Getting people out of unemployment: A spatial perspective across Auckland

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Abstract

Reducing the unemployment rate is an aim of most governing authorities. This paper presents a socio-economic analysis of area-level employment rate changes across Auckland using Census area-level data for the time period 1996 to 2006. Exploratory spatial data analyses suggest the presence of strong spatial patterns in intra-city employment rates changes. Application of seemingly unrelated regressions highlight forces, such as education, that are associated with increases in part time and full time employment relative to being unemployed.

Keywords: Unemployment; Seemingly unrelated regressions; Queen spatial weights

JEL Classification: R20; E24; J21; C30

Acknowledgments: The authors would like to thank Mary Hedges, Saten Kumar and Paul Voss for helpful comments on earlier drafts.

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1. Introduction

The propensity to be employed, unemployed or inactive is a key focus of research for many OECD countries. The restated OECD Jobs Strategy is aimed at promoting labour market participation and employment, with extra weight given to take into account the concerns of low-income groups (OECD, 2006). In many world cities, and Auckland in particular, the current vision statement of the local government indicates three clear goals, with one of these goals aimed at the outcome of Auckland city being productive with high employment (Auckland City, 2009).

This paper investigates the presence and determinants of spatial variations in changes in employment rates in the Auckland region of New Zealand, between 1996 and 2006. Such an analysis is pertinent if the movements out of being unemployed is not spatially homogenous. Exploratory spatial analysis is used to identify movements in and out of unemployment and towards three alternatives – exiting from the labour force, moving into part time employment, or moving into full time employment. Determinants of changes in employment patterns across the 369 areas of Auckland are an important concern for the overall economy of New Zealand. More than a quarter of the country's population live in this region.

There is a growing recognition that creating more and better jobs is a major task for local government authorities. Most countries have increased their efforts and resources towards social policies to support the rapidly growing number of unemployed, and labour market policies to transition these individuals back towards a status of employment. However, additional funds are limited and governments face difficult choices on how best to respond to the different demands of the labour market. Additionally, given the strong likelihood that improved employment growth will induce higher participation among low-income and disadvantaged groups (such as females, low-skilled and low-educated workers, youth, and Maori and Pacific Islanders), investigating the determinants of movements in and out of employment in Auckland's many and varied areas and whether these determinants are spatially influenced is the key objective of this research.

The remainder of this paper is organized as follows. Section 2 provides a review of the two strands of literature that are paramount to this study: first the importance of spatial imbalances in unemployment and potential determinants of movements from unemployment to the different employment states (full time, part time, and out of the labour force), and second a brief review of the literature and significance of spatial analysis and spatial autocorrelation. Section 3 outlines the area-specific census data used in this study and presents a descriptive analysis. Section 4 covers the data analysis methodology employed, while section 5 interprets the key results found, and the final section of this paper provides general conclusions and possible directions for future research.

2. Literature Review

This paper seeks to investigate the importance of various socio-economic factors that determine changes in aggregate employment rates within cities. In particular, this study will focus on the 369 areas within the city of Auckland, New Zealand, and focus on the determinants of movements from unemployment to the three alternative states of full time employment, part time employment, and out of the labour force. In general, factors that influence an individual's propensity to be unemployed include their education level, age, past experience of being unemployed, dependents in household, geographic immobility, level of benefits, stigma attached with being unemployed, relative prices (such as the median wage level, and including the minimum wage), etc. Economists often categorise these determinants into three types of unemployment: cyclical, frictional, and structural.

We can rule out cyclical unemployment because of the time period of focus in this study. This paper investigates the spatial distribution of employment in the Auckland region of New Zealand, between 1996 and 2006, during which time there was mostly recovery from a recession in 1997/8. There was also no major industrial change over this time period, so we can rule out significant structural unemployment. All industry sectors experienced either stable or increasing levels of growth during the majority of this time.[1] For example, there was particularly strong growth in construction and dairy (St. John and Fargher, 2004, p. 30). The final category of unemployment (frictional) covers a wide range of potential determinants, involves movements between jobs, and often results because of imperfect information in the labour market.

Besides a simple exploratory analysis of determinants of movements into and out of employment in Auckland, one of the principal aims of this study is to investigate which determinants may be spatially influenced. A spatial perspective is particularly important if the employment dynamics of area i is not independent of the employment dynamics of its neighbours. That may occur if the propensity of an individual to behave in a certain way (i.e. their state of employment) varies with the prevalence of that behaviour in their reference group. In the following analysis, we will explicitly account for these spatial influences, by assuming the reference group of the individual is not only the average behaviour of the area they live in, but the average employment behaviour of the surrounding areas. Manski (1993) indicated that it is not possible to infer whether the average behaviour of a reference group impacts an individual in that group, unless there is prior information specifying the composition of the group. He also indicated that deduction on how average behaviour of a reference group impacts an individual's behaviour is more plausible if the attributes/characteristics that define the reference group and the factors impacting the outcome are moderately related. Given that the outcome we are interested in investigating in this study is employment state, the same variables influencing employment propensity are also the variables available for the reference groups at the area-level (for the 369 Auckland areas) – information on education, household structure, ethnicity, and home ownership.

If a spatial perspective is important in analysing determinants of area level employment trends and area i is not independent of its neighbours, this violates the underlying standard regression assumptions and normal regression estimates could be inefficient and potentially biased. For example, although analysis by Vipond (1984) recognized the importance of spatial factors when investigating unemployment differentials within Australia's largest city of Sydney, the study employed standard multiple regression analysis of census data to explore the influence and significance of location on these differentials. Consequently, their econometric estimates of the effect of explanatory variables would most likely have been inefficient, due to spatial autocorrelation.[2] One of the clearest expositions of the reasons behind spatial autocorrelation has been provided by Voss *et al.* (2006), and based on the work by Wrigley *et al.* (1996), who emphasise the importance of, amongst other things, *feedback*, *grouping forces* and *grouping responses*.

Voss *et al.* (2006) state the potential for *feedback* forces to influence individuals and households preferences and activities. *Ceteris paribus*, the smaller the spatial scale of analysis then the greater the potential feedback because of the higher likelihood and

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1 This is determined using productivity/performance data from the NZ Time Series for all industry classifications, between 1996 and 2006.

2 Positive spatial autocorrelation has similar values appearing together, while negative spatial autocorrelation has dissimilar values appearing in close association.

frequency of contact between people. For reasons related to the adoption/diffusion theory (Rodgers, 1962) and the agent interaction theory (Irwin and Bockstael, 2004) we should generally expect there to be the potential for spillovers of employment behaviour with a positive correlation in employment rates between contiguous areas. If being in full time employment is seen to be positively contributing to life and satisfaction, which is sometimes illustrated by conspicuous consumption (Veblen, 1899; Bourdieu, 1979), then this positive employment impression is likely to be shared with friends and neighbours, including friends and neighbours within the area and within contiguous areas.

