A spatial-econometric perspective on regional labour market adjustment and social security benefit uptake in New Zealand[*]

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Abstract: In many countries downward trends in official unemployment rates have often coincided with increases in hidden unemployment, particularly among low skilled older workers, who end up on long term social security benefits, such as the sickness or invalids benefit. International research has shown that there is an important regional dimension to this phenomenon. Particularly in peripheral regions, the types of jobs that are being created may not offer opportunities for older and less mobile workers.

This paper aims to analyze the determinants of regional variation in labour force participation and in non-participation in work by category (viz. unemployment, sickness, incapacity and single parents caring for dependent children) in New Zealand during the period 1986-2006 using a panel of data drawn from the five yearly Census of Population and Dwellings aggregated to functionally defined local labour market areas (LMAs). Issues of spatial spillovers in social security benefit uptake are addressed with models of spatial dependence. Besides estimation of global parameters of reduced form equations, the paper also reports geographically weighted regression (GWR) models to explore parameter variation across the LMAs.

We find that there is evidence of spatial autocorrelation in labour force participation, unemployment benefit uptake and sickness benefit uptake, but not in invalids benefit uptake and domestic purposes benefit uptake. The evidence for spatial heterogeneity is weak and such heterogeneity appears completely absent in 2006. This suggests that the estimated global parameters regarding determinants of labour force participation and benefit uptake are informative regarding the underlying processes across all LMAs in New Zealand.

Keywords: hidden unemployment, social security, local labour markets, spatial econometrics, New Zealand

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1. Introduction

In many countries, governments have pursued policies to enhance labour market flexibility and reduce long-term unemployment. Such policies have contributed to improved labour market outcomes, although it is sometimes difficult to separate out the effects of the policies from the impact of concurrent buoyant economic conditions. In any case, declines in official unemployment rates have often coincided with increases in hidden unemployment, particularly among low-skilled older workers, who end up on long term social security benefits, such as the sickness or invalids benefit, or who may (semi) retire.

International research has shown that there are large regional differences in the uptake of social security benefits, but formal econometric modelling of this spatial variation has to date been relatively limited (McVicar, 2006). There are many examples in the literature of regions in which certain traditional industries such as textile manufacturing, mining or agricultural produce processing were the primary source of employment that vanished during the globalisation and liberalisation of regional economies in recent decades. Particularly older and low-skilled workers, whose jobs vanished in this economic transformation process, have found it difficult to obtain employment in emerging, usually knowledge intensive, sectors. Geographic mobility of such workers tends to be low. The stresses of layoffs, job insecurity and unemployment often impact on physical and mental health of the older workers. Some form of incapacity benefit is then often institutionally (through implicit understandings between employers, medical practitioners and social security providers) seen as a preferred outcome compared with long-term unemployment. This is particularly the case in peripheral regions. The example of mining towns in the UK, where hidden unemployment remains extensive, is well documented in the literature (e.g., Beatty et al. 2007).

In New Zealand, the number of people receiving the unemployment benefit halved between 2001 and 2006, as a result of buoyant economic conditions and a high rate of job creation. Similarly, the number of persons receiving the domestic purposes benefit (primarily females) dropped by 12 percent. Yet at the same time there was a sharp increase of one third in the number receiving the sickness benefit and a growth in the number receiving the invalids benefit of 11.6 percent and 18.6 percent for males and females respectively.

A simple explanation at the macro-level of this apparent paradox, of measured unemployment declining in the upswing of the business cycle but hidden unemployment concurrently increasing, is that periods of rapid job creation coincide with an asymmetry in inflows into and outflows from non-participation. Job creation leads to a falling flow from employment into all forms of non-participation, including retirement and incapacity benefit enrolment. Job creation also leads to an increase in the flow from unemployment into jobs, but the flow from the sickness and invalid benefit rolls into jobs is far less responsive to the upswing in the business cycle, given that benefit receipt does not require active job search and the net financial gains from employment, would be relatively little for beneficiaries with low education and skill levels.

At the regional level, the outcomes in terms of non-participation and benefit uptake will depend on compositional factors with respect to the characteristics of the population and the local labour market, but also on institutional factors, where there may be some regionally-specific variation in implementation of policies, even within a nationally determined framework. In addition, geography may matter, particularly with respect to labour market outcomes in surrounding local labour markets and their impact on local wage setting and geographic mobility. Finally, local responses may vary in unmeasured ways that lead to spatial heterogeneity.

The present paper analyses the determinants of regional benefit usage by category (viz., unemployment, sickness, incapacity and single parents caring for dependent children) in New Zealand using a panel of data drawn from the 5 yearly Census of Population and Dwellings aggregated to 58 functionally defined local labour market areas (LMAs). For comparison, models of regional labour force participation are also estimated. No attempts are made to identify the "best" specification for a particular type of benefit usage, but instead the same reduced form regression model is applied to all dependent variables. Three waves of census data are considered (1996, 2001 and 2006), with 1991 data used where lagged variables are required.

The theoretical framework that drives the specification of the panel model takes account of changes in the level and structure of the demand for labour, the composition of the labour force (age and occupational structure, the incidence of poverty and health indicators such as the incidence of smoking), benefit replacement rates and changes in eligibility rules. This framework builds on, for example, research by Beatty et al. (2000) in the UK and by Bartik (2002) in the US.

Preliminary analysis of New Zealand social security data, using time series of social welfare data, rather than census data, indicated that the buoyant economic conditions of the new millennium years up to 2004 benefitted all regions, but not all workers, and comparable workers in different regions often in different ways (Baxendine et al. 2005). Nonetheless, there appeared to be some spatial convergence in aggregate benefit uptake outcomes across LMAs for younger people: peripheral regions with high aggregate benefit uptake rates in the 1990s under the age of 40 experienced the greatest declines in these rates during the economic boom. Overall, however, regional dispersion in benefit uptake rates has been steadily increasing across New Zealand regions since 1986 (see Pool et al., 2006, Table 4) and the results at LMA level reported below in this paper show that this trend has continued since 2001.

The use of census data has considerable benefits for econometric modelling in this context given the wide range of available variables and the opportunity to disaggregate the data into conceptually meaningful regions, namely labour market areas. However, there can be both spatial heterogeneity and spatial dependence in the models of regional social security uptake. Hence, besides estimation of global parameters of reduced form equations, the paper considers geographically weighted regression (GWR) methods to explore geographic parameter variation (spatial heterogeneity). Issues of spatial spillovers in social security benefit uptake are addressed with models of spatial dependence. Specifically, these are the panel versions of spatially lagged dependent variable models and spatial autocorrelation models.

The next section describes the regional data that are used for the analysis. This is followed by a short description of the New Zealand social security system in Section 3. The variables that were used in the econometric modelling are defined in Section 4. Section 5 provides benchmark OLS results. Spatial econometric models are defined in Section 6 and the parameter estimates of these models are reported in this section as well. Section 7 focuses on the issue of spatial heterogeneity by means of geographically weighted regression models. Finally, Section 8 sums up.

2. New Zealand regional data

The data for our analysis were obtained from the quinquennial New Zealand Census of Population and Dwellings 1991, 1996, 2001 and 2006. The Labour Market Area (LMA) data have been built up from census area unit level and made available for this research by Motu Economic and Public Policy Research. It has long been recognised that functional economic areas are the most appropriate unit of analysis for examining regional economic activity (Stabler and Olfert, 1996, p. 206) as administrative areas such as Regional Council regions or territorial authorities tend to be rather arbitrary in terms of their boundaries in so far as they are reflective of economic relations. Administrative areas have largely served as the basis for most regional analysis in the past as most official statistics have been gathered or aggregated to administrative boundaries. These days, however, it is possible to build up regional data with any defined boundaries from very small geographical units of measurement, using GIS and related systems.

