solution to the non-contiguous LGA problem has been to use the spatial scale of the Statistical Sub-Division (SSD).

However, the main unit of geography used is the modelling is non-metropolitan LGAs. In Australia the state and territory governments have the power to create and delimitate local government areas and their boundaries. As such, the number and boundaries of LGAs can change over time (ABS 2006, p. 20). This is why the ABS must concord data for these areas over time to create data that can reliably be compared over time.

In a small number of cases the second geographical unit used was the SLA[1] where those are based on the boundaries of incorporated bodies of local government.

There are also large areas of Australia that are not administered by incorporated local government bodies. Those unincorporated areas tend to be in remote mainly inland areas that are largely uninhabited, and where they are inhabited they tend to be settlements with concentrations of Indigenous peoples. For such unincorporated area usually an SLA is designated.

The final spatial unit of analysis used in some of the remote parts of the Northern Territory was the SSD[2], which comprise one or more SLAs.

Overall across Australia a total of 493 spatial units drawn from the above three units of geography have been used as the spatial framework for the modelling reported in this paper. For the sake of simplicity the term LGA will be used throughout this paper to refer to the spatial units used in the analysis of non-metropolitan regions.

The size of these spatial units - in both areal extent and population and thus labour force - varies greatly across Australia. This does present a problem in modelling. It would probably be advisable for future analyses to be conducted on a partitioning of LGAs by size categories.

Model variables

All except four of the variables used in the operational model of endogenous regional growth were derived from readily available data provided in the Census of Population and Housing for the years 1996, 2001 and 2006.

In the choice of those variables we were guided by our review of the literature on endogenous regional economic growth and development in which hypothesised potential factors that might be regarded as dimensions or constructs that influence regional economic development and the performance of regions have been validated in previous modelling. That includes surrogate measures of regional resource endowments, industrial structure, population or market size, human capital, social capital, creative capital, entrepreneurship, leadership and institutional arrangements. As well our choice of variables was guided by the experience of our previous modelling research in Australia (reported in Stimson et al. forthcoming, 2008),

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[1] Statistical Local Areas (SLAs) often are LGAs or may be aggregated into LGAs. An LGA is an SLA if it fits entirely within an SSD and is broadly similar in size, economic significance and user needs for statistics to other LGAs in Australia. An LGA will be composed of two or more SLAs when the above conditions are not met. This can occur if an LGA is divided by the boundary of one or more SSDs or where the LGA is substantially different in size, economic significance and user needs for statistics to other LGAs. Unincorporated SLAs are defined for unincorporated on-shore area(s) and/or off-shore island(s) in an SSD or are defined for that part of an unincorporated area which is considered of sufficient economic significance as to warrant the formation of a separate SLA (ABS, 2006, p.11).

[2] Statistical Sub-Divisions (SSDs) are defined as socially and economically homogeneous regions characterised by identifiable links between the inhabitants. Moreover, in the non-urban areas (that is, outside the capital cities or areas with population clusters of 25,000 or more people), an SSD is characterised by identifiable links between the economic units within the region, under the unifying influence of one or more major towns or cities (ABS, 2006, p.14).

in which particular variables were derived from census data to represent surrogate measures for some of those constructs which *a priori* we viewed as potentially having explanatory power in contributing to spatial variations in patterns of endogenous regional performance in the context of regional analysis in Australia.

The variables used in the modelling are listed and described in Table 1.

Table 1: Definition of the variables used in the model

Variable label	Variable description
Dependent variable	
REG_SHIFT	Regional Shift (1996 to 2006) / Labour Force (1996)
Independent or explanatory variables	
SPEC_96	Specialization Index for 1996 (Herfindahl-Hirschman Index)
SPEC_CH	Change in Specialization Index from 1996 to 2006 (Herfindahl-Hirschman Index)
SCI	Structural Change Index (1996 to 2006)
SCI_CH	Change in the Structural Change Index (from 1996 - 2001 TO 2001-2006)
L_INC_96	Median Individual Income - 1996 Annual (Log) (real)
L_INC_CH	Change in Median Individual Income - 1996 to 2006 Annual (Log) (real)
UNEMP_96	Unemployment rate in 1996 (%)
UNEMP_CH	Change in Unemployment rate from 1996 to 2006 (pps)
L_POP_96	Log of population (1996)
L_POP_CH	Change in Log of population (1996 TO 2006)
LQ_MAN_96	Location Quotient for the Manufacturing Industry in 1996
LQ_INF_96	Location Quotient for the Information media & telecommunications Industry in 1996
LQ_FIN_96	Location Quotient for the Financial & insurance services Industry in 1996
LQ_PRO_96	Location Quotient for the Professional, scientific & technical services Industry in 1996
LQ_MAN_CH	Change in the Location Quotient for the Manufacturing Industry, 1996 to 2006
LQ_INF_CH	Change in the Location Quotient for the Information media & telecommunications Industry, 1996 to 2006
LQ_FIN_CH	Change in the Location Quotient for the Financial & insurance services Industry, 1996 to 2006
LQ_PRO_CH	Change in the Location Quotient for the Professional, scientific & technical services Industry, 1996 to 2006
POSTGRAD_96	Proportion of labour force with a Postgraduate Degree of higher in 1996
BACHELOR_96	Proportion of labour force with a Bachelor Degree of higher in 1996
TECHQUALS_96	Proportion of labour force with technical qualifications in 1996
POSTGRAD_CH	Change in the Proportion of labour force with a postgraduate degree of higher, from 1996 to 2006
BACHELOR_CH	Change in the Proportion of labour force with a bachelor degree of higher, from 1996 to 2006
TECHQUALS_CH	Change in the Proportion of labour force with technical qualifications, from 1996 to 2006
SYMBA_96	Proportion of Symbolic Analysts (Managers + Professionals) in Employment in 1996
SYMBA_CH	Change in the proportion of Symbolic Analysts (Managers + Professionals) in Employment from 1996 to 2006
VOLUNTEER_06	Proportion of Volunteers in Working Age Population (15-64) in 2006
CREATIVE_06	Proportion of Total employment in Creative Industries in 2006
A_COAST	Border is adjacent to coastline (No = 0; Yes = 1)
P_METRO	Border is adjacent to metropolitan statistical division (No = 0; Yes = 1)
D_URBAN	Classified as Urban under Australian Classification of Local Government system (1 = Yes, 0 = No)
D_REMOTE	Classified as Remote under Australian Classification of Local Governments system (1 = Yes, 0 = No)

Note: The variables that are surrogate measures for human capital, social capital and creative capital are in italics.

Source: The authors.

The dependent variable

There are difficulties encountered in the use of census data to derive a satisfactory measure of the outcome state which is the *dependent variable* in a model investigating endogenous regional economic performance. We need to derive a variable measuring regional economic growth (or decline) over a specified period of time period of time, and in doing so are restricted to a maximum period of 10 years (that is, across three census periods) because data beyond that is not adjusted to a standardized set of geographic boundaries.