Geographically close areas with similar aggregate employment profiles might be influenced by *grouping forces*. Clusters of high employment rates might be due to a number of reasons including the spatial grouping of similarly work-oriented and work-successful people around appropriate schools,[3] amenities that are status symbols and/or associated with activities that are of interest to similarly-defined individuals, such as being close to the riverfront or a prestigious golf course. One issue here is whether people with similar employment profiles group together as a result of their income and purchasing power or whether being resident in an area where employment rates and incomes are high also results in one's own employment profile (and thence income) being relatively high. Social capital issues may well be relevant here.[4]

Entry into employment can result in the outmigration of workers from relatively deprived areas to more affluent areas. Such *grouping responses* may be positive or negative and can result in some areas being employment black-spots with the least well-off being forced out of affluent areas, because of the inability to pay high rents and other housing costs, and into less-affluent areas.

Overall, spatial autocorrelation in a regression may indicate that the model is under-specified or that clustering is serendipitous. Although such non-independence of observations may be random it is also possible that employment rates in area *i* are influenced by spatial contagion effects from area *i*'s neighbouring areas. Thus spatial autocorrelation may exist because there is a 'spatial process' (usually diffusion or spread) moving across areas.

The relevance of spatial influences was also shown by Patacchini and Zenou (2007), who developed a model based on data from 297 Travel-to-work-areas in the UK, and showed spatial correlation existed between unemployment rates of different regions. Their results indicated a significant spatial dependence that has been growing over time. Despite this finding, to date, most empirical research on explaining unemployment disparities has typically ignored the spatial correlation between regional unemployment rates, and the importance of spatial factors when investigating movements into and out of unemployment within a region.[5] In fact, evidence of diffusion or spread in employment rates has been largely anecdotal, and this has been primarily due to the lack of appropriate data at small spatial scales. As a consequence, few studies have employed spatial econometric techniques to take account of the possible spillover effects of employment rates at the small spatial scale.[6]

One study that has made use of spatial econometric models when investigating patterns of unemployment within a city (Chicago) was Conley and Topa (2002). They

[3] High employment rates are often found in the areas of the most prestigious school zones.

[4] Winkelmann (2009) provides an interesting discussion of the inter-linkages between social capital, unemployment and well-being.

[5] A limited number of studies find evidence of spatial dependence in unemployment rates (See Molho, 1995; Burgess and Profit, 2001; Overman and Puga, 2002), but do not delve further into the causes of such patterns

[6] Livanos (2009) finds that the area of residence is a factor that affects the odds of being unemployed and, in common with other studies, appears to use dummy variables to capture the region of residence without theoretical justification for their inclusion.

focussed on the time period 1980 to 1990 and by acknowledging the relevance of spatial influences and employing methodology that explicitly accounted for it, they were able to identify the characteristics that contributed the most to explaining the strong clustering in the unemployment data for this city – racial and ethnic composition variables.

Given the lack of research on this front, one of the main contributions of this paper is to investigate the importance of a number of socio-economic factors that determine changes in the employment rates within a major metropolitan city (specifically, Auckland), by explicitly taking into account spatial effects in the modelling process. This is an important area of study as intra-regional imbalances in non-employment are a concern for local government authorities, due to not only the economic cost of increased unemployment, but also the social costs.[7] These involve costs to individuals, their families and their communities. For individuals, these could include feelings of being deprived, frustrated, reduced life expectancy (Safaei, 2008), increased suicide (Chuang and Huang, 1997; Ruhm, 2000; Gerdtham and Johannesson, 2003; Andres, 2005; Neumayer, 2004; Yang and Lester, 1995) and drug abuse rates (Webber, 2010). Families often face increased breakups and domestic violence rates. As for the impact on the community, areas of high unemployment experience a decline in average incomes and consequently spending levels, and often face rising relative poverty and income inequality (Saunders, 2002). Additionally, because younger workers tend to be more mobile, these regions with high unemployment over a prolonged period of time, can be left with an ageing workforce, which makes them unattractive for businesses to invest and locate in (Barnes *et al*., 2009). Given the private and social costs of unemployment, especially intra-regional disparities, determining the factors that influence rising levels of non-employment are clearly an imperative research issue.

3. Method

Movement out of a state of unemployment results in an individual going towards one of three possible alternatives: full time employment; part time employment; or out of the workforce. In this respect states of employment are naturally mutually exclusive and should be seen as substitutes. Consequently, any empirical investigation needs to explicitly consider this substitution effect.

Seemingly unrelated regression

Application of ordinary least squares (OLS) regression to changes in the employment state of an individual (or a group of individuals) would be inappropriate for three main reasons. First, employment states are negatively correlated but OLS models would lack explicit appreciation of their explicit substitution. Second, and connected with the first, one of the standard assumptions in regression modelling is that residuals of separate models are uncorrelated; for instance, the errors u_i from a full employment OLS model and v_i from a part time employment OLS model, associated with the observation for area i, would be expected to be uncorrelated. Correlations of residuals across regression models illustrate that there is additional explanatory information in the data that has not been exploited through an OLS model.[8] However residuals from models of different unemployment states are expected to be strongly positively correlated because in areas where the rate of full employment is higher

7 For further discussion on social costs of unemployment see Ramazzotti and Rangone (2004), Kuhn *et al.* (2007) and Morris (2002).

8 Another source of potentially problematic correlation between residuals is spatial autocorrelation between adjacent areas. We attempt to control for this by including a spatially-lagged dependent variable.

than predicted, at least one of the other employment states must be lower than predicted, leading to large residual variances in both equations. An OLS approach would ignore the correlation in the residuals across equations and would produce inefficient estimates even though they would be unbiased and consistent. Third, employment rates are bounded between zero and 100 percent but OLS estimates are based on continuous data following normal distributions; hence application of OLS could result in the possible generation of estimates that are greater than 100 percent and less than zero percent.

The problem of unbounded predicted values is surpassed through the logistic transformation of area-specific pairwise comparisons of employment states. After the selection of an employment state as the reference category the natural log of the employment state between it and other employment states is obtained, thereby mapping bounded employment states (i.e. 0–100 percent) onto an unbounded ($-\infty$ to $+\infty$) employment state ratio.