Consequently, there has been growth in the use of functional economic areas, notably in the analysis of various labour market phenomena (see, for instance, Casado-Diaz, 2000; Newell and Papps, 2001; ONS and Coombes, 1998; Watts, 2004). Newell and Papps (2001) used travel to work data from the 1991 and 2001 censuses to define LMAs in New Zealand. This research yielded 140 LMAs for 1991 and 106 for 2001. This level of breakdown is too refined for linking to regional characteristics that come from sources other than the census. A level of disaggregation that permits the building up of a regional analysis with a wide range of regional indicators is that of 58 LMAs. The boundaries and names of these LMAs are shown in Figure 1.

3. The New Zealand social security system

The New Zealand social welfare system provides for four major transfer payments for the working age population: the unemployment benefit, the sickness benefit, the invalids benefit and the domestic purposes benefit.[1.] A brief description of the eligibility criteria for each benefit is contained in Table 1. These taxable benefits are statutory rights as opposed to insurance based payments with eligibility continuing as long as a person meets the eligibility criteria and is under 65, at which point eligibility for New Zealand Superannuation commences.[2] The level of payment available under these benefits is typically modest relative to the median wage, having been reduced in value markedly in the early 1990s (Stephens, 1992), though provision exists to supplement these payments through various additional allowances for hardship, accommodation and the like.[3] In addition, beneficiaries with children may be eligible for the 'Working for Families Tax Credit'.[4]

Figure 2 shows changes over the last decade in the distribution of the overall labour force participation rate (population aged 15 and over) across LMAs, based on 1996, 2001 and 2006 census data. Figures 3 to 6 show the corresponding distributions of the four main social security benefits: unemployment, sickness, invalids and domestic purposes benefit. The mean LMA participation rate increased over the period 1996-2006 from around 65 percent to 68 percent (see also Table 2), while the mean LMA unemployment benefit rate reduced by more than half over the decade, from a little over 10 percent to less than 4 percent. At the same time, the mean LMA invalids benefit rate increased from just over 2 percent of the population to about 3.5 percent, an increase of more than half. The mean LMA sickness benefit rate decreased slightly about 0.3 percentage points from 1996 to 2001 before increasing again about 0.5 percentage points between 2001 and 2006 to a rate of about 2.8 percent in 2006. Lastly, the mean LMA domestic purposes benefit rate fell by close to 1 percentage point over the decade to a rate of about 3.9 percent in 2006.

Looking at the dispersion of values for each of the benefit rates and the participation rate between LMAs over the decade, as measured by the inter quartile range (IQR) and coefficient of

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[1] In addition to these four main benefits there exist a wide variety of other benefits for widows, orphans and veterans. Details of the available benefits, payment rates and eligibility criteria are available from http://www.winz.govt.nz/.

[2] New Zealand superannuation is a non-means tested, non-contributory payment made to those aged 65 and over. The gross payment for a single person living alone is currently around 50 percent of the median wage.

[3] In April of 1991 eligibility criteria for accessing benefits was tightened, the period before benefit payments commenced following application was increased and the average benefit payments were reduced by around 10 percent (Stephens, 1992). Despite changes in government and policy direction since then these changes have remained entrenched.

[4] For details see http://www.workingforfamilies.govt.nz/

variation (CV), there is evidence of increasing dispersion over the 2001-2006 sub period with increases in both the CV and IQR for all benefit types and participation rates. During the previous quinquennium, however, the inter-LMA dispersion declined in the case of the unemployment benefit rate, the sickness benefit rate and the domestic purposes benefit rate. Certainly, with respect to the invalids benefit rate, the long-term regional divergence earlier identified by Pool et al. (2006) has been reinforced by the post 2001 change.

4. Variables for regression analysis

To explore determinants of the interregional and temporal variation in LMA labour force participation and benefit uptake rates, a range of variables selected to capture various features of the regional labour market. The approach adopted here is not to find the best possible model for any given benefit uptake rate, but to instead consistently apply the same set of reduced form equations to all benefit rate equations and to compare differences in structure across equations.

Given that the structure of our data is in the form of a spatial panel, it is well known that even the fixed effects estimator is inconsistent when some of the explanatory variables are endogenous. While various forms of instrumenting are available in panel settings (see, e.g., Vella and Verbeek, 1999), we take the simplest approach of lagging potentially endogenous variables and assuming that such lagged variables are uncorrelated with the idiosyncratic error term e_{it}, so that the parameter estimates may be assumed consistent. Robust standard errors are calculated throughout.

The variables used in this paper are shown in Table 3. The use of the lagged home ownership variable **(*laghomeown*)** stems from Oswald's work (1996, 1997a, 1997b, 1999) on the relationship between homeownership and unemployment. Our own work (Cochrane & Poot, 2008) on the Oswald hypothesis in the New Zealand context, using 1986 to 2001 census data, found some support for Oswald's conjecture that an increase in homeownership of 1 percentage point leads to an increase in the unemployment rate of 0.2 percentage points.[5]

The lagged unemployment (***lagunemployment***) variable is intended to include the past health of the local labour market, capturing the effects (if any) of hysteresis (Baddeley et. al., 1998, Pehkonen & Tervo, 1998). The qualification variable (***lagnoqual***) serves as a proxy for the stock of skill of the LMA's labour force. It is well known that the low skilled have fared poorly in the contemporary labour market with rapidly declining demand for low-skilled workers being typical of many economies (Nickell and Bell, 1995; Goux, and Maurin, 2000; Machin, 2001). There are also strong indications of a link between prevailing skills levels and rates of benefit uptake (Black et al, 2002).

[5] Cochrane and Poot (2008a) find coefficients ranging between 0.14 and 0.34.

Wilson et *al.* (2005) point to the impact of the age profile of the population on rates of uptake of particularly the sickness and invalids benefits in the New Zealand context. They find that around half of the rise in the invalids benefit uptake is explained by population growth, the ageing of the population, and the rise in the age of eligibility for New Zealand Superannuation. A variable (***lagoldworkingage***), reflecting our labour market focus, is used to control for this.

The variable ***lagsolo*****,** the percentage of single parent families, is included as solo parenthood is a prime requirement for receipt of the DPB. There is also evidence of divorce or relationship dissolution leading to ill health (Richards et al, 1997). On the other hand, there is also evidence of feedback effects from unemployment on divorce, and hence solo parenthood (see Kraft, 2001). Again, such endogeneity is at least partially controlled by the adopted lag structure.

As with other developed economies, the majority of employment growth in the post 1991 period in New Zealand has been concentrated in the service sector. As an indicator of specialisation in industries that have experienced such growth, ***lagservice***, is included. Lastly, ***lagmaori*** is the proportion of the usually resident population that identify as Māori. The New Zealand system of ethnic classification allows for an individual to identify with multiple ethnicities hence this construct should not be seen as denoting the proportion of those who see themselves as exclusively Māori. Māori generally have poorer outcomes in the labour market in New Zealand than the Pakeha (European) majority (Chapple and Rea, 1998), although the extent to which the statistical significance of such a variable is a proxy for a number of unspecified determinants that disproportionally affect Māori or whether there is a residual ‘ethnic’ effect remains debatable (e.g. Gould, 2003).