The proxy measure of endogenous regional growth (and decline) that we use as the *dependent variable* [REG_SHIFT] in the model is the *differential* or *regional shift component* derived from a *shift-share analysis* of employment change over the decade 1996 to 2006, standardised by the size of an LGA's labour force at the beginning of the period (that is, at the 1996 census). That is the same proxy measure use in the previous Australian study by Stimson, Robson and Shyy (forthcoming, 2008) and alos by Stough et al. (2007) in their U.S. study of metropolitan areas. The Haynes and Dinc (1997) method was used for the shift-share analysis.

The independent or explanatory variables

The set of 32 *independent* or *exploratory variables* used in the modelling are listed in Table 1. All but four were derived from census data and include both static and dynamic variable measures for a range of LGA characteristics. They purport to measure the effects of constructs that the literature has suggested might impact on endogenous regional growth or decline. They include measures of industrial structure - including industry specialisation - and structural change, population size, labour force participation, human capital (skills) and income distribution, occupational shifts, social capital and creative capital. In addition a number of locational proxies were included.

These independent variables are described in the sub-sections that follow.

Industry specialisation and structural change measures

There are four variables used in the model to measure regional industrial specialisation/diversification and structural change. The first two related to a Specialisation Index in 1996 (SPEC_96), which measures the level of concentration of employment in the full range of broad industry sectors. It is calculated by:

$$\sum_{i=1}^{N} s_i^2$$

where:

i is the industry

N is the number of industries

s is the share of total employment in a particular industry.

The change in the Specialisation Index between 1996 and 2006 is measured by SPEC_CH.

The next two variables in the model relate to industry structural change. There is a Structural Change Index (SCI) which measures the compositional change in the structure of employment in a particular geography. It was calculated using the procedure outlined by the Productivity Commission (1998, p.69). The formula for calculation is:

$$\frac{1}{2}\sum|x_{i,t} - x_{i,t-1}|$$

where:

$x_{i,t}$ and $x_{i,t-1}$ represent each industry's share of total employment at time (*t*) and (*t-1*), respectively.

The change in the Specialisation Index (SCI_CH) measures the change in this index between the 1996-01 Censual period and the 2001-06 Censual period.

Income measures

There are two income variables in the model. The first measure, L_INC_96, is the log of the median level of real income for the geographic area in 1996. This was inflated to 2005-06 price levels by the relevant Gross State Product deflator for where the LGA is located. The inflation was done to allow a comparison with 2006 income data. The second income variable, L_INC_CH, measures the change in the log of real median income from 1996 to 2006.

Unemployment measures
There are two unemployment variables in this the model. The first, UNEMP_96, measures the level of unemployment in 1996 compared with the size of the labour force. The second, UNEMP_CH, measures the change in the unemployment rate from 1996 to 2006.

Industry employment location quotient measures
There are two major categories of location quotient measures used in the model. The first category measured location quotients for particular industries in 1996. These were selected because they were considered important contributors to endogenous growth. They are: Manufacturing Industry (LQ_MAN_96); Information media & telecommunications Industry (LQ_INF_96); Financial & Insurance Services Industry (LQ_FIN_96); and the Professional, Scientific and Technical Services Industry (LQ_PRO_96). The second category of location quotient variables was the change in those location quotients from 1996 to 2006 (that is: LQ_MAN_CH; LQ_INF_CH; LQ_FIN_CH; and LQ_PRO_CH).

Human capital measures
The human capital measures used in the model are based on the highest level of qualification at the time of the relevant Census of Population and Housing. There were two main categories of human capital measures in this analysis. The first category of variables measured the number of people with a particular level of qualification as a proportion of the working age population (15-64). The levels of qualification selected were: Postgraduate degree (POSTGRAD_96); Bachelor degree (BACHELOR_96); and, those with technical qualifications[3] (TECHQUALS_96). The second category of variables was the change in these human capital measures from 1996 to 2006 (that is: POSTGRAD_CH; BACHELOR_CH; and, TECHQUALS_CH).

Occupational structure measures
Following the propositions put forward by Reich (1991), an important driver of regional endogenous growth performance is likely to be the proportion of workers in information economy activities. In the model the broad occupation groups in the census were combined to approximate Reich's three categories, namely: the proportion of symbolic analysts at 1996 (SYMBA_96); and, the change in that proportion over the period 1996 to 2006 (SYMBA_96).

Social capital measure
It was not until the 2006 census that any information was collected which might be used as a surrogate measure for social capital. In that census the only meaningful variable is the people who report being involved in volunteering. As such, it is the only proxy for social capital that can be derived from census of population and housing data. The variable used in the model,

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[3] This includes the categories of: Advanced Diploma and Diploma, Certificate nfd, Certificate I&II, Certificate III&IV.

VOLUNTEER_06, measures the proportion of Volunteers in the working age population (15-64) in 2006.

Creative capital measure

Identifying and constructing a measure of creative capital was also a challenge. Part of the reason for this is the difficulty in gaining employment data at the disaggregated industry level to discern 'creative' industries at the spatially disaggregated level of the LGA.

The method we undertook was to use 2-digit employment by industry data from the working population profile of the census for each geographic area. This was the only data we used that was based on the place of work count method rather than the place of enumeration count method. The process of identifying the 2-digit industries that were considered to be 'creative' involved a manual scan of each industry and a judgement of whether it qualified as a 'creative industry'. [4] The number of jobs in these industries was then divided by the total number of jobs to identify the proportion of jobs in creative industries in each LGA (CREATIVE_06), which is the surrogate measure of creative capital used in the model.

Locational attributes

A number of dummy variables are used in the model as locational attributes of LGAs. The first variable (A_COAST) is a measure of whether the LGA is adjacent to the coast, and if it is then the variable is assigned '*1*', if it is not then the variable is assigned '*0*'. The second variable (P_METRO) is a dummy variable where '*1*' is assigned when the geographic areas borders an LGA that is contained within a metropolitan capital city statistical division, with '*0*' being assigned when it is not. Finally, an urban dummy variable (D_URBAN) and a remoteness dummy variable (D_REMOTE) are used measures derived from the Australian Classification of Local Governments (ACLG)[5] . For these area dummy variables, '*1*' is assigned when a LGA is either Urban and Remote or '*0*' if it is not.

Modelling methodology

Following the approach used in the previous study by Stimson, Robson and Shyy (forthcoming, 2008), a two-stage regression design is used in the modelling:

1. Initially an *Ordinary Least Squares (OLS)* technique is employed to estimate a *general model* of regional endogenous growth across the non-metropolitan LGAs of Australia.

[4] The industry categories used to compile the creative industries variable are Construction services; Information, media and telecommunications; Publishing except internet and music); Motion picture and sound recording activities; Broadcasting (except internet); Internet publishing and broadcasting; Library and other information services; Computer system design and related services; Tertiary education; Arts and recreation; services; Creative and performing arts services.