The selection of an employment state base category will permit the analysis of differences between only two employment states; the denominator shown in equation (1) is unemployment. However inspection of equation (1) leads to the realisation that differences in employment states between full time and part time employment are not explicitly calibrated here, suggesting the need for a full set of base categories for comprehensive estimation, as shown in equations (1) – (3).[9]

To facilitate the estimation of a model that captures different rates in employment states we estimate a set of seemingly unrelated regressions in an attempt to achieve greater efficiency in the estimates, such that:

$$\begin{aligned} \ln(FT_i / U_i) &= X\beta_{i1} + \varepsilon_{i1} \\ \ln(PT_i / U_i) &= X\beta_{i2} + \varepsilon_{i2} \\ \ln(Out_i / U_i) &= X\beta_{i3} + \varepsilon_{i3} \end{aligned} \qquad (1)$$

$$\begin{aligned} \ln(FT_i / PT_i) &= X\beta_{i1} + \varepsilon_{i1} \\ \ln(U_i / PT_i) &= X\beta_{i2} + \varepsilon_{i2} \\ \ln(Out_i / PT_i) &= X\beta_{i3} + \varepsilon_{i3} \end{aligned} \qquad (2)$$

$$\begin{aligned} \ln(FT_i / Out_i) &= X\beta_{i1} + \varepsilon_{i1} \\ \ln(PT_i / Out_i) &= X\beta_{i2} + \varepsilon_{i2} \\ \ln(U_i / Out_i) &= X\beta_{i3} + \varepsilon_{i3} \end{aligned} \qquad (3)$$

[9] Note that there initially appears to be an (inverted) duplication in the dependent variables with, for example, $\ln(PT_i / U_i)$ in equation (1) and $\ln(U_i / PT_i)$ in equation (2). Supposition of a (negative) *identity* is incorrect as the estimation of these two dependent variables are based on the simultaneous estimation of two other different dependent variables. Of course, this assertion of incorrectness is based on the belief that the sets of regressions need to be estimated simultaneously; obtaining statistical proof of this theoretical stance, and hence testing the validity of cross-equation parameter restrictions, will be based on the Breusch-Pagan test. Nevertheless, the *quantitative* estimates of explanatory variable coefficients for (seemingly identical) dependent variables will be very highly correlated and similar in magnitude. It is expected that *qualitatively* identical results would be obtained.

where ε represents residuals for each area that are correlated across equations (e.g. $\varepsilon_{i1}, \varepsilon_{i2}$ and ε_{i3} within equation (1)), X is a set of independent explanatory variables and β is a set of coefficients to be estimated.

Spatial components

Spatial regression can be used to investigate the influence of spatial relationships. Two types of regression models are typically employed: the spatial error model and the spatial lag model. If there were strong theoretical reasoning to believe that the errors of an OLS regression would be spatially autocorrelated then the appropriate technique would be to estimate a spatial error model specified as:

$$y = X\beta + u \tag{4}$$

$$u = \rho Wu + \varepsilon \tag{5}$$

where y represents the dependent variable, X represents the independent variables and the constant term, β is the regression parameters which are to be estimated and u is the error term. This error term in equation (4) is presumed to have a covariance structure given in equation (5) where ρ is a spatial lag parameter to be estimated, W is a weights matrix defined by the area's neighbourhood such that Wu captures the spatial lags of the model's disturbance term, u, and ε is the independently distributed error term. Elements w_{ij} from the W matrix capture the influence on area i of its neighbours, j. Spatial error models are typically employed when the list of explanatory variables does not contain a variable which captures the spatial autocorrelation that appears in the dependent variable.

An alternative spatial perspective is to have a spatially lagged dependent variable,[10] such that:

$$y = \lambda Wy + X\beta + u. \tag{6}$$

In this formulation, Wy captures the spatially-weighted average of the dependent variable for an area's neighbouring locations and λ is the spatial lag parameter to be estimated. This would capture spatial autocorrelation and represent our spatially evolving stigma attached to being unemployed.

It is entirely possible that there is a spatially-lagged dependent variable effect along with a spatially lagged error term. We proceed with estimating a spatial-lag model, as our discussion of feedback, grouping forces and grouping responses suggests, and then complementing the results with estimations of the importance of spatially-weighted independent variables to check the stability of the results and for extra potentially spatially-relevant factors contributing to the change in the transition rates between employment states. Therefore our final models will take the form:

$$\begin{aligned}
\ln(FT_i / U_i) &= \lambda W(\ln(FT_i / U_i)) + X\beta_{i1} + \rho Wu_{i1} + \varepsilon_{i1} \\
\ln(PT_i / U_i) &= \lambda W(\ln(PT_i / U_i)) + X\beta_{i2} + \rho Wu_{i2} + \varepsilon_{i2} \\
\ln(Out_i / U_i) &= \lambda W(\ln(Out_i / U_i)) + X\beta_{i3} + \rho Wu_{i3} + \varepsilon_{i3}
\end{aligned} \tag{7}$$

[10] See also Patacchini and Zenou (2007) who also used an empirical model which included a spatially lagged dependent variable in their analysis of spatial dependence in travel-to-work unemployment rates.

4. Data

The data used in this paper is area-specific Census data for the Auckland region sourced from Statistics New Zealand.[11] The Census occurs every 5 years in New Zealand. It provides data on the percentage of an area's population that is classified as being in unemployment or in full time and part time employment, as well as the percentage that are out of the labour force. Our empirical analysis focuses on the changes between two Census data sweeps which fairly closely coincides with the end of the recession and the end of the boom, thereby covering a period of sustained global unemployment rate falls in New Zealand: 1996 and 2006. Figure 1 indicates the overall trend in the aggregate unemployment rate for Auckland across this time period.

{Insert Figure 1 about here}

While Auckland has enjoyed a relative decline in its unemployment rate of 5.2 percent in March 1996 to 3.9 percent in March 2006 (a fall of 1.3 percentage points), this has not been uniformly experienced across the 369 areas. For example, some areas (such as Penrose and Ferguson) had a decline in their unemployment rates as high as 6-7 percentage points, while some areas (such as Matheson Bay and Dannemora) faced a *rise* in their unemployment rates of approximately 3.5 percentage points across that time period.

Our first step in attempting to identify patterns of movements out of a state of unemployment is to identify whether there are groups of areas that are following similar trends. Application of a hierarchical clustering algorithm to 1996 and 2006 percent values of full time and part time employment, unemployment and out of the labour force data generate three clusters of areas, which are shown in Figure 2 in black, grey and white. Inspection of Figure 2 shows no clear spatial patterns revealed through this method, suggesting that it is possible that patterns of employment status are not spatially-associated.

{Insert Figure 2 about here}

Figure 3 displays area level data for changes in full time employment, part time employment and out of the labour force when ranked by the change in full time employment. Visual inspection leads to two main observations. First, areas with large movements into full time employment had relatively large drops in the numbers moving out of the labour force. Second, variations in changes in part time employment do not appear to be related to changes in these other two employment categories.