The major lacuna in the available variables is the lack of a ‘health’ variable. Although changes in the health status of the general population has been largely discounted in the literature as a major driver of changing benefit uptake levels (e.g. Bound and Burkhauser, 1999; Beatty et al., 2000; Alcock et al., 2003; Autor and Duggan, 2003; Faggio and Nickell, 2003), it would have been desirable to investigate this specifically within the New Zealand context. Future development of this research intends to incorporate such a variable, perhaps utilising the census question on smoking, or administrative and survey health data from the Ministry of Health. [6]

The dependent variables, the census unemployment benefit rate (**ubrate**), census sickness benefit rate (**sbrate**), census invalids benefit rate (**ibrate**) and the census domestic purposes rate (**dpbrate**) have been calculated on the basis of the census income source question. This question asks about the sources from which an individual aged 15 years and over received personal income in the 12 months ending 31 March 2006. Hence it is not a point measure of the percentage of

[6] In 1996 and 2006 the New Zealand census asked “Do you smoke cigarettes regularly?” and “Have you ever been a regular smoker of one or more cigarettes a day?”.

persons in receipt of a benefit on census day nor does it exclude the possibility that a person has moved between benefits or between a benefit and paid employment over the course of the year. Despite these draw backs it would seem reasonable that these rates are indicative of the level of uptake of these benefits in a LMA. Further, whatever the shortcomings of this approach, no other source of this data is readily available at this regional level.

Finally, the labour force participation rate (**lfprate**) measures, as usual, the percentage of the LMA population aged 15 and over that was either employed during the week before the census or actively seeking work in the month leading up to the census.

5. OLS results

For each of the main four benefits considered, the self-reported proportion of persons receiving the benefit in the year previous to the census enumeration was regressed on the variables described above in a standard pooled OLS estimation. An identical estimation is performed for the participation rate. Because regional dummies were included, the OLS estimator turns into the Least Squares Dummy Variable (LSDV) estimator, with coefficients equal to those of the Fixed Effects (FE) estimator without fixed effects for census years. Robust standard errors were used to address concern of heteroscedasticity arising from the markedly differing populations of the LMA. The results of this regression are shown in Table 4.

Inspecting the results it can be seen that with the exception of the service sector and solo parent family variables all the selected explanatory variables are significant in at least one of the regressions. It can also be seen that where a determinant of the unemployment benefit rate and of the invalids benefit rate is significant in both equations, the signs are opposite. Thus, the sign of the Māori ethnicity variable is positive in the invalids benefit rate equation and at the same time negative in the unemployment benefit regression. Because the fixed effects estimator describes the response to within region variation over time, i.e. over the business cycle, in regions in which the Māori population has been growing faster the unemployment benefit rate reduced while the invalids benefit rate increased. This outcome could be linked to Māori on a long term benefit moving to regions where the cost of living is lower (e.g., Morrison and Waldegrave, 2002).

The Moran statistic for all the regressions, aside from that for the DPB, is significant at conventional levels indicating the presence of spatial autocorrelation in the residuals for these OLS regressions. In the presence of spatial dependence, OLS estimators are usually not optimal (Rao, 1973; Haining 1990; 2001). Moreover, variance estimates are biased downward the presence of positive spatial autocorrelation, thereby increasing the likelihood of type 1 errors (Underwood, 1997). The presence of positive spatial autocorrelation that is not taken into account in regression analysis also upwardly biases the coefficient of determination, exaggerating the fit of the model

Haining (1990; 2001). Consequently, neglecting the possibility of spatial autocorrelation can lead to seriously biased parameter estimates and a flawed and misleading investigation (O'Sullivan & Unwin, 2003, 28-30).

In addition to the deficiencies of the OLS estimator in the presence of spatial autocorrelation, this approach also fails to utilise the panel nature of the data. This is particularly serious in cases such as our modelling as it is highly unlikely that all the factors influencing the uptake of benefits or the decision to participate in the labour force will be observed. As it is quite likely that some of the omitted variables will be correlated with the included variables, OLS will yield biased parameter estimates.

6. Spatial econometric models

Given the difficulties that the presence of spatial dependence in data presents for OLS estimators a number of methods, by now relatively well known, have been developed to account for spatial dependence. Commonly this is done in one of two ways. The first is spatial lag dependence, which pertains to spatial correlation in the dependent variable. The alternative is spatial error dependence in which the error terms are spatially correlated (Anselin, 1988). [7] In the former case, spatial dependence is incorporated by including a function of the dependent variable observed at other locations on the right hand side (Anselin, 1988, p. 5)

$$y_i = g(\mathbf{y}_{J_i}, \mathbf{\Theta}) + \mathbf{x}'_i\boldsymbol{\beta} + \varepsilon_i, \qquad (1)$$

where J_i includes all the neighbouring locations j of i. However, i is not treated as a neighbour of itself. Hence J_i is constrained such that $j \neq i$. While the function g can be very general, and even non-linear, it is typically simplified by using a spatial weights matrix. In matrix notation then, simplifying g through the use of the spatial weights matrix $\mathbf{W}$, we have the spatial lag model, what has been called the 'mixed regressive, spatial autoregressive model' (Anselin, 1988) as shown in equation (2):

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad (2)$$

[7] Anselin (forthcoming, p. 5) draws attention to other less common approaches, such as the spatial cross-regressive models of Florax and Folmer (1992).

with ρ being the spatial autoregressive coefficient and **ε** a vector of independent and identically distributed (i.i.d.) error terms.[8]

In the latter instance, that of the spatial error dependence, spatial dependence is introduced not through the inclusion of an additional variable in the model but rather by specifying a spatial process for the random disturbance term (Anselin, forthcoming). Formally, in the case of a spatial auto regressive process (SAR), we have:[9]

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \text{ with } \boldsymbol{\varepsilon} = \lambda\mathbf{W}\boldsymbol{\varepsilon} + \mathbf{u}, \tag{3}$$

where **y** is a vector of observations on the dependent variable, **W** is the spatial weights matrix, **X** is a matrix of observations on the explanatory variables, **ε** is a vector of spatially autocorrelated error terms, **u** a vector of i.i.d. errors, and λ and **β** are parameters (Anselin, 2001, 2005, forthcoming).

Extension of the cross sectional spatial lag model of equation (1) to a panel is relatively straight forward (Anselin et al., forthcoming). Starting with the cross sectional spatial weights matrix $\mathbf{W}_N$ where the subscript N denotes the matrix dimension, and the weights are assumed constant over time, the full weights matrix for a panel of T time periods becomes

$$\mathbf{W}_{NT} = \mathbf{I}_T \otimes \mathbf{W}_N, \tag{4}$$

where $\boldsymbol{I}_T$ is an identity matrix of dimension T. From this it follows that for the spatially lagged dependent variable (**Wy**) we have:

$$\mathbf{Wy} = \mathbf{W}_{\mathrm{NT}}\,\mathbf{y} = (\mathbf{I}_T \otimes \mathbf{W}_N)\,\mathbf{y}. \tag{5}$$

This leads to the specification of the spatial panel lag model as:

$$\mathbf{y} = \rho\,(\mathbf{I}_T \otimes \mathbf{W}_N)\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{6}$$

with ρ being again the spatial autoregressive coefficient.

Turning to the spatial error model we have, following the derivation above, a vector of spatially lagged error terms (**Wε**) such that;

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[8] The spatial autoregressive coefficient indicates the degree to which the dependent variable at location i ,y_i, is influenced by the values of y in neighbouring areas, y_{Ji}.

$$\mathbf{W\varepsilon} = \mathbf{W}_{NT}\,\boldsymbol{\varepsilon} = (\mathbf{I}_T \otimes \mathbf{W}_N)\,\boldsymbol{\varepsilon} \quad (7)$$

and

$$\mathbf{y} = \mathbf{X\beta} + \boldsymbol{\varepsilon}, \text{ with } \boldsymbol{\varepsilon} = \lambda(\mathbf{I}_T \otimes \mathbf{W}_N)\,\boldsymbol{\varepsilon} + \mathbf{u} \quad (8)$$

with λ being the autoregressive error parameter and **u** a vector of i.i.d. errors.