[5] This is a method of classification by the Commonwealth Department of Transport and Regional Services (2007, p. 12), which categorises councils using the population, the population density and the proportion of the population that is classified as urban for the council. A LGA was classified as 'Urban' if its population is greater than 20,000 or alternatively, if the population is lower than 20,000 it must have a the population density of more than 30 persons per sq km, or 90 per cent or more of the local governing body population is urban (Department of Transport and Regional Services, 2007, p.213). A LGA is classified as 'Remote' if it had a population less than 20,000 and has a population density less than 30 persons per sq km in addition to having less than 90 per cent of local governing body population is urban.

2. Then a *step-wise* approach is used to determine a *specific model*. Each step involves withdrawing one independent variable from the model. That variable deleted has the highest probability that its absolute *p*-value is ≥0.05. The model is then regressed, and new estimates of the model were obtained. This process is repeated until the variable with the highest probability that its absolute *p*-value is <0.05 is identified.

One key feature for a reasonable OLS regression is non-constant variance in the residuals, and a test is run to evaluate this on the estimated variable.

Most importantly, the regression analyses conducted also incorporate a spatially weighted regression approach to account for the effects of spatial autocorrelation. The neighbourhood matrix approach is used in this instance. Both a *spatial error model* and a *spatial lag model* are run, and the *Moran's I test* and the *Lagrange Multiplier Test Statistics* for spatial autocorrelation are calculated.

Note that in the modelling reported here it was decided to remove some influential observations (spatial units) from the general model. The technique used was the Cooks Distance Method. The threshold for removing an observation selected was *p*=0.5 (that is, there was a 99.5% confidence that no other observation influenced the model). That resulted in five spatial units being removed from the analysis, all in either the Northern territory or in Western Australia[6].

Results

This section of the paper we discuss the results of the application of the modelling methodology outlined above:

1. First, the spatial patterns of variation in endogenous regional employment growth (and decline) across the non-metropolitan LGAs in Australia are mapped and discussed.

2. Second, the results of the OLS two-stage regression design modelling are discussed, focusing in particular on the *specific model* results.

3. Third, that is followed by a discussion of the results of two spatially weighted regression model applications using a neighbour contiguity adjustment procedure to derive a spatially weighted data matrix and running both a *spatial error* model and a *spatial lag* model.

4. Fourth, differences in the results derived from these OLS and spatially weighted regression models are evaluated. The contribution of the independent variables to the total variance in the modelling is discussed, and the relative contribution that variables which are measures of factors is hypothesised as being potential explanatory variables (that is, the variables listed in Table 1) are evaluated with respect to explaining the variation in LGA performance on the dependent variable over the decade 1996 to 2006.

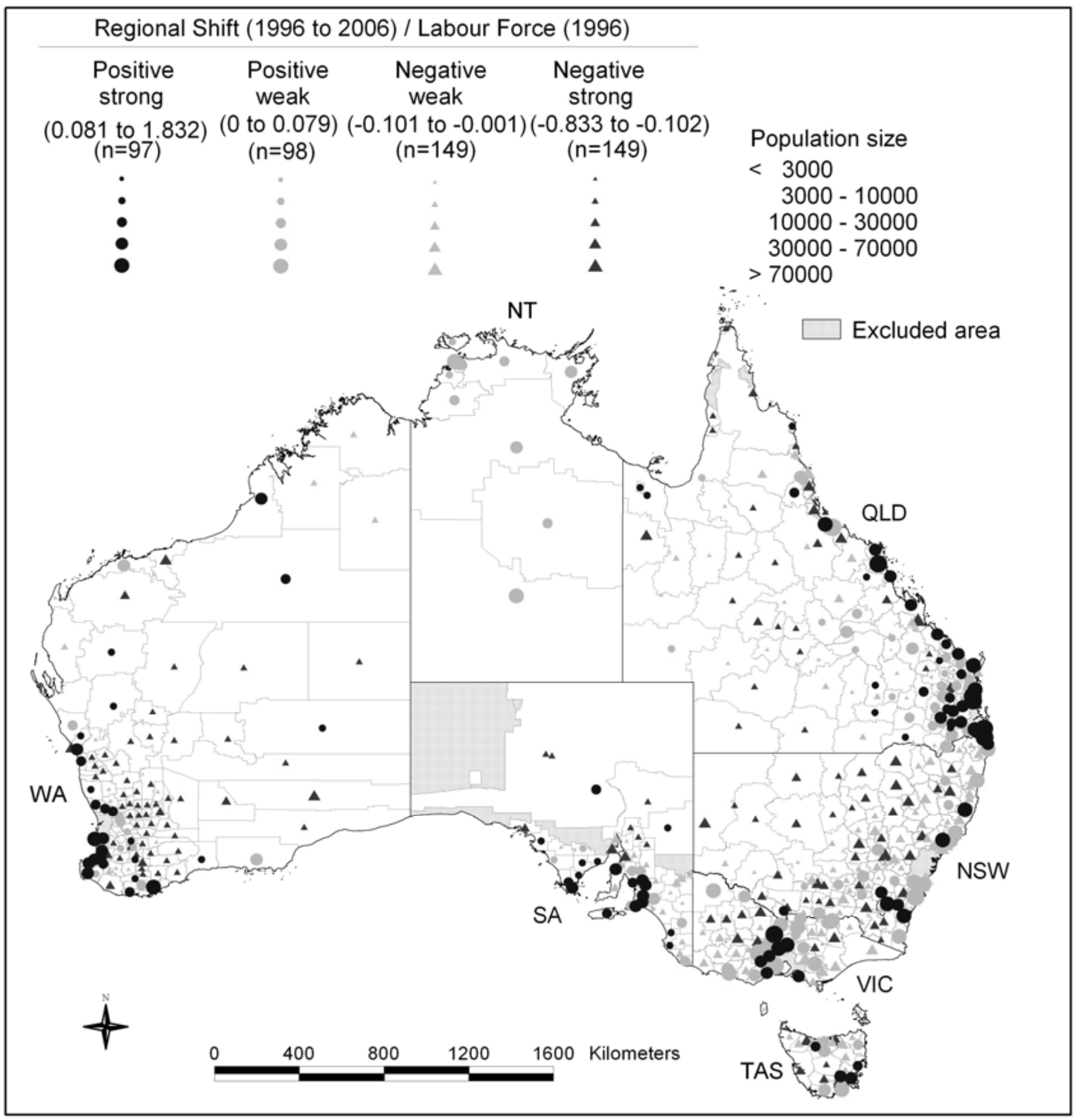
[6] The observations removed from the general model were Daly (Northern Territory, with a cook score of 11.6); Murchison (Western Australia, with a cook score of 1.1); Ravensthorpe (Western Australia, with a cook score of 1.0); and, Palmerston Eat Arm (Northern Territory, with a cook score of 0.5).