{Insert Figure 3 about here}

Figure 4 examines the relationships between $\ln(FT_i / U_i)$, $\ln(PT_i / U_i)$ and $\ln(Out_i / U_i)$. Note that although Figure 3 suggests a negative correlation between movements into full time employment and going out of the labour force, Figure 4 also provides evidence that the movements out of unemployment and into the three other labour market states are positively correlated. This coincides with *a priori* expectations and supports the application of the seemingly unrelated regression approach.

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[11] A full list of the 369 Auckland ~~mesh block~~ areas is available from the authors on request.

{Insert Figure 4 about here}

As a complement to Figure 4, Table 1 presents correlation coefficient estimates of the movements from unemployment into the various other workforce states. As an illustration, the value of 0.867 indicates that the movement out of unemployment and into full time employment is highly correlated with a movement out of unemployment and into part time employment across areas in Auckland between 1996 and 2006. A number of relevant extensions follow.

{Insert Table 1 about here}

First, aggregate movements from unemployment and into full time and part time employment states are correlated across areas for 1–parent families and this correlation declines slightly with greater proportions of 1–parent families. This may be due to parental responsibilities which may impede work-related activities (suggesting greater movement into part time work) or the greater need for money (suggesting the movement into full time work). The same patterns are not observable for the other two sets of transitions, although the correlation coefficients are consistently smaller.

Second, aggregate movements from unemployment into full time and part time employment states are correlated across areas for 2–parent families and this correlation increases slightly with greater proportions of 2–parent families. The same patterns can be observed and are stronger for the transitions from unemployment and into full time employment and out of the labour force. Common to all three transitions out of unemployment are that the correlations are very high for areas with high proportions of 2–parent families. Interestingly these correlations increase in strength with greater proportions of 2–parent families, whereas the correlations reduced with greater proportions of 1–parent families. Reasons for this difference are worthy of further research.

Third, aggregate movements from unemployment and into full time and part time employment states are strongly correlated across areas though relatively constant across dependency rates, suggesting that a high dependency rate does not necessarily stimulate people into greater (or fewer) hours of work. There is a different pattern in the correlation coefficients for the transitions from unemployment and into full time (or part time) employment when compared to the transition out of the labour force; here the correlations strengthen when the sample is constrained to those areas where dependency is relatively high, suggesting that going into full time employment or leaving the labour force may be substitutes for some. Parental tax credits were introduced in New Zealand in October 1999 and provide assistance to low income families with dependents aged 18 or younger. For many low income families, this extra assistance may make it worth leaving the labour force, relative to the alternative of full time employment minus childcare costs.

Of great interest however is that all correlations in Table 1 are positive. This implies that in areas where there were aggregate movements out of unemployment, there were aggregate movements towards **all** the alternatives of full time, part time employment, and being out of the labour force. Additionally, in areas where the converse was true, i.e. where there were aggregate movements into unemployment, these individuals could have come from full time, part time or out of the workforce states.

Overall, this exploratory data analysis suggests a number of important lessons. First, there are variations across areas for transitions out of an employment state though it is uncertain whether relative location influences these transition patterns. Second, transitions out of a state of unemployment and into either full time or part time employment and even going out of the labour force are strongly positively correlated across the sample of areas, though the strength of correlation varies depending on various conditions.

The literature review and this initial descriptive analysis has highlighted a number of socio-economic factors that might affect the unemployment rate. Keeping these factors in mind and considering the variables available from the Census data, the following explanatory variables are used in the upcoming analysis (within the context of equations (1) to (3) indicated earlier):

- Initial ratios (i.e. 1996 values of dependent variable)
- Rental values and home ownership
- Vehicle access
- Sex ratio
- Dependency ratio, 1-parent families, 2-parent families,
- Qualifications (degree, school, post-degree, post-school, no qualifications)
- Overseas migrants
- Ethnicity (Pacific, Maori, Asian, European)

5. Results

Exploratory spatial data analysis

One way of examining the geography of aggregate employment rate patterns between 1996 and 2006 is to exploit the spatial nature of the data set. This has two elements: first maps which provide a visual indication of the importance of contiguity and spatial patterns, and second Moran's I values.[12] Figures 5 to 7 present the first part of the exploratory spatial data analysis. They map natural log ratios of full time employment to unemployment, part time employment to unemployment and out of the labour force to unemployment, each at the start of the sample period under study (1996), respectively.

{Insert Figure 5 about here}
{Insert Figure 6 about here}
{Insert Figure 7 about here}

Figures 5 to 7 show that there are spatial patterns in $\ln(FT_i / U_i)$, $\ln(PT_i / U_i)$ and $\ln(Out_i / U_i)$ respectively. In all three cases, we produce Moran's I values to statistically test for spatial autocorrelation. Relatively high unemployment rates, when compared to all three alternative employment states around the areas of Mangere and Manukau, are highlighted in Figure 5.

The Moran's I value produced for each of these three variables reject the null hypothesis that there is no spatial clustering. Specifically, the Moran's I in Figures 5 to 7 are 0.468, 0.509 and 0.350 respectively, and all three values are statistically significant at the 99 percent confidence level.[13] Areas with high unemployment rates (and low rates of other

[12] To undertake these tasks we employ the GeoDa open source software. This is free software and was developed at the Spatial Analysis Lab at the University of Illinois. It can be downloaded from: https://www.geoda.uiuc.edu/.

[13] Throughout this paper we employ a queen contiguity spatial weights matrix to capture the spatial effect, that is any area that shares a common boundary with area *i*, and estimate statistical significance for Moran's I values based on the randomisation approach with 999 permutations.

employment status) are contiguous to areas with high unemployment rates; this pattern holds throughout all three variables: darker colours indicate greater unemployment rates. In Figure 5, the darkest areas are in South Auckland (particularly Mangere and Manukau), which corresponds to areas of relatively young population and areas with a relatively higher ethnic mix, and higher proportion of Maoris and Pacific Islanders (for e.g. was more than 42% Maori in 2006). In the middle of the spectrum, we have grey areas (such as North Shore) where the population is older and there is a much lower proportion of Maoris and Pacific Islanders (for e.g. in 2006, Takapuna and Lake Pupuke both had rates of Maoris and Pacific Islanders at less than 4% and 2% respectively). The lightest areas of the map include the large areas of Rodney (towards the North West) and Franklin (towards the South West), which have little unemployment, relative to full time employment. These are areas of lifestyle blocks and farming communities, where many individuals are self employed. The dark and light grey colours follow a relatively similar pattern in Figures 6 and 7.