Spatial weights

Before considering the estimation of the benefit and participation regressions using spatial panel techniques it is necessary to consider the construction of the spatial weights matrix used to specify the spatial relation between LMAs. Unfortunately, though the selection of the spatial weights matrix is a crucial decision in a spatial econometric analysis, there exists no clear cut means of making this decision with most such decisions being done in an ad hoc fashion governed primarily by convenience, convention and rules of thumb (Griffith, 1996, p 65).[10] The difficulties entailed in this decision are compounded also by the plethora of different specifications available. Getis and Aldstadt (2004) identified no fewer than eight commonly used methods and a wide range of lesser known ones, while Conley & Topa (2002) expand the number of possibilities to include non-spatial metrics.[11]

In this paper the weights matrix is constructed on the basis of the reciprocal of the squared travel time between the major urban centres of each LMA. The matrix takes a block diagonal form, as shown in equation (4) above. Effectively, LMAs in one time period form an interacting block with no neighbours in another time period. Alternatively this can be interpreted as there being an infinite distance between any LMAs in a specific time period and all other LMAs at other points in time. Before carrying out spatial regressions, the weights matrix has been row standardised. This Because our adopted specification, linked to the squared travel time, leads to a weights matrix that is rather dense, particularly in row standardised form, alternative weights matrices will be considered (and their impact on the model likelihood score compared) in future research.

[9] While the spatial process is commonly modelled as SAR a number of other processes are possible including conditional autoregressive processes (CAR) and spatial moving average (SMA) processes (Anselin, forthcoming).

[10] Stetzer (1982) and Florax and Rey (1995) find that over-specification of the spatial weights matrix leads to a loss of statistical power while under-specification induces an increase in power in the presence of positive spatial auto correlation , and a loss in power in the presence of negative spatial correlation. Both under- and over-specification produce an increase in the mean squared error for spatial econometric models (Griffith, 1996, p 66-67).

[11] Getis and Aldstadt cite bandwidth distance decay, Gaussian distance decline and tri-cube distance decline functions as examples. To this list should be added their own AMOEBA methodology (Aldstadt & Getis, 2006)

Spatial panel results and comparison with OLS estimator[12]

Table 5 contains the results of spatial panel models (with regional dummies) while Table 6 shows a comparison of the results of the OLS, lag and error models. In general there is strong agreement between the OLS and spatial panel models as to what variables are significant and the sign on the coefficients of the significant variables. The overall fit of the models is very high, although inflated by the regional dummy variables.[13]

For the participation rate all estimates identify the lagged no qualification variable as significant, with parameter estimates ranging from –0.088 (lag model) to –0.123 (OLS). The inverse relationship between the lack of qualifications and labour force participation is a plausible result. Similarly, there is evidence of the usual discouraged worker effect (an inverse relationship between labour force participation and unemployment rates) but it is not significant in the spatial lag model. The positive impact of growth in the number of older workers (aged 50-64) on LMA labour force participation is the result of the increase in the age of eligibility of New Zealand superannuation that was phased in during the 1990s (but again not significant in the spatial lag model). In the lag model, the lagged home ownership variable is significant with a negative parameter (higher homeownership lowers labour force participation and also increases unemployment benefit uptake, along the lines of the Oswald hypothesis – see the unemployment benefit regressions). However, in neither the OLS nor error models does this variable approach significance. The lagged Māori variable is significant in the spatial error model (again with a negative coefficient) and very close to significance at the 5 percent level in the lag model, with similar parameter estimates of –0.118 and –0.129 respectively. The spatial correlation coefficient is between 0.2 and 0.3, but not significant at the 5 percent level in the spatial lag model.

The results for the unemployment benefit are unambiguous, the lagged home ownership and no qualifications variables are significant with positive coefficients – indicating increased unemployment benefit levels with higher homeownership and lower qualifications – while the lagged Māori variable is significant with a negative coefficient across all three estimators. The parameter estimates for the homeownership level are between 0.094 (lag) and 0.126 (OLS), around one half of the parameter estimate in Cochrane and Poot (2008). In that research, however, the dependent variable was the unemployment rate as opposed to the unemployment benefit uptake rate here. The spatial lag model for the unemployment benefit suggests a relatively high level of spatial correlation (r is about 0.4), which is consistent with spatial econometric research on local German

[12] All calculations in this paper where performed in Stata 10 utilising the lag and error .ado files provided by Maurizio Pisati (maurizio.pisati@galactica.it) and the GWR .ado of Mark S. Pearce (m.s.pearce@ncl.ac.uk). Both of which are available from the Stata .ado repository.

[13] OLS models without regional dummies had *R*-square ranging from 0.55 for the invalids benefit rate equation to 0.88 for the domestic purposes benefit rate equation.

labour markets by Longhi et al. (2006) who found that while wages tend to be ‘sticky’ over time, unemployment rates have high spatial persistence.

In respect of the estimates for the sickness benefit the three estimators agree on the significance of the lagged unemployment rate (positive coefficient). This suggests that sickness benefit take up is countercyclical and this is consistent with labour force participation being procyclical. The sickness benefit take up is a form of hidden unemployment of lower skilled workers in declining and peripheral regions, as suggested by Beatty et al. (2000). Perhaps rather surprisingly, the lagged no qualification variable is statistically significant with a negative sign, indicating that in LMA where the proportions of low skilled workers declined relatively fast, sickness benefit receipt uptake increased. This may be indicative of a transformation process in which new jobs are taken up by the relatively higher skilled younger workers, whereas the less favourable labour market for older workers may lead to worsening health outcomes, or the use of the sickness benefit as a substitute for the unemployment benefit. Interestingly, the extent of spatial correlation in the spatial lag model is in the sickness benefit rate equation similar to that of the unemployment benefit rate equation (with r about 0.4 in both cases).

The parameter estimates for the invalids benefit are fairly clear cut with the lagged older worker and Māori variables both being significant and positive for all three estimators. A relatively fast increase in the population aged 50 to 64 does lead to a greater invalids benefit uptake. Again this is consistent with the process of outflows of older unskilled workers in peripheral regions from employment to non-employment leading disproportionally to increases in invalids benefit uptake rather than unemployment benefit uptake (the old working age coefficients in the unemployment benefit equation was negative as we saw earlier, which is consistent with this interpretation). This phenomenon may be particularly relevant for Māori. The error model additionally finds a significant negative coefficient on the lagged homeownership variable, i.e. an increase in homeownership in a region leads to a lower invalids benefit uptake. We have seen earlier that greater homeownership leads to longer job search (the Oswald effect) but it is possible that the associated wealth effect discourages a flow from the unemployment benefit roll to the long term disability benefit roll.

Lastly the domestic purposes benefit estimates agree across all three estimators, finding significant positive coefficients on the lagged no qualifications variable and significant negative coefficients on the lagged older working age variable. Both these results are as expected since single parenthood is more common among less educated persons and there is also an age composition effect in that the domestic purposes benefit uptake would be greater in relatively more youthful regions. Neither the invalids benefit nor the domestic purposes benefit equations suggest statistically significant spatial correlation. For the domestic purposes benefit model, this is consistent with Moran's *I* in the OLS model not being statistically significant, but the discrepancy between Moran's *I* result for the OLS model of the invalids benefit rate and the corresponding spatial correlation parameters in Table 5 is surprising.

7. Geographically weighted regression models

The spatial lag and error models presented above are global in nature, in that they return a unique parameter estimate for each variable and a form of spatial dependency that applies to all regions equally. In addition to spatial dependency, the possibility of non-stationarity of parameter estimates arising from spatial heterogeneity is also of interest. Such non-stationarity may arise from specific forms of spatial heterogeneity in the data. For instance, not all LMAs are likely to be equally influenced by the surrounding LMAs. Highly accessible LMAs, say metropolitan areas with dense road nets and large concentrations of economic activity, will exert stronger effects on their neighbours than relatively isolated and peripheral regions (Longhi et al, 2006, p 723).