Patterns of endogenous regional employment growth and decline

An important task was to be able map the geographic patterns, across Australia, of both the dependent variable - REG_SHIFT - and the explanatory variables that are lasted in Table 1. The method used is to produce maps displaying the pattern for a variable by using shaded symbols which differentiate the spatial units of analysis according to population size categories of LGAs, and which classifies the level of performance on a particular variable.

Figure 1 shows the pattern of performance on the REG_SHIFT dependent variable that is a proxy for endogenous regional performance as measured by growth/decline on the regional or differential shift component of a shift share analysis of regional employment change - standardised by size of the regional labour force at the beginning of the period - over the decade 1996 to 2006. This measure may generate a *negative* or *positive* score for a LGA:

Figure 1: Pattern of endogenous regional employment performance, 1966 to 2006



Source: The authors.

1. A *positive score* indicates a LGA has endogenous processes or factors within the region that are creating employment growth over and above that which is occurring as a result of the national and the industry shifts that are occurring. It is indicative that a region has particular local attributes that are advantageous in creating comparative and competitive advantage for the region.

2. In contrast, a *negative* score indicates a LGA has endogenous processes or factors within the region that are conducive to declining employment. While the region may have been experiencing aggregate growth in employment, after taking account of the impact of national and industry shift effects there is a residual negative endogenous effect which has been detrimental to the job generation processes within the region.

The rank order listing of LGAs in the top quintile and in the bottom quintile of the distribution of scores on this dependent variable is provided in the Appendix.

Figure 1 shows that across Australia there is a preponderance of regions with negative scores (*N*=298), representing 60% of the non-metropolitan LGAs which have been experiencing negative endogenous processes. And 305 of the regions have been experiencing strong negative performance. Thus, only the minority 40% of non-metropolitan LGA regions (*N*=195) have been experiencing positive endogenous processes, and only 20% have been experiencing strong positive endogenous experiences.

A number of characteristics seem to be apparent from the pattern in Figure 1:

- the incidence of negative endogenous regional performance is most heavily concentrated in those places down the settlement hierarchy in LGAs with smaller populations
- the incidence of positive endogenous regional performance is more associated with larger population LGAs
- there is a greater incidence of negative endogenous regional employment performance across the inland areas of Australia, and in particular in the smaller remote places
- however, positive endogenous regional employment growth is associated with a number of remote locations and in particular with mining towns
- some of the larger LGAs across the wheat-sheep belt of inland Australia - the rural heartlands - have positive endogenous regional employment growth
- there is a mixture of both positive and negative endogenous regional performance along the coastal areas of Australia, and it appears that positive growth is more associated with larger population places
- it seems to be the case that close proximity to a metropolitan state capital city is associated with positive endogenous employment growth performance.

As will be demonstrated later, the modelling will test for the degree to which some of those apparent locational attributes are or are not significant explanatory factors in differentiating between non-metropolitan LGAs in their performance on this REG_SHIFT outcome dependent variable.

OLS regression model results

The general model

The results of the OLS general model, using all the variables that are listed in Table 1, are provided in

Table 2. The model had a high explanatory power, with the adjusted R^2 value at 0.89 (that is, the variables explained 89% of the variance in the dependent variable).

Several statistically significant relationships with the regional shift proxy (the dependent variable REG_SHIFT) were found:

- there are *positive* relationships with these explanatory variables: SPEC_CH, SCI_CH, L_POP_CH, LQ_PRO_96, LQ_MAN_CH, POSTGRAD_96, POSTGRAD_CH, BACHELOR_CH, TECHQUALS_CH, SYMBA_96
- there are *negative* relationships with these explanatory variables: UNEMP_96, UNEMP_CH, LQ_PRO_96, BACHELOR_96, SYMBA_CH.

Table 2: The general model

Coefficients:	Estimate	Std. Error	T value	Pr(>|t|)	
(Intercept)	-0.36	0.22	-1.64	0.10	
SPEC_96	0.08	0.06	1.45	0.15	
SPEC_CH	0.61	0.10	6.41	0.00	***
SCI	0.00	0.00	1.85	0.06	.
SCI_CH	0.00	0.00	2.23	0.03	*
L_INC_96	0.02	0.02	0.81	0.42	
L_INC_CH	0.00	0.03	0.16	0.87	
UNEMP_96	-0.01	0.00	-4.06	0.00	***
UNEMP_CH	-0.02	0.00	-8.74	0.00	***
L_POP_96	-0.01	0.01	-0.62	0.54	
L_POP_CH	2.23	0.06	34.67	0.00	***
LQ_MAN_96	0.02	0.01	1.92	0.06	
LQ_INF_96	0.00	0.02	0.30	0.76	
LQ_FIN_96	0.00	0.02	-0.02	0.98	
LQ_PRO_96	-0.07	0.03	-2.61	0.01	**
LQ_MAN_CH	0.03	0.01	2.17	0.03	*
LQ_INF_CH	-0.01	0.01	-0.48	0.63	
LQ_FIN_CH	0.04	0.02	1.63	0.10	
LQ_PRO_CH	-0.04	0.03	-1.38	0.17	
POSTGRAD_96	1.30	0.64	2.02	0.04	*
BACHELOR_96	-1.17	0.34	-3.47	0.00	***
TECHQUALS_96	0.01	0.13	0.09	0.93	
POSTGRAD_CH	0.92	0.46	2.00	0.05	*
BACHELOR_CH	1.65	0.29	5.77	0.00	***
TECHQUALS_CH	0.86	0.14	6.29	0.00	***
SYMBA_96	0.40	0.06	6.59	0.00	***
SYMBA_CH	-0.53	0.11	-4.97	0.00	***
VOLUNTEER_06	-0.11	0.06	-1.81	0.07	
CREATIVE_06	0.16	0.15	1.09	0.28	
A_COAST	0.00	0.01	0.60	0.55	
P_METRO	0.01	0.01	0.72	0.47	
D_URBAN	0.00	0.01	-0.49	0.62	
D_REMOTE	-0.01	0.01	-0.81	0.42	

Significance. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.06116 on 457 degrees of freedom
Multiple R-squared: 0.8999, Adjusted R-squared: 0.8929
F-statistic: 128.4 on 32 and 457 DF, p-value: < 2.20E-16

Note: The variables that are surrogate measures of human capital. Social capital and creative capital are in italics.

Source: The authors.