Seemingly unrelated regression results

Application of seemingly unrelated regressions (SUR) to equation (1) with 1996-2006 change data as the dependent variables (with unemployment as the base category) and 1996 values of explanatory variables provide results presented in Table 2. Here, as in all sets of regressions which follow, the Breusch-Pagen test for independence of the SUR rejects the null hypothesis of no correlation between the error terms, which provides statistical support for the premise that the residuals of each regression are strongly correlated with the residuals of the other regressions within in each SUR cluster.[14]

{Insert Table 2 about here}

As expected, the aggregate rate of movement out of unemployment is dependent on the initial level of unemployment. More interestingly, perhaps, is that areas with higher rental values have lower movements out of unemployment. This may be because rental values are higher in areas where employment rates (and therefore wage receipts and house-rental purchasing power) are already high; such an effect may be only marginal. Areas where rental values are relatively low experienced greater transitions out of being in unemployment and into either full time or part time employment. This may be because originally low rental values permitted either relatively low employment rates (with only one breadwinner in the house) or offered people less incentive to obtain a job. The same effect is not identified for home ownership.

Areas with greater dependency rates are associated with no significant aggregate movement into full time employment, perhaps because of additional parental responsibilities and a lack of time to devote to full time employment, but are strongly positively related with an aggregate movement either into part time employment (for instance, working while children are at school) or out of the labour force. Aggregate movements out of the labour force may be due to the increased social assistance available via parental tax credits since 1999. Additionally, across New Zealand in 1996 a child tax credit was set up to reward low income families with dependent children, where the parents were employed. This was replaced in 2006 by the In-Work Payment (now renamed the In-Work-Tax-Credit), and is designed to help families who work a minimum number of hours each week. Thereby, making it more worthwhile for mothers to take on part time work

[14] Breusch-Pagen test results are consistently statistically significant at the 99 percent confidence level.

After accounting for the family dependency effect, areas with greater proportions of 2–parent families are seen to have greater aggregate movements into part time work, perhaps to ensure a second breadwinner in the household. Areas with greater proportions of 1-parent families were more likely have slower rates out of unemployed, perhaps due to inflexible working conditions that would coincide with parental responsibilities which inhibit entering the labour force even if this was preferred.

Education appears to play an important role in reducing unemployment rates across areas. Areas with greater post-school qualified labour had workers that were more likely to enter part time employment. Areas with greater proportions of degree holders had workers who were more likely to enter full time employment, but were also likely to enter part time employment or leave the active labour force. Surprisingly areas with greater proportions of post-graduate qualified workers were likely to leave full employment and become unemployed.[15]

Areas with greater proportions of overseas residents were seen to have increasing levels of unemployment having moved out of full time work or from entering the active labour force.[16]

Table 2 also suggests that there are areas where larger pools of people from specific ethnic groups are less likely to move out of unemployment. These groups are Maoris and Asian, but not Pacific, and are relative to a European base category. Past research has found Maori fare relatively less well compared to other ethnicities in gaining paid employment and there is evidence of Maoris bearing a disproportionate burden of unemployment in New Zealand (Winkelmann, 1997, 1999).

The presence of a spatial property identified as being potentially important in earlier exploratory spatial data analysis and argued to be capturing feedback, grouping forces and grouping responses is included throughout in the regression through the use of a spatially lagged dependent variable.[17] The highly statistically significant positive coefficients suggest that areas surrounding area *i* are strongly positively correlated with the change in employment rates. This implies that local government policies designed to reduce unemployment rates should not ignore the employment dynamic properties in neighbouring areas.

Estimates of further augmentations of the model to incorporate spatially-lagged explanatory variables are presented in Table 3.[18] Two spatially-lagged variables appear to possess important explanatory power: initial values and rental values. It is well-known that property values evolve spatially (Samaha and Kamakura, 2008). However the identified importance of the spatially-lagged initial value further corroborates the proposition that there is a spatially evolving force which influences individuals' movements into and out of a state of unemployment. Higher rental values in surrounding areas also increase the movement into either full or part time employment. Again this could be the influence of the housing market on the ability to consume other goods, and may stimulate the need for two earners within a household.

{Insert Table 3 about here}

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[15] This may be capturing a local skill-mismatch (Zenou, 2009, chs 7 & 8) or less-skill-bias technical changes (Acemoglu, 2003).) or high reservation wages.

[16] There is a substantial amount of migration into and out of New Zealand, which may be behind this statistic.

[17] A queen contiguity weights matrix is employed throughout.

[18] A statistical observation supporting the inclusion of these extra variables is that the R^2 value has increased throughout (i.e. comparing Tables 2 with 3, 4 with 5, and 6 with 7).

Part time and out of the labour force denominators

The entire set of results presented above is based on estimates with unemployment as the denominator. Such results do not allow for policy formation associated with, for instance, the potential need for moving workers between part time and full time work. Accordingly Tables 4 and 5 show comparable results with part time employment as the denominator.

{Insert Table 4 about here}
{Insert Table 5 about here}

A number of interesting observations can be identified in Tables 4 and 5. First workers in areas with higher dependency ratios are likely to move into part time work from full time employment and when out of the labour force; however if they are in part time work then they are also likely to become unemployed. Residents of areas with high proportions of 2–parent families are also likely to move out of full time and into part time employment or move out of part time employment and into unemployment (or even exit the labour force). Areas with greater proportions of people with degrees are likely to move out of part time and into full time employment while people in areas with greater proportions of post-school qualifications are likely to move into the part time employment from being out of the labour force. Non-Europeans are less likely to enter part time employment and are more likely to remain unemployed.

The results above are based on estimates with either unemployment or part time employment as the denominators. Such results do not allow for policy formation associated with, for instance, the potential need for moving workers into the labour force and into either full time or part time employment. Accordingly Tables 6 and 7 show comparable results with out of the labour force as the denominator.

{Insert Table 6 about here}
{Insert Table 7 about here}

A number of interesting observations can be identified in Tables 6 and 7. First Asians are more likely to remain out of the labour force than other ethnic groups. Areas with greater proportions of people with post-school qualifications are more likely to enter the labour force and become either full or part time employed, though they are less likely to enter the labour force and become unemployed. This is not the case for areas with greater proportion of degree holders, as they appear likely to enter the labour force but could either become unemployed or enter full time employment; more research here may prove useful. Areas with higher dependency ratios are more likely to remain out of the labour force. Most importantly, however, is that the spatially evolving variable is again statistically significant and positive.

6. Conclusion

This paper has presented a highly-policy relevant extension to the literature on unemployment dynamics based on the proposition that spatially evolving phenomena have the potential to influence either directly or indirectly expectations, motivations, values and aspirations and therefore the impetus to change workers' employment statuses.