To account for spatial heterogeneity a number of locally linear spatial models have been developed, notably the spatial expansion model of Casetti (1972, 1992), the DARP model proposed by Casetti (1982) and Casetti and Can (1998) and, probably best known of all, the family of non-parametric locally linear regression models introduced in McMillen (1996), McMillen and McDonald (1997) and Brunsdon et al. (1996). The latter models are often called geographically weighted regression (GWR) models (LeSage, 1998). While a detailed discussion of the derivation of the GWR estimator will not be entered into here, a particularly concise treatment can be found in LeSage (1998, 154-156). The main distinguishing feature of the GWR methodology is the use of a distance weighted sub-sample of observations to produce locally linear estimates for every point in space. This maybe thought of as analogous to a kernel density estimator.

Table 7 reports the results of the test to determine whether the GWR model describes the data significantly better than the global regression model. The results for the 1996, 2001 and 2006 cross sections indicate that the GWR model describes the data in some instances in the 1996 and 2001 cross sections better than in global model. However, this does not hold true for the 2006 period. It appears that the buoyant labour market conditions of 2006 coincided with a decrease in heterogeneity in modelling labour market and benefit uptake outcomes, although we earlier saw that the statistical dispersion of the distribution of outcomes across LMAs has in fact seen a long-term upward trend.

Table 8 investigates spatial heterogeneity in the individual explanatory variables for each of the benefit types and the participation rate. The interesting conclusion from this table is that five of the seven instances of statistically significant spatial heterogeneity involved the lagged Māori variable. This suggests that the extent to which the Māori variable proxies for an unmeasured disadvantage or ethnic preferences effect varies across regions of New Zealand. This would merit further investigation.

8. Conclusion

In this paper we investigated the extent to which the spatial-temporal variation in local labour market outcomes and social security benefit uptake can be linked to compositional effects regarding the workers' human capital and demographic characteristics, the level and composition of labour demand, and the geography of local labour markets. While there have been many studies that link local labour market outcomes to a range of demand and supply factors, the consideration of spatial spillovers has been hitherto a rather neglected area of research in New Zealand.

On the whole, we find that geography matters. Conventional fixed effect panel models fail the test of spatially independent errors, except in the case of the domestic purposes benefit rate. Thus, the non-spatial models may lead to inefficient and biased parameter estimates that can be improved upon by imposing a specific spatial structure. Such models were estimated and yielded statistically more satisfactory, but often qualitatively similar results to OLS. Nonetheless, the use of spatial models provided additional benefits in that they can give insights into the nature of spatial spillovers: the likelihood that behaviour in one region is affected by outcomes in other regions (the spatial lag model) or the possibility that exogenous shock impacting on regions may be spatially correlated (e.g., for reasons linked to infrastructure and land use).

In the case of the unemployment benefit rate and the sickness benefit rate, we saw evidence of the former: high unemployment and sickness benefit uptake are spatially clustered and the patterns are persistent over time, which is confirmed by the spatial lag model providing the best explanation. On the other hand, with respect to the invalids benefit and the domestic purposes benefit, such spatial spillovers are not apparent and indeed they may be harder to justify theoretically. In the case of labour force participation, spatial spillovers can be both in the form of spatial lags (although with our data only significant at the 10 percent level) and in the form of spatial error promulgation. This is plausible in terms of the mechanisms that underlie local labour market outcomes, such as wage setting behaviour, interregional migration and the impact of national exogenous shocks such as exchange rate changes being affected by industrial structure, which is partially determined by geography.

Finally, we find that the evidence of cross-sectional spatial heterogeneity at the level of the 58 LMAs is only weak, and the least detectable in 2006. This provides some support for the stability and interpretation of the estimated coefficients. The only exception to this is the apparent spatial instability of the coefficient of the ethnicity variable. As noted earlier, this issue warrants further investigation.

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Table 1 New Zealand social security benefits and eligibility criteria

Benefit	*Eligibility*
Unemployment (UEB)	• Need to be aged 18 or over, or aged 16-17 and living with a partner and children who are supported by the applicant • Not be working full-time, but actively looking for a full-time job • Able to start work now
Sickness (SB)	• In a job now, but have had to stop working or reduce hours and income because of sickness, injury, pregnancy or disability, or • Unemployed or working part-time, and finding it hard to look for and do full-time work because of sickness, injury, pregnancy or disability
Invalids (IB)	• 16 or over and: • Unable to regularly work 15 hours or more a week because of a sickness, injury or disability which is expected to last at least 2 years; or • Life expectancy is expected to be less than 2 years and the applicant is unable to regularly work 15 hours or more a week; or • Blind with a specified level of restriction in the visual field or in the sharpness of vision
Domestic Purposes (DPB)	• A parent of a child under 18 who is dependent on the applicant and • the applicant is not living with the other parent or a partner and • has lost the support of, or is not being adequately maintained by a partner and • aged 18 or over (or 16-17 if legally married or in a civil union before separation).

See http://www.winz.govt.nz/get-assistance/main-benefit/ for further details.

Table 2 Summary statistics, LMA labour force participation and benefit uptake rates 1996, 2001 and 2006

	Census participation rate	Census unemployment benefit rate	Census sickness benefit rate	Census invalids benefit rate	Census domestic purposes benefit rate
			1996		
N	58	58	58	58	58
mean	65.02	10.32	2.68	2.23	4.83
minimum	55.24	5.40	1.32	0.38	1.77
maximum	80.68	21.13	5.22	4.89	9.26
sd[1]	4.50	2.88	0.76	0.74	1.45
cv[2]	0.07	0.28	0.28	0.33	0.30
IQR[3]	4.57	3.24	0.95	0.73	1.90
			2001		
N	58	58	58	58	58
mean	66.23	7.91	2.39	3.23	4.76
minimum	56.85	4.08	1.15	0.53	1.51
maximum	80.18	14.95	4.58	6.41	9.49
sd[1]	4.36	2.20	0.63	1.10	1.51
cv[2]	0.07	0.28	0.26	0.34	0.32
IQR[3]	4.59	2.34	0.70	1.11	1.46
			2006		
N	58	58	58	58	58
mean	68.41	3.77	2.84	3.52	3.91
minimum	58.65	0.78	0.64	0.44	0.78
maximum	82.71	10.05	5.94	8.18	7.49
sd[1]	4.34	1.91	0.84	1.30	1.33
cv[2]	0.06	0.51	0.30	0.37	0.34
IQR[3]	5.02	2.49	0.81	1.19	1.59

1 sd = Standard deviation
2 cv = Coefficient of variation
3 IQR= Inter quartile range (Q75-Q25)

Table 3 Variable labels and description

Variable	Description
laghomeown	The percentage of private dwellings owned by the occupant in an LMA, lagged 1 census period.
lagunemployment	The census based percentage of persons unemployed in an LMA, lagged 1 census period.
lagnoqual	Percentage of persons 15 years and over reporting no qualifications in an LMA, lagged 1 census period.
lagoldworkingage	Percentage of persons aged 50-64 in an LMA, lagged 1 census period.
lagsolo	The percentage of solo parent families in an LMA, lagged 1 census period.
lagservice	The percentage of employment in the service sector in an LMA, lagged 1 census period.
lagmaori	The percentage of people identifying as Maori in an LMA[14], lagged 1 census period.
ubrate	The percentage of the population aged 15-64 who have received unemployment benefit in the previous year
sbrate	The percentage of the population aged 15-64 who have received sickness benefit in previous year
ibrate	The percentage of the population aged 15-64 who have received invalids benefit in previous year
dpbrate	The percentage of the population aged 15-64 who have received domestic purposes benefit in previous year
lfprate	The percentage of the population aged 15-64 who were either in paid work, or actively seeking work in the month before the census

[14] The New Zealand Census does not assign individuals a unique ethnicity but aggregates responses to the ethnicity question to each ethnicity an individual specifies, i.e. if a person reports their ethnicity as being Māori and Chinese the counts of both Māori and Chinese ethnicities the counts for both ethnicities are increased by 1. Here the percentage of people identifying as Māori in an LMA is calculated as the 100*the number of those identifying as Māori divided by the usually resident population.