Table 3: Summary statistics of correlations between independent variables

Explanatory variables	Max correlation with any independent variable	Number of independent variables with a high correlations (>0.5)
SPEC_96	0.90	5
SPEC_CH	0.86	12
SCI	0.76	4
SCI_CH	0.97	5
L_INC_96	0.67	3
L_INC_CH	0.86	2
UNEMP_96	0.78	6
UNEMP_CH	0.96	11
L_POP_96	0.76	2
L_POP_CH	0.85	10
LQ_MAN_96	0.92	6
LQ_INF_96	0.97	6
LQ_FIN_96	0.97	7
LQ_PRO_96	0.85	4
LQ_MAN_CH	0.65	7
LQ_INF_CH	0.90	5
LQ_FIN_CH	0.86	2
LQ_PRO_CH	0.65	1
POSTGRAD_96	*0.94*	*6*
BACHELOR_96	*0.97*	*3*
TECHQUALS_96	*0.80*	*5*
POSTGRAD_CH	*0.75*	*9*
BACHELOR_CH	*0.93*	*6*
TECHQUALS_CH	0.96	8
SYMBA_96	0.85	8
SYMBA_CH	0.96	5
VOLUNTEER_06	*0.92*	*7*
CREATIVE_06	*0.94*	*7*
A_COAST	0.74	5
P_METRO	0.71	1
D_URBAN	0.85	4
D_REMOTE	0.85	8

Source: The authors.

Thus, the OLS general model results indicate that the variables most likely to be significant in having a positive impact on explaining spatial variations across non-metropolitan regions of Australia in endogenous regional employment performance may relate to a change in industry specialisation and a change in a structural change index, regional population growth, the initial concentration of employment of professional, scientific and technical services and a change in the concentration of employment in manufacturing, the human capital skills of the region, and in particular the initial incidence of workers with post-graduate qualifications and a change in the incidence of workers with post-graduate, bachelor degree level and technical qualifications, and the initial incidence of symbolic analysis in the region. These factors enhance the endogenous regional employment growth performance of a non-metropolitan region.

On the other hand, it seems that there is a negative effect on endogenous regional employment performance of a non-metropolitan region related to the level of unemployment and the change in the incidence of unemployment, the initial concentration of employment in professional, scientific and technical services, the initial incidence of workers with bachelor degree qualifications, and a change in the incidence of symbolic analysis.

As was foreshadowed earlier, one issue in the OLS general model approach is the level of correlation between the independent variables (that is multi-colinearity). As shown in **Error! Not a valid bookmark self-reference.**3, the SPEC_CH variable had the highest number of other independent variables that were highly correlated (>0.5) at 12 out of 33. This was followed by the UNEMP_CH variable at 11 out of 33, and the L_POP_CH variable at 10 out of 33.

The specific model

To address this level of multi-colinearity, the stepwise backward iterative elimination method is used to determine a *specific model* that exhibited the minimum number of statistically significant variables, but maximised the explanatory power of the model. The threshold for eliminating a variable was whether it had the highest *p*-value of 0.05. The specific model result is shown in Table4. Again the R^2 value is high at 0.89.

In the specific model:

- the variables found to have a *positive* statistically significant impact on the endogenous growth variable at a 95% confidence level are: SPEC_CH, SCI, SCI_CH, L_POP_CH, LQ_FIN_CH, BACHELOR_CH, TECHQUALS_CH, SYMBA_96
- the variables found to have a *negative* statistically significant impact on the endogenous growth variable at a 95% confidence level are: UNEMP_96, UNEMP_CH, LQ_PRO_96, BACHELOR_96, SYMBA_CH, VOLUNTEER_06.

Table 4: Specific model

Coefficients:	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	-0.18	0.02	-8.13	0.00	***
SPEC_CH	0.54	0.06	9.31	0.00	***
SCI	0.00	0.00	2.00	0.05	*
SCI_CH	0.00	0.00	2.32	0.02	*
UNEMP_96	-0.01	0.00	-6.08	0.00	***
UNEMP_CH	-0.02	0.00	-9.60	0.00	***
L_POP_CH	2.24	0.05	44.44	0.00	***
LQ_PRO_96	-0.04	0.02	-2.40	0.02	*
LQ_FIN_CH	0.04	0.02	2.08	0.04	*
BACHELOR_96	*-0.84*	*0.21*	*-4.08*	*0.00*	***
BACHELOR_CH	*1.66*	*0.25*	*6.67*	*0.00*	***
TECHQUALS_CH	*0.90*	*0.12*	*7.50*	*0.00*	***
SYMBA_96	0.40	0.06	7.25	0.00	***
SYMBA_CH	-0.51	0.10	-5.34	0.00	***
VOLUNTEER_06	*-0.11*	*0.05*	*-2.17*	*0.03*	*

Significance codes: 0.00 '***' 0.00 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.06 on 475 degrees of freedom
Multiple R-squared: 0.8949, Adjusted R-squared: 0.8918
F-statistic: 289.00 on 14.00 and 475 DF, p-value: < 2.20E-16

Source: The authors

Thus, from the specific OLS model, on the one hand it would seem that a change in industrial specialisation, the initial structural change index of a region and a change in that index, regional population growth, the initial concentration of employment in financial services, a change in the incidence of workers with a bachelor degree and with technical qualifications, and the initial incidence symbolic analysts may all have a *positive or enhancing effect* is had on endogenous regional employment performance.

On the other hand, a *negative or detrimental impact* on endogenous regional employment performance seems to come from a region having an initial higher level of unemployment and experiencing a change in the incidence of unemployment, having an initial higher incidence of employment in professional, scientific and technical services, having an initial

Spatially weighted regression model results

The next stage in the analysis was to use a spatially weighted regression modelling approach whereby a neighbourhood weights matrix is used in the regression analysis to adjust for spatial autocorrelation effects.

Moran's I test was run to test for spatial autocorrelation[7]. From this, we discovered that the probability of spatial autocorrelation in the specific model was statistically significant at the 99.9% confidence level (with a *p*-value of less than 0.01). Furthermore, the Moran's I statistic was positive, which indicates that nearby LGAs have similar rates, indicating global spatial clustering.

There are two options to adjust for spatial autocorrelation effects. These are:

- the *spatial error model*
- the *spatial lag model*.

The results of that modelling are shown for the *specific model* (stepwise approach) in Tables 5 and 6, and it is evident that there some significant differences in the results compared to the OLS specific model.

As seen in Table 5, for the *spatial error specific model* the SCI_CH, LQ_FIN_CH, and VOLUNTEER_06 variables are no longer statistically significant in explaining spatial variations in endogenous regional employment performance over the decade 1996 to 2006 across the non-metropolitan regional of Australia. And the L_POP_CH variable becomes a more significant explanatory factor.

Turning to the *spatial lag specific model* results in Table 6, all the variables that were significant in the OLS specific model remain significant explanatory variables, but the LQ_PRO_CH and VOLUNTEER_06 variables are of greater significance while the BACHELOR_96 variable is of lesser significance in the in the spatial lag specific model.

In both the *spatial error* and the *spatial lag* specific models, the following variables are all significant explanatory factors: SPEC_CH, SCI_CH, UNEMP_96, UNEMP_CH, L_POP_CH, LQ_PRO_96, BACHELOR_96, BACHELOR_CH, TECHQUALS_CH, SYMBA_96, SYMBA_CH.