Evidence to support this claim rests on the validity of the spatially-lagged changes in employment status and empirical support is provided through the use of exploratory spatial data analysis and seemingly unrelated regressions with spatially-lagged variables. Using

Census data for area-level employment rate changes across 369 areas of Auckland between 1996 and 2006 and application of seemingly unrelated regressions, our results suggest that some characteristics, such as education, are associated with increases in part time and full time employment relative to being unemployed. Spatial autocorrelation remains concerning the aggregate transition out of a state of unemployment, and this is worthy of further local authority policy-related research should governing authorities wish to reduce the spatial disparities in unemployment. As reducing the unemployment rate is an aim of most governing authorities, which typically have jurisdiction over specific geographical entities, the evidence presented in this paper suggests that such governing authorities cannot assume each area is independent. Spatial considerations must be taken into account when using targeted policy to help lift areas out of unemployment.

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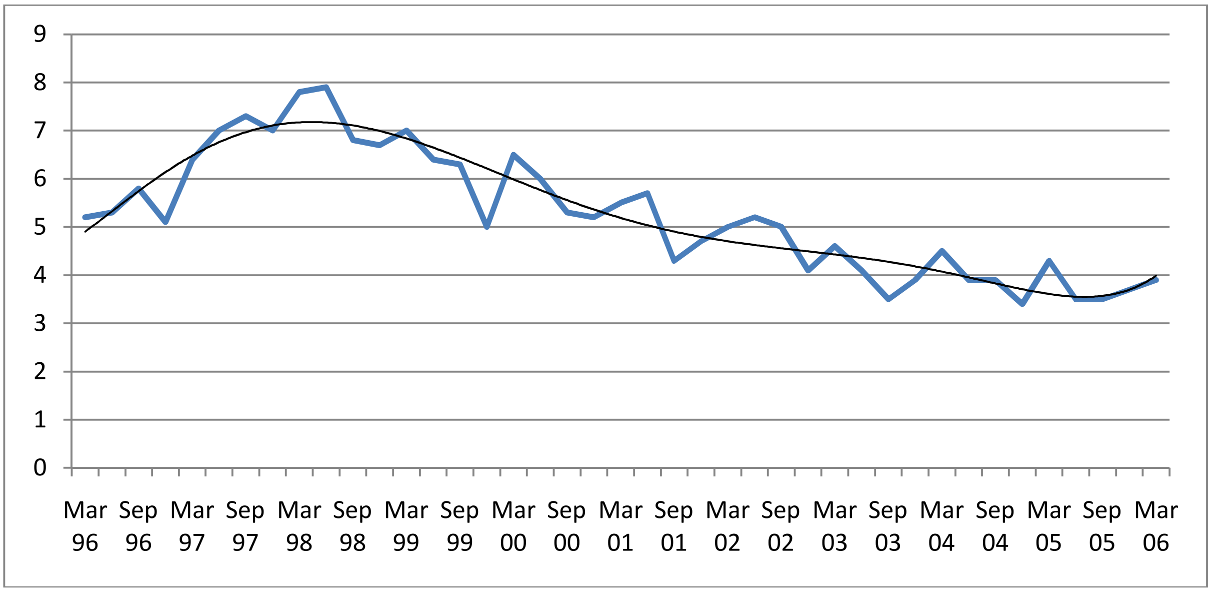
Figure 1: Auckland unemployment rate 1996:Q1 – 2006:Q1



Source: HLFQ.S2F3QB series from PCInfos.

Figure 2: Map of hierarchical clustering algorithm estimation results

Figure 3: Areas ranked by change in full time employment

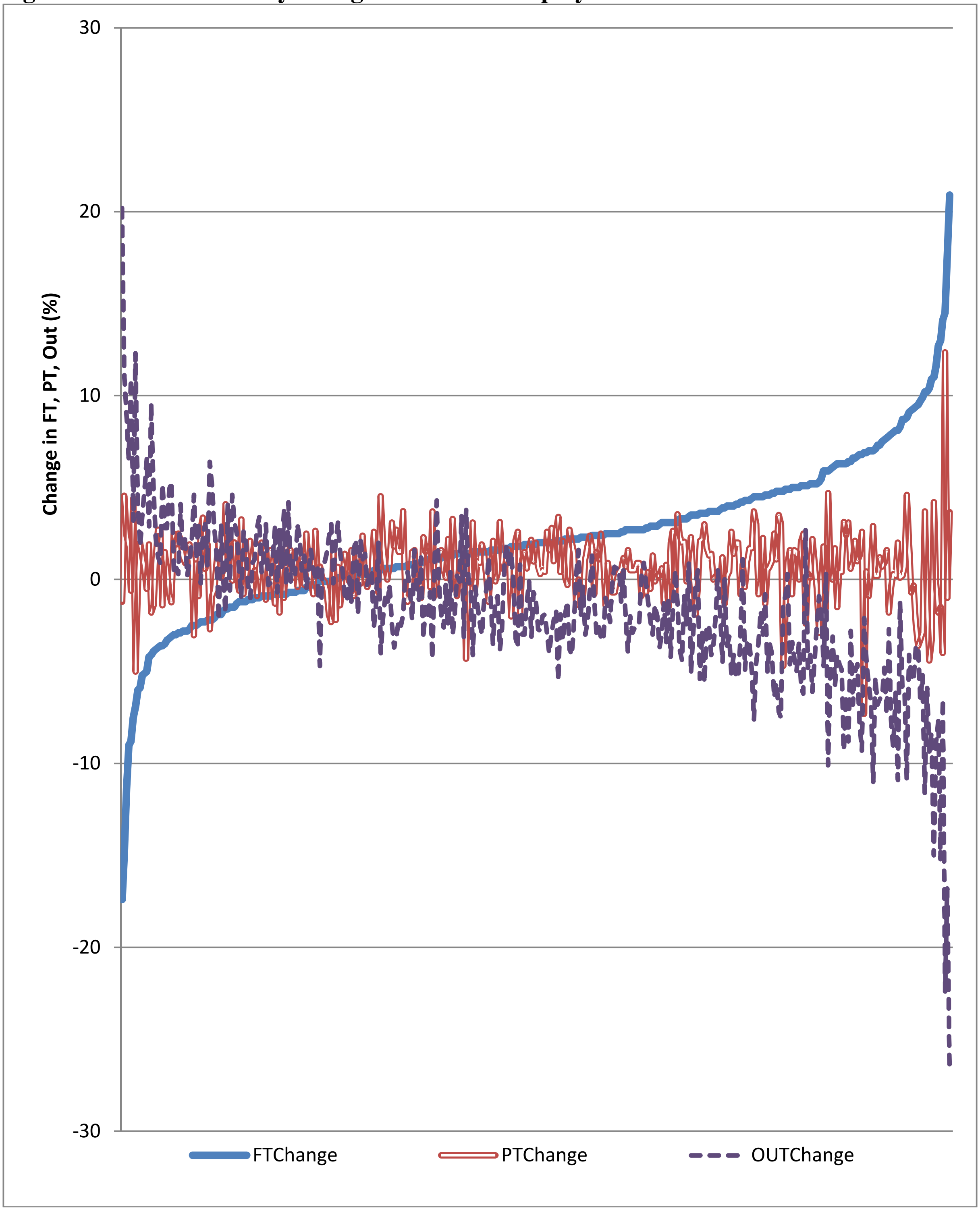


Figure 4: Scatter plot of movements from unemployment to FT (x-axis), PT (y-axis) and out of the labour force (z-axis)