Table 4 OLS (LSDV, FE) regression with robust errors and regional fixed effects

	Participation Rate		Unemployment benefit rate		Sickness benefit rate		Invalids benefit rate		Domestic purposes benefit rate	
	Coef.	**P>|t|**	**Coef.**	**P>|t|**	**Coef.**	**P>|t|**	**Coef.**	**P>|t|**	**Coef.**	**P>|t|**
R-square	0.976		0.960		0.916		0.927		0.980	
lag homeown	-0.028	0.612	0.126	0.004	-0.003	0.810	-0.018	0.373	0.017	0.247
lag unemployment	-0.681	0.001	0.183	0.378	0.173	0.015	-0.108	0.332	0.068	0.304
lag noqual	-0.123	0.009	0.233	0.000	-0.053	0.001	0.015	0.466	0.050	0.000
lag oldworkingage	0.296	0.048	-0.885	0.000	0.056	0.230	0.163	0.014	-0.154	0.000
lagsolo	0.227	0.127	-0.082	0.522	-0.045	0.298	0.007	0.907	-0.059	0.137
lagservice	0.060	0.387	-0.041	0.581	-0.023	0.128	0.005	0.879	0.016	0.385
lagmaori	-0.108	0.135	-0.319	0.001	0.020	0.439	0.222	0.000	0.036	0.242
constant	66.742	0.000	8.458	0.155	3.288	0.049	-1.296	0.623	2.343	0.198
Moran *I*	2.037		3.733		3.722		3.662		1.639	
p-value	0.042		0.000		0.000		0.000		0.101	

N.B Grey shade cells indicate significance at 5 percent level

Table 5 Spatial regression with robust errors and regional fixed effects

	Participation Rate		**Unemployment benefit**		**Sickness benefit rate**		**Invalids benefit rate**		**Domestic purposes benefit rate**	
	Lag	***Error***	***Lag***	***Error***	***Lag***	***Error***	***Lag***	***Error***	***Lag***	***Error***
Squared corr	0.977	0.976	0.966	0.959	0.929	0.916	0.932	0.926	0.981	0.980
Log likelihood	-185.359	-185.151	-178.483	-180.147	25.911	22.932	-45.557	-41.165	27.556	27.192

Variable	Coef	**P>|t|**	Coef	**P>|t|**	Coef	**P>|t|**	Coef	**P>|t|**	Coef	P>|t|	Coef	**P>|t|**	Coef	**P>|t|**	Coef	**P>|t|**	Coef	**P>|t|**	Coef	**P>|t|**
lag homeown	-0.025	0.043	-0.041	0.357	0.094	0.002	0.115	0.000	-0.001	0.930	0.004	0.683	-0.019	0.249	-0.032	0.049	0.015	0.195	0.017	0.146
lag unemployment	-0.569	0.165	-0.615	0.000	-0.057	0.722	0.221	0.111	0.142	0.006	0.134	0.016	-0.045	0.635	-0.104	0.226	0.053	0.301	0.064	0.214
lag noqual	-0.088	0.041	-0.122	0.002	0.113	0.009	0.228	0.000	-0.034	0.002	-0.050	0.000	0.018	0.237	0.029	0.118	0.035	0.002	0.048	0.000
lag oldworkingage	0.240	0.119	0.279	0.021	-0.672	0.000	-0.835	0.000	0.041	0.240	0.054	0.129	0.159	0.002	0.215	0.000	-0.137	0.000	-0.156	0.000
lag solo	0.193	0.115	0.218	0.061	0.043	0.662	-0.140	0.157	-0.054	0.096	-0.044	0.176	-0.024	0.627	-0.012	0.775	-0.047	0.155	-0.054	0.092
lag service	0.066	0.055	0.090	0.124	-0.036	0.477	-0.096	0.101	-0.011	0.328	-0.021	0.091	-0.018	0.437	-0.009	0.704	0.011	0.441	0.012	0.418
lag maori	-0.129	0.054	-0.118	0.037	-0.237	0.001	-0.258	0.001	0.032	0.100	0.019	0.348	0.198	0.000	0.225	0.000	0.033	0.164	0.035	0.156
constant	52.149	0.000	66.377	0.000	5.816	0.165	11.322	0.006	1.500	0.202	2.884	0.033	-0.620	0.769	-0.482	0.807	1.705	0.255	2.483	0.082
rho (lag)/ lambda (error)	0.218	0.097	0.266	0.028	0.406	0.000	4.360	0.688	0.424	0.000	3.880	0.579	2.150	0.588	4.520	0.675	0.200	0.081	0.194	0.115

N.B Grey shade cells indicate significance at 5 percent level

Table 6 Comparison of the OLS, lag and error models

	Participation			Unemployment			Sickness benefit rate			Invalids benefit rate			Domestic purposes benefit rate		
	OLS	*Lag*	*Error*	*OLS*	*Lag*	*Error*	*OLS*	*Lag*	*Error*	*OLS*	*Lag*	*Error*	*OLS*	*Lag*	*Error*
lag homeown		-√		+√	+√	+√						-√			
lag unemployment	-√		-√				+√	+√	+√						
lag noqual	-√	-√	-√	+√	+√	+√	-√	-√	-√				+√	+√	+√
lag oldworkingage	+√		+√	-√	-√	-√				+√	+√	+√	-√	-√	-√
lag solo															
lag service															
lag maori			-√	-√	-√	-√				+√	+√	+√			
rho (lag)/ lambda (error)	**N/A**		+√	**N/A**			**N/A**	+√		**N/A**			**N/A**		

N.B. √ Indicates significance at 5 percent level

Table 7 Significance tests for GWR

	Year		
	1996	**2001**	**2006**
Participation rate	0.146	**0.009**	0.606
Census Unemployment benefit rate	**0.040**	**0.009**	0.076
Census Sickness benefit rate	**0.009**	0.989	0.075
Census Invalids benefit rate	0.259	**0.027**	0.186
Census Domestic purposes benefit rate	**0.008**	**0.027**	0.055