In comparing the results of the *spatial error specific model* and the *spatial lag specific model*, we see the following:

---

[7] For the specific model, the Moran I statistic standard deviate = 3.6756, p-value = 0.0001187
alternative hypothesis: greater

Observed Moran's I	Expectation	Variance
0.0973747747	-0.0070965101	0.0008078735

- the SCI variable has lesser explanatory significance the former the spatial error model than in the spatial lag model

Table 5: Spatial error model: specific model coefficients

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-0.19	0.02	-8.09	0.00	***
SPEC_CH	0.52	0.06	9.27	0.00	***
SCI	0.00	0.00	2.54	0.01	*
SCI_CH	0.00	0.00	1.28	0.20	
UNEMP_96	-0.01	0.00	-5.57	0.00	***
UNEMP_CH	-0.02	0.00	-9.37	0.00	***
L_POP_CH	2.27	0.05	43.45	0.00	***
LQ_PRO_96	-0.05	0.02	-2.91	0.00	***
LQ_FIN_CH	0.03	0.02	1.73	0.08	
BACHELOR_96	-0.82	0.20	-4.03	0.00	***
BACHELOR_CH	1.69	0.24	6.97	0.00	***
TECHQUALS_CH	0.90	0.12	7.68	0.00	***
SYMBA_96	0.40	0.06	7.18	0.00	***
SYMBA_CH	-0.51	0.09	-5.57	0.00	***
VOLUNTEER_06	-0.10	0.05	-1.82	0.07	

Significance codes: 0.00 ‘***’ 0.00 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Lambda: 0.053845 LR test value: 13.18 p-value: 0.00028299
Asymptotic standard error: 0.012582 z-value: 4.2794 p-value: 1.8739e-05
Wald statistic: 18.313 p-value: 1.8739e-05

Log likelihood: 685.758 for error model
ML residual variance (sigma squared): 0.0035109, (sigma: 0.059253)
Number of observations: 490
Number of parameters estimated: 17
AIC: -1337.5, (AIC for lm: -1326.3)

Source: The authors

- the UNEMPLOY_96, LQ_FIN_CH, and BACHRLOR_96 variables are of lesser explanatory significance in the spatial lag model than in the spatial error model
- in the spatial error model the SCI_CH and the VOLUNTEER_06 variables are not significant explanatory factors whereas they are in the spatial lag model
- the L_POP_CH variable is significant in both models but in different directions, it being positive in the spatial error model and negative in the spatial lag model
- the BACHELOR_96 and the BACHELOR_CH variables are significant in both models, but in different directions, with the BACHELOR_96 having a negative effect in the spatial error model and a positive effect in the spatial lag model, while the BACHELOR_CH variable has a positive effect in the spatial error model and a negative effect in the spatial lag model.
- the SYMBA_CH variable is significant in both models but the direction of influence is different, it being negative in the spatial error model and positive in the spatial lag model.

These differences between the *spatial error model* and the *spatial lag* models in the significance of variables and for some of them in the direction of their influence on the dependent variable is an issue of interest and perhaps of concern, and it makes it important to be able to ascertain which of the models might be more valuable or the ‘preferred’ model for furnishing explanation of variation in the dependent variable (REG_SHIFT).

Table 6: Spatial lag model: specific model coefficients

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-0.19	0.02	-8.09	0.00	***
SPEC_CH	-0.18	0.02	-8.24	0.00	***
SCI	0.54	0.06	9.44	0.00	***
SCI_CH	0.00	0.00	2.04	0.04	*
UNEMP_96	0.00	0.00	2.35	0.02	*
UNEMP_CH	-0.01	0.00	-6.16	0.00	***
L_POP_CH	-0.02	0.00	-9.76	0.00	***
LQ_PRO_96	2.25	0.06	40.12	0.00	***
LQ_FIN_CH	-0.04	0.02	-2.41	0.02	*
BACHELOR_96	0.04	0.02	2.08	0.04	*
BACHELOR_CH	-0.84	0.20	-4.15	0.00	***
TECHQUALS_CH	1.66	0.25	6.78	0.00	***
SYMBA_96	0.90	0.12	7.60	0.00	***
SYMBA_CH	0.40	0.05	7.34	0.00	***
VOLUNTEER_06	-0.51	0.09	-5.43	0.00	***

Significance codes: 0.00 '***' 0.00 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Rho: -0.0015433 LR test value: 0.089998 p-value: 0.76418
Asymptotic standard error: 0.0050134 z-value: -0.30783 p-value: 0.75822
Wald statistic: 0.094756 p-value: 0.75822

Log likelihood: 679.213 for lag model
ML residual variance (sigma squared): 0.0036604, (sigma: 0.060501)
Number of observations: 490
Number of parameters estimated: 17
AIC: -1324.4, (AIC for lm: -1326.3)
LM test for residual autocorrelation
test value: 13.682 p-value: 0.00021653

Source: The authors

Thus, in order to determine which of these two models might represent the 'better' approach for modelling the determinants of spatial variation in endogenous regional employment performance over the decade 1996 to 2006 across non-metropolitan LGAs across Australia. To assist with this, *Lagrange multiplier diagnostics* for spatial dependence were run[8]. It would seem that the *spatial error model* is the preferred model to use. This is because the probability of the spatial autocorrelation (both with the normal language multiplier and the robust version) being present in the error term is statistically significant at the 99.9% level of confidence (with p-values of less than 0.01), whilst for the lag model it is not (with *p*-values of 0.77 for the normal Lagrange Multiplier and 0.12 for the robust version).

We might thus surmise the following:

[8] The Lagrange Multiplier results are:

- LM spatial error model= 11.7, df = 1, p-value = <0.01
- LM spatial lag model = 0.09, df = 1, p-value = 0.77
- RLM spatial error model = 14.0, df = 1, p-value = <0.01
- RLM spatial lag model = 2.4, df = 1, p-value = 0.12.
-

1. Across the non-metropolitan regions a stronger endogenous regional employment growth performance might be enhanced as result of a change in regional industry specialisation and will be influences by the structural change index of a region. It will be enhanced by a change in population (that is, growth) and a change (increase) in the incidence of workers with a bachelor degree or with technical qualifications. And it will be enhanced by a higher initial incidence of workers in symbolic analyst occupations.

2. In contrast, an initial higher level of unemployment, an initial higher concentration of workers in professional, scientific and technical services industries, and a change in the incidence of unemployment (increase), and an initial higher incidence of workers with bachelor degree qualifications, and a change in the incidence of people in symbolic analyst occupations all seem to have a detrimental effect on endogenous regional employment performance.

Conclusion and implications

In this paper we have set out to both explicitly measure endogenous regional growth (and decline) and to develop and apply an operational model to identify those factors that make a significant contribution in explaining the variation in regional performance across a space economy. The modelling using both OLS regression and spatially weighted regression is applied to an analysis of endogenous regional employment growth (and decline) over the decade 1996 to 2006 across the non-metropolitan LGAs of Australia, and it identifies those factors that are significant in explaining variability in the endogenous regional employment performance.