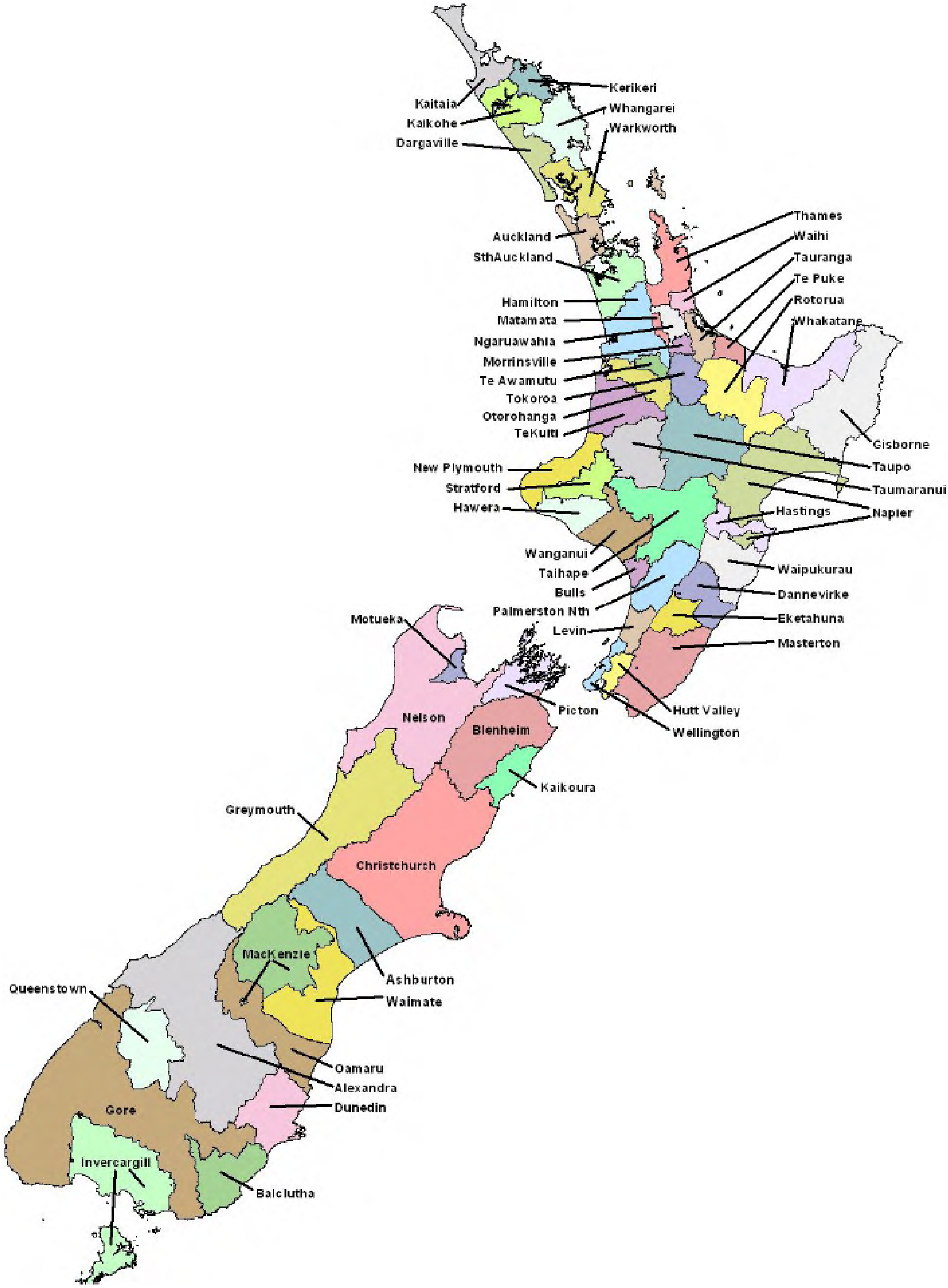
NB Bold numbers indicate significance at the 5 percent level

Table 8 Significance test for spatial non-stationarity

	Census Participation rate		Census Unemployment benefit rate		Census Sickness benefit rate		Census Invalids benefit rate		Census Domestic purposes benefit rate	
	1996									
laghomeown	0.100	(0.116)	0.043	(0.477)	0.019	(0.750)	0.008	(0.427)	0.021	(0.749)
lagunemployment	0.182	(0.618)	0.233	(0.654)	0.273	(0.117)	0.014	(0.876)	0.342	(0.054)
lagnoqual	**0.205**	**(0.002)**	0.021	(0.974)	0.036	(0.663)	0.005	(0.719)	0.039	(0.542)
lagoldworkingage	0.107	(0.686)	0.085	(0.81)	0.036	(0.922)	0.019	(0.447)	0.085	(0.536)
lagsolo	0.095	(0.488)	0.146	(0.404)	0.088	(0.303)	0.021	(0.280)	0.102	(0.317)
lagservice	0.106	(0.061)	0.029	(0.878)	0.022	(0.783)	0.002	(0.848)	0.024	(0.736)
lagmaori	0.016	(0.843)	0.085	(0.018)	**0.045**	**(0.035)**	0.005	(0.533)	0.028	(0.213)
constant	1.161	(0.93)	3.011	(0.539)	1.053	(0.837)	0.360	(0.633)	2.032	(0.429)
	2001									
laghomeown	5.121	(0.400)	0.072	(0.684)	0.010	(0.048)	0.589	(0.992)	0.019	(0.853)
lagunemployment	0.072	(0.684)	0.177	(0.965)	0.017	(0.524)	0.061	(0.128)	0.142	(0.348)
lagnoqual	0.177	(0.965)	0.059	(0.910)	0.001	(0.947)	0.067	(0.938)	0.034	(0.522)
lagoldworkingage	0.059	(0.910)	0.225	(0.490)	0.010	(0.426)	0.059	(0.357)	0.058	(0.577)
lagsolo	0.225	(0.490)	0.182	(0.542)	0.010	(0.264)	0.128	(0.252)	0.066	(0.285)
lagservice	0.182	(0.542)	0.060	(0.649)	0.002	(0.755)	0.118	(0.186)	0.043	(0.053)
lagmaori	0.060	(0.649)	0.079	(0.175)	**0.008**	**(0.041)**	0.018	(0.778)	0.016	(0.565)
constant	0.079	(0.175)	5.121	(0.400)	0.465	(0.145)	**0.073**	**(0.000)**	2.954	(0.107)
	2006									
laghomeown	0.044	(0.308)	0.045	(0.599)	0.030	(0.082)	0.054	(0.073)	0.028	(0.174)
lagunemployment	0.140	(0.364)	0.262	(0.300)	0.061	(0.477)	0.036	(0.852)	0.064	(0.450)
lagnoqual	0.068	(0.220)	0.068	(0.371)	0.009	(0.845)	0.028	(0.582)	0.017	(0.609)
lagoldworkingage	0.058	(0.449)	0.052	(0.758)	0.014	(0.766)	0.017	(0.770)	0.018	(0.600)
lagsolo	0.070	(0.312)	0.045	(0.866)	0.029	(0.353)	0.020	(0.709)	0.011	(0.812)
lagservice	0.053	(0.059)	0.003	(1.00)	0.007	(0.702)	0.003	(0.978)	0.009	(0.625)
lagmaori	**0.042**	**(0.042)**	0.034	(0.242)	0.011	(0.241)	**0.032**	**(0.023)**	0.003	(0.947)
constant	4.076	(0.120)	3.332	(0.478)	1.501	(0.174)	2.863	(0.076)	1.084	(0.564)

* Bold numbers and grey shading indicate significance at the 5 percent level

Figure 1 New Zealand Labour Market Areas



Source - Maré and Timmins (2004, p 18)

Figure 2 Box plot of LMA labour force participation rates, 1996, 2001 and 2006

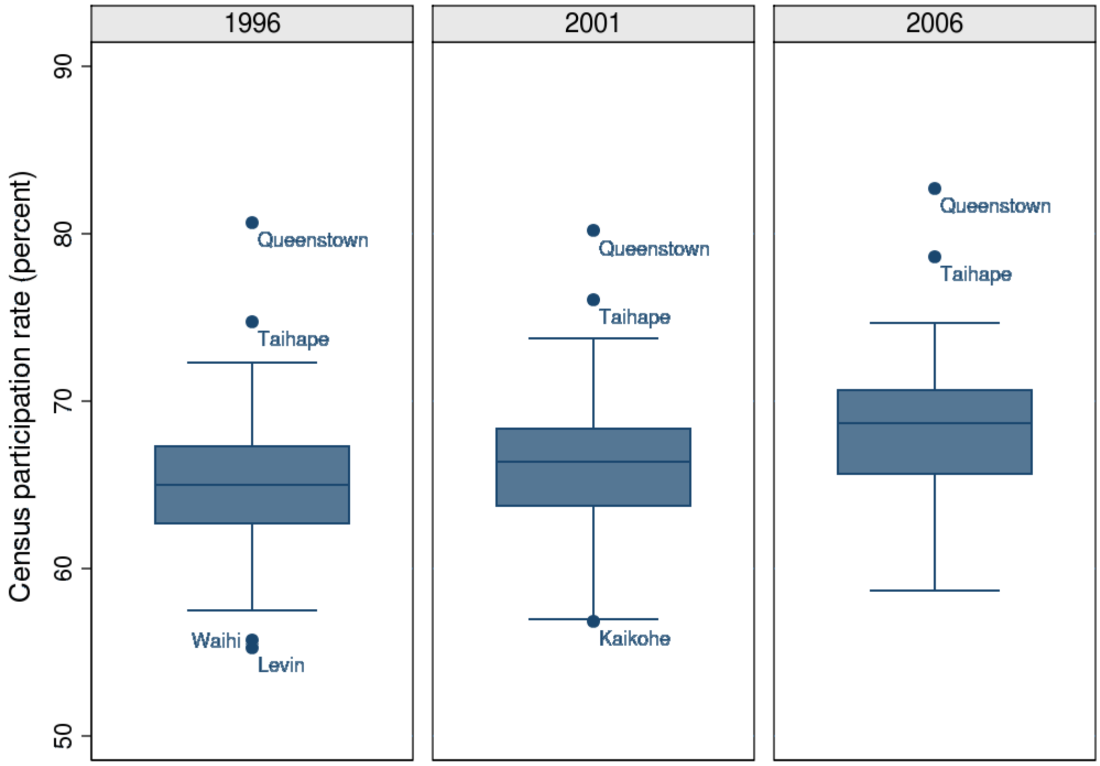


Figure 3 Box plot of LMA unemployment benefit receipt rates, 1996, 2001 and 2006

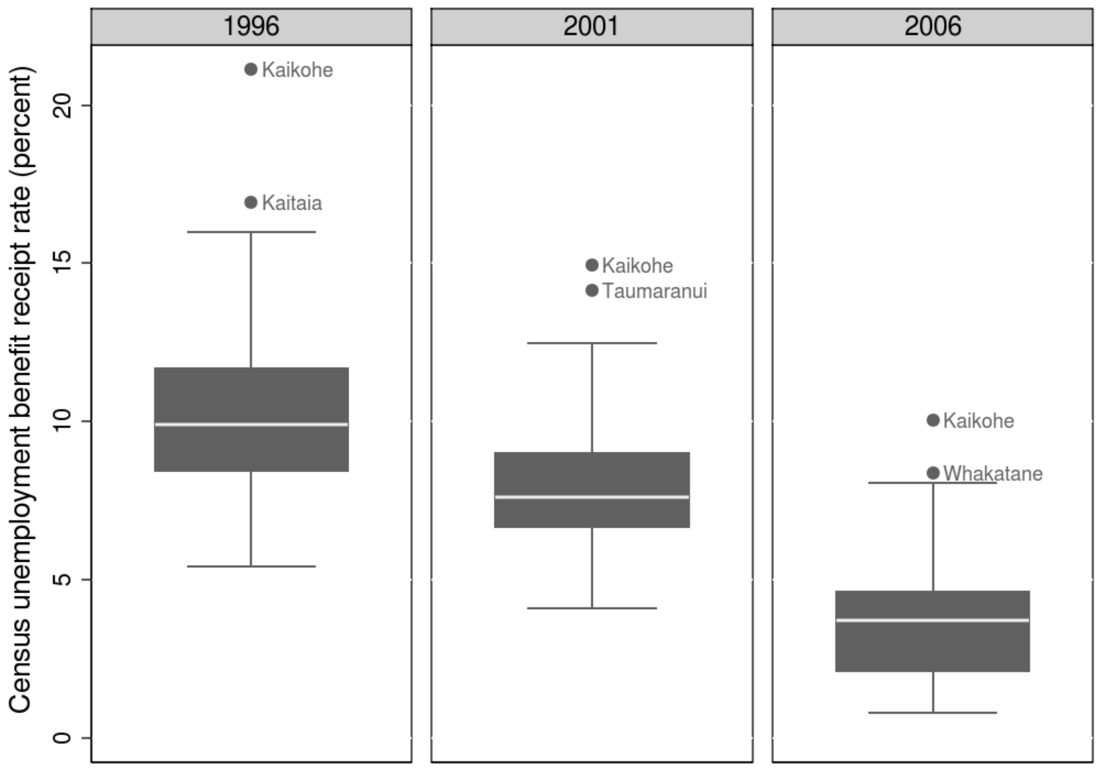


Figure 4 Box plot of LMA sickness benefit receipt rates, 1996, 2001 and 2006

Figure 5 Box plot of LMA invalid benefit receipt rates, 1996, 2001 and 2006

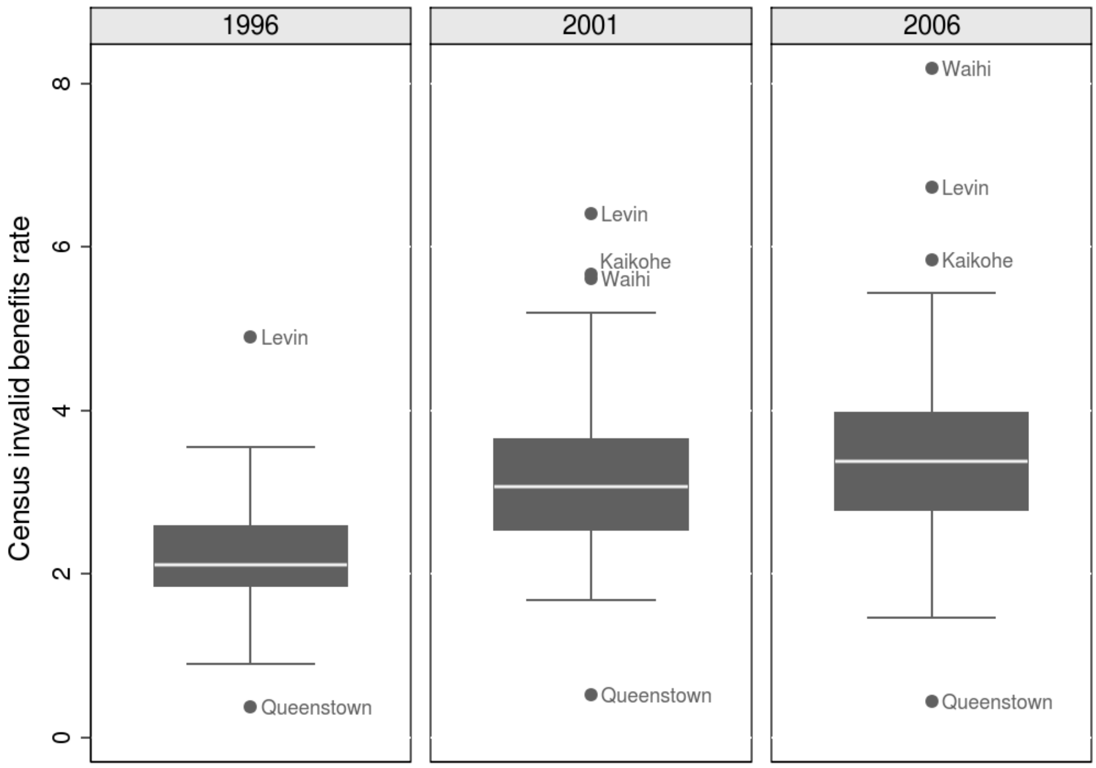


Figure 6 Box plot of LMA domestic purposes benefit receipt rates, 1996, 2001 and 2006