It has been shown that there exists considerable variation in endogenous regional employment performance across the non-metropolitan LGAs of Australia. Not surprisingly there are subtly different model outcomes depending whether an OLS regression approach is used or whether a spatially weighted regression approach is used to adjust for spatial autocorrelation, in this case using a weighted neighbourhood approach. A two stage modelling approach is used, with the focus in this paper being on discussing the results obtained from a *specific model* using a stepwise regression approach. It is suggested that in this instance a *spatial error model* is preferred to a *spatial lag model*.

There are a number of potential policy implications that might arise from the results of the modelling presented in this paper:

1. It is apparent that spatial variations in endogenous regional employment growth/decline over the decade 1996 to 2006 across the non-metropolitan regional (that is, LGAs) of Australia are a result of the interplay of a range of factors relating to constructs that have been hypothesised in the literature as being important influences on regional economic development and performance. These include variables that are surrogate measures for industrial structure, population size and growth, human capital, labour force engagement, and occupational structure.

2. It does not seem that specific variables relating to social capital and cultural capital play much of an explanatory role, and in some of the modelling where the social capital proxy variable is significant it seems to have a negative effect on endogenous regional performance

3. The four locational proxy variables used in the modelling do not have any significant explanatory impact on endogenous regional employment performance, debunking the widely held popular view that a rural and regional location proximate to the cities or on the coast will result in a better economic outcome.

4. If one accepts that the spatial error specific model is the 'preferred' modelling approach, then it is apparent that those factors that have a significant *positive impact* on endogenous regional employment performance are represented by the model variables that measure:
   - a change in regional industry specialisation
   - the structural change index of a region
   - a change in population (that is, growth)
   - a change (increase) in the incidence of workers with a bachelor degree and the incidence of workers with technical qualifications
   - a higher initial incidence of workers in symbolic analyst occupations.

   In contrast, those factors that have a negative impact on endogenous regional employment performance are rep[resented by the model variables that measure:
   - an initial higher level of unemployment
   - an initial higher concentration of workers in professional, scientific and technical services industries
   - a change in the incidence of unemployment (increase), and an initial higher incidence of workers with bachelor degree qualifications
   - a change in the incidence of people in symbolic analyst occupations.

It is important, however, to appreciate the limitations of the modelling discussed in this paper. In particular, the reliance on data available from the census means that it has not been possible to incorporate into the model an appropriate set of variables that are surrogates for entrepreneurship, leadership and institutional factors which are explicitly incorporated as important intervening variables within the model framework that has been proposed by Stimson, Stough and Salazar (2005) and which is elaborated in Stimson and Stough (forthcoming, 2008). And the use of LGAs as the spatial unit for analysis in the operational model is far from ideal. Furthermore, the use of employment rather than an alternative such as value added as the measure for the regional or differential shift component derived from a regional shift-share model as a proxy for endogenous regional performance is possibly an issue, but once again there are data availability limitations in using such an alternative measure. Finally, further experimentation is needed with alternative approaches to the neighbourhood weights matrix approach to the spatially weighted regression modelling discussed here as a way to address the issue of spatial autocorrelation, and that might include an approach that used distance buffering to derive a spatially weighted data matrix to use in the regression analysis.

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Appendix

Ranking of LGAs in the top and the bottom quintiles for the distribution of scores on the dependent variable

Top quintile

Rank order	LGA/spatial unit	State/ Territory	Regional shift 1996-06/ labour force (1996)
1	Ravensthorpe (S)	WA	1.831479864
2	Burke (S)	QLD	0.977726415
3	Murchison (S)	WA	0.821719010
4	Roxby Downs (M)	SA	0.683677961
5	Capel (S)	WA	0.600514366
6	Perry (S)	QLD	0.516191509
7	Dardanup (S)	WA	0.473890930
8	Chittering (S)	WA	0.444309708
9	Cleve (DC)	SA	0.405430425
10	Nebo (S)	QLD	0.396959418
11	Busselton (S)	WA	0.395035524
12	Light (RegC)	SA	0.390263615
13	Crow's Nest (S)	QLD	0.383112024
14	Caloundra (C)	QLD	0.368520086
15	Franklin Harbour (DC)	SA	0.364365328
16	Mandurah (C)	WA	0.342254239
17	Cambooya (S)	QLD	0.322572902
18	Bungil (S)	QLD	0.315838645
19	Maroochy (S)	QLD	0.301289552
20	Miriam Vale (S)	QLD	0.299642975
21	Gingin (S)	WA	0.294515716
22	Chinchilla (S)	QLD	0.278326140
23	Upper Gascoyne (S)	WA	0.276415397
24	Hervey Bay (C)	QLD	0.269907565
25	Irwin (S)	WA	0.261256093
26	Harvey (S)	WA	0.259834346
27	Broome (S)	WA	0.257393705
28	Surf Coast (S)	VIC	0.253961543
29	Chapman Valley (S)	WA	0.251594438
30	Gold Coast (C)	QLD	0.248613081
31	Mount Barker (DC)	SA	0.240911594
32	Beaudesert (S)	QLD	0.238280130
33	Victor Harbor (C)	SA	0.237748867
34	Augusta-Margaret River (S)	WA	0.236822768
35	Golden Plains (S)	VIC	0.232590750
36	Alexandrina (DC)	SA	0.225064046
37	Burnett (S)	QLD	0.219370220

Denmark (S)	WA	0.210954291
Laverton (S)	WA	0.209268435
Thuringowa (C)	QLD	0.208843392
Jondaryan (S)	QLD	0.206533449
Toodyay (S)	WA	0.203688983
Bass Coast (S)	VIC	0.201392895
Palerang (A)	NSW	0.199401028
Greenough (S)	WA	0.191983394
Unincorp. Pirie	SA	0.187011491
Hope Vale (S)	QLD	0.184664915
Doomadgee (S)	QLD	0.179673702
Murray (S)	WA	0.176099441
Lower Eyre Peninsula (DC)	SA	0.174172379
Woocoo (S)	QLD	0.171952538
Murray (A)	NSW	0.171266488
Tweed (A)	NSW	0.169842218
Mitchell (S)	VIC	0.160243075
Robe (DC)	SA	0.158931775
Queanbeyan (C)	NSW	0.158687875
Warroo (S)	QLD	0.153434671
Cranbrook (S)	WA	0.150293821
Dandaragan (S)	WA	0.143873343
Kingston (DC)	SA	0.139511015
Donnybrook-Balingup (S)	WA	0.138808126
Port Lincoln (C)	SA	0.134525948
Noosa (S)	QLD	0.132001029
Mallala (DC)	SA	0.126925414
Yass Valley (A)	NSW	0.126799268
Hastings (A)	NSW	0.124426601
Copper Coast (DC)	SA	0.124113446
Mackay (C)	QLD	0.122224989
Livingstone (S)	QLD	0.120597005
Sarina (S)	QLD	0.118028330
Cuballing (S)	WA	0.117316504
East Pilbara (S)	WA	0.115747944
Maitland (C)	NSW	0.114948755
Eurobodalla (A)	NSW	0.111765287
Tumby Bay (DC)	SA	0.111172345
Barossa (DC)	SA	0.106809295
Calliope (S)	QLD	0.105934119
Greater Bendigo (C)	VIC	0.105541041
Albany (C)	WA	0.104565251
Woodanilling (S)	WA	0.102511223
Herberton (S)	QLD	0.101341461
Streaky Bay (DC)	SA	0.101296031
Esk (S)	QLD	0.099408116

84	Moorabool (S)	VIC	0.098921554
85	Kangaroo Island (DC)	SA	0.097545319
86	Laidley (S)	QLD	0.096130881
87	Nanango (S)	QLD	0.095740614
88	Clifton (S)	QLD	0.095708501
89	Byron (A)	NSW	0.092307946
90	Brighton (M)	TAS	0.091660017
91	Waggamba (S)	QLD	0.091617599
92	Kentish (M)	TAS	0.087855189
93	Whitsunday (S)	QLD	0.083667360
94	Glamorgan/Spring Bay (M)	TAS	0.082768898
95	Macedon Ranges (S)	VIC	0.082648940
96	Rosalie (S)	QLD	0.082375044
97	Sorell (M)	TAS	0.080669460
98	Ballina (A)	NSW	0.079480467
99	Roebourne (S)	WA	0.079343231

Bottom quintile

Rank order	LGA/spatial unit	State/ Territory	Regional shift 1996-06 / labour force 1996
493	Unincorporated NSW	NSW	-0.832926263
492	Sandstone (S)	WA	-0.788455409
491	Menzies (S)	WA	-0.767086971
490	Cue (S)	WA	-0.705339984
489	Meekatharra (S)	WA	-0.645362574
488	Palm Island (S)	QLD	-0.620412869
487	Yilgarn (S)	WA	-0.556435028
486	Coolgardie (S)	WA	-0.535858362
485	Alpine (S)	VIC	-0.503947367
484	Leonora (S)	WA	-0.490003510
483	Mornington (S)	QLD	-0.436105449
482	Umagico (S)	QLD	-0.421382062
481	Morawa (S)	WA	-0.416269973
480	Mount Magnet (S)	WA	-0.409298285
479	Unincorp. Flinders Ranges	SA	-0.396405586
478	Mansfield (S)	VIC	-0.383247065
477	Bulloo (S)	QLD	-0.362936310
476	West Coast (M)	TAS	-0.358959622
475	Pormpuraaw (S)	QLD	-0.348387981
474	Cook (S)	QLD	-0.325140021
473	Koorda (S)	WA	-0.319302919
472	Mount Isa (C)	QLD	-0.319117860
471	Carnamah (S)	WA	-0.309424732
470	Coober Pedy (DC)	SA	-0.305054367
469	Unincorp. Far North	SA	-0.301192452
468	Richmond (S)	QLD	-0.288092520
467	Ilfracombe (S)	QLD	-0.286925957

466	Tambellup (S)	WA	-0.285942809
465	Peterborough (DC)	SA	-0.283669157
464	Snowy River (A)	NSW	-0.280093372
463	Central Darling (A)	NSW	-0.274952791
462	Port Hedland (T)	WA	-0.268676011
461	Brewarrina (A)	NSW	-0.266461156
460	Bruce Rock (S)	WA	-0.263460242
459	Katanning (S)	WA	-0.263200984
458	Kalgoorlie/Boulder (C)	WA	-0.260777308
457	Bourke (A)	NSW	-0.257422762
456	Tammin (S)	WA	-0.257107639
455	Wujal Wujal (S)	QLD	-0.254336964
454	Ashburton (S)	WA	-0.251892849
453	Boddington (S)	WA	-0.249448342
452	Dundas (S)	WA	-0.248830252
451	Northam (T)	WA	-0.246760736
450	Collie (S)	WA	-0.239033677
449	Westonia (S)	WA	-0.234412628
448	Barcaldine (S)	QLD	-0.233828178
447	Wyalkatchem (S)	WA	-0.233647684
446	Dumbleyung (S)	WA	-0.233357350
445	Nungarin (S)	WA	-0.233286372
444	Yalgoo (S)	WA	-0.233205893
443	Cherbourg (S)	QLD	-0.231990855
442	Perenjori (S)	WA	-0.231298382
441	Cobar (A)	NSW	-0.224155223
440	Flinders Ranges (DC)	SA	-0.220045299
439	Kondinin (S)	WA	-0.218558859
438	Kellerberrin (S)	WA	-0.217720217
437	Paroo (S)	QLD	-0.217185323
436	Walgett (A)	NSW	-0.216040651
435	Quairading (S)	WA	-0.215554412
434	Broken Hill (C)	NSW	-0.212716392
433	Kent (S)	WA	-0.211735201
432	Trayning (S)	WA	-0.208199985
431	Merredin (S)	WA	-0.206588481
430	Burdekin (S)	QLD	-0.206162797
429	Yarriambiack (S)	VIC	-0.205996741
428	Buloke (S)	VIC	-0.205130123
427	Warren (A)	NSW	-0.204843152
426	Charters Towers (C)	QLD	-0.201562987
425	Whyalla (C)	SA	-0.197161367
424	Narrogin (T)	WA	-0.196419182
423	Coorow (S)	WA	-0.195304785
422	Lithgow (C)	NSW	-0.193417879
421	Geraldton (C)	WA	-0.192284333

420	Queenscliffe (B)	VIC	-0.191595136
419	Gnowangerup (S)	WA	-0.188434580
418	Moree Plains (A)	NSW	-0.188306069
417	Jerilderie (A)	NSW	-0.187517537
416	Monto (S)	QLD	-0.187373637
415	Mingenew (S)	WA	-0.186183927
414	Narrandera (A)	NSW	-0.185973983
413	Hinchinbrook (S)	QLD	-0.184272111
412	Manjimup (S)	WA	-0.181314241
411	Parkes (A)	NSW	-0.180659204
410	Central Highlands (M)	TAS	-0.179540752
409	Goulburn Mulwaree (A)	NSW	-0.176793732
408	Three Springs (S)	WA	-0.176244242
407	Injinoo (S)	QLD	-0.172710282
406	Gunnedah (A)	NSW	-0.171455817
405	Bombala (A)	NSW	-0.167572809
404	Blackall (S)	QLD	-0.165981264
403	Northern Grampians (S)	VIC	-0.164665379
402	Narrabri (A)	NSW	-0.159210645
401	Corrigin (S)	WA	-0.157765485
400	Goomalling (S)	WA	-0.157550987
399	Deniliquin (A)	NSW	-0.157538543
398	Urana (A)	NSW	-0.157278632
397	Jerramungup (S)	WA	-0.155690836
396	Forbes (A)	NSW	-0.152950753
395	Coonamble (A)	NSW	-0.152391375