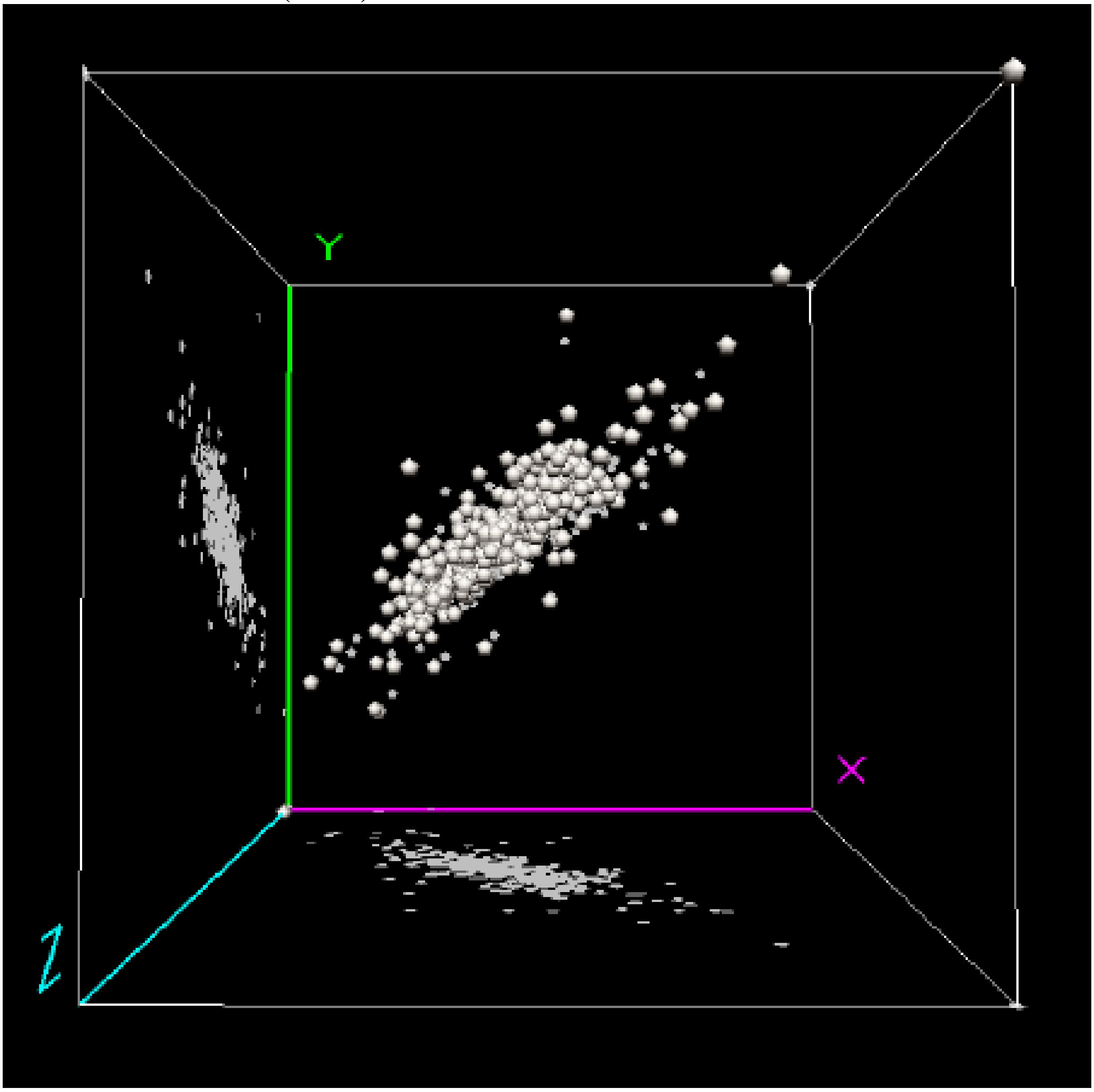


Figure 5: ln(FT/U) in 1996

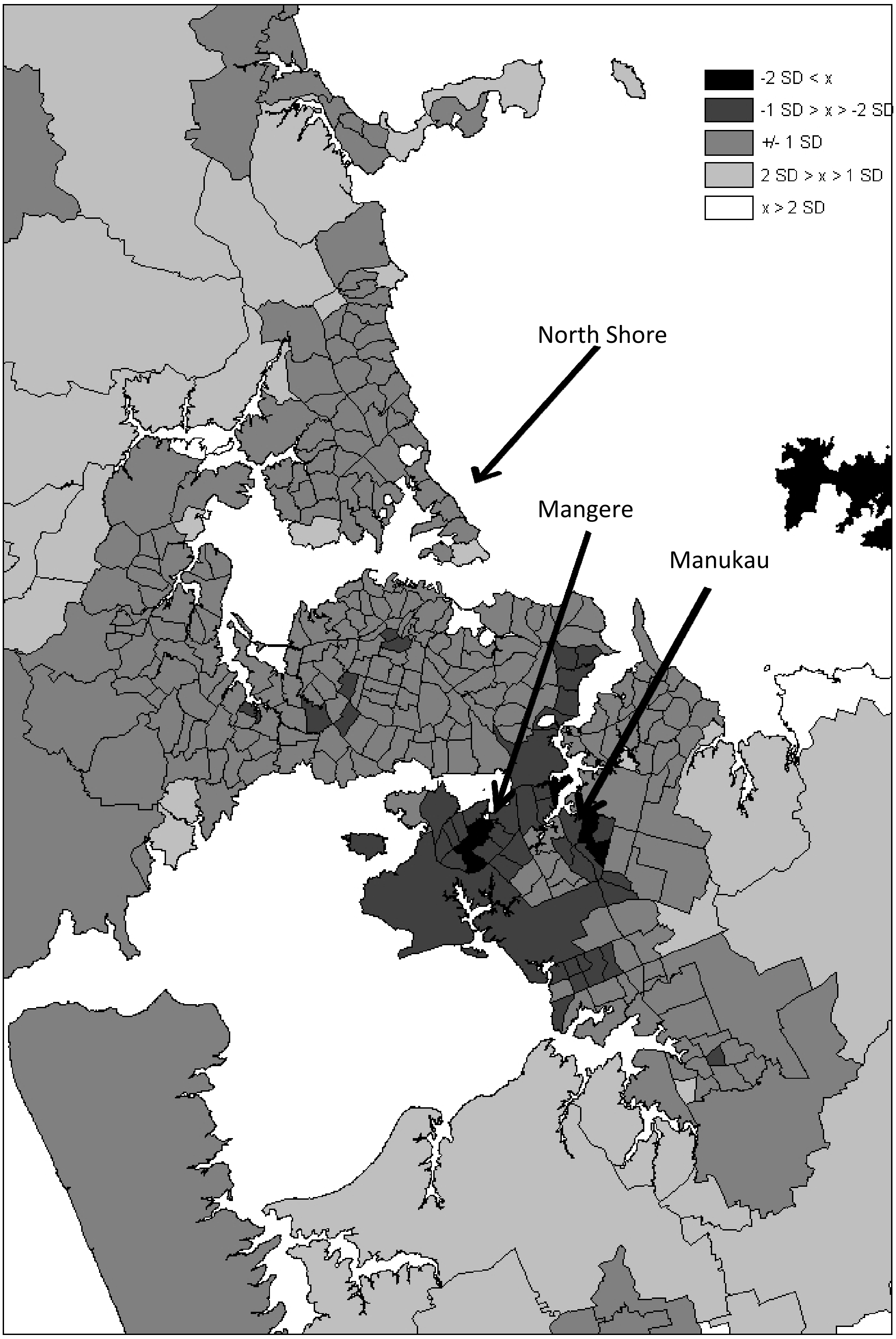


Figure 6: ln(PT/U) in 1996

Figure 7: ln(Out/U) in 1996

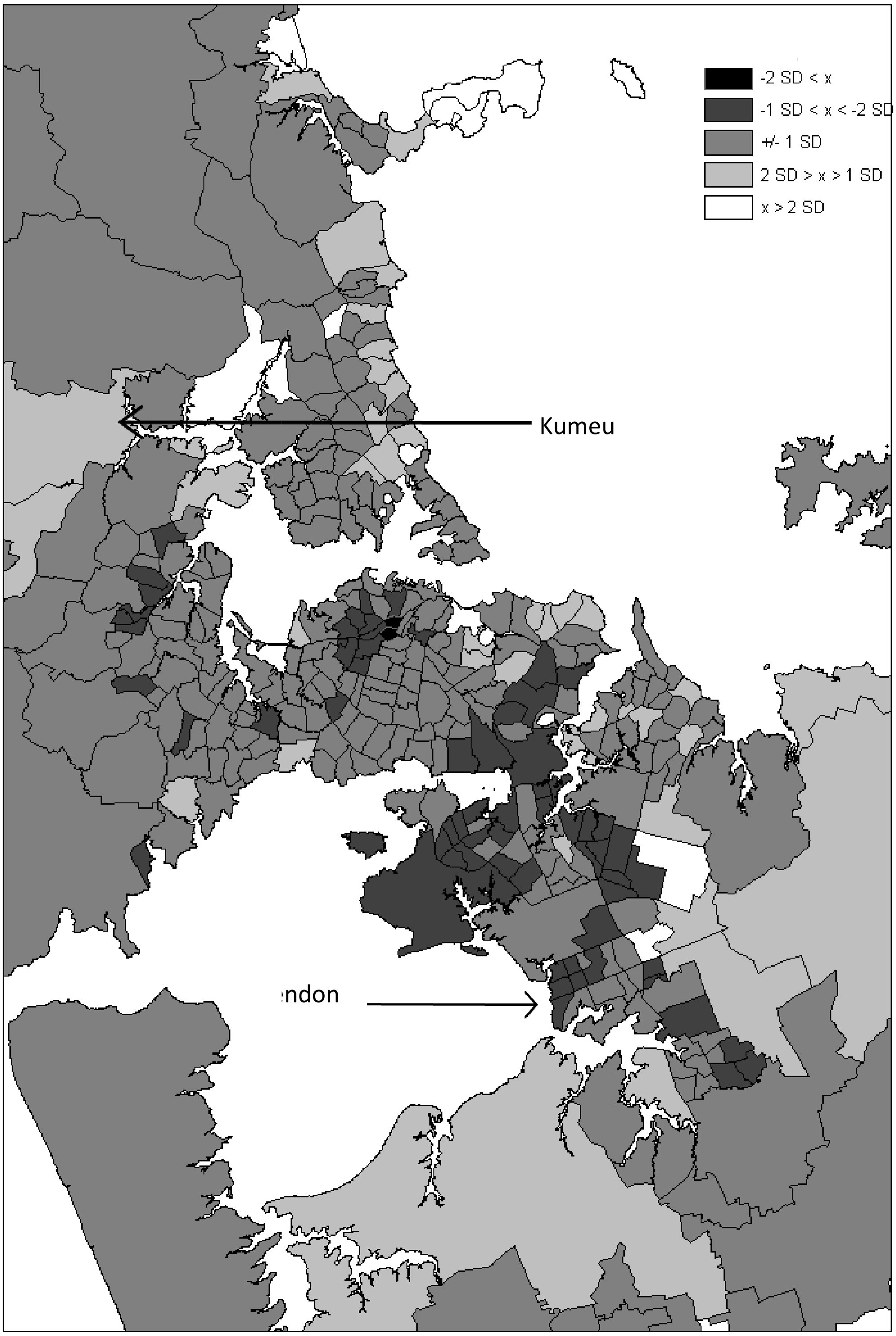


Table 1: Correlation coefficients: movements from unemployment into various states

Condition:	FT : PT	FT : Out	PT : Out	Sample size
	0.867	0.782	0.762	369
If the percentage of 1-parent families in area in 1996 is more than:				
35%	0.779	0.769	0.681	18
25%	0.802	0.774	0.722	69
15%	0.851	0.772	0.755	203
5%	0.855	0.761	0.738	366
If the percentage of 2-parent families in area in 1996 is more than:				
60%	0.979	0.959	0.956	12
50%	0.888	0.840	0.757	140
40%	0.879	0.813	0.761	311
30%	0.879	0.792	0.757	352
If the total dependency ratio in area in 1996 is more than:				
80%	0.898	0.903	0.901	7
60%	0.893	0.817	0.848	63
40%	0.882	0.822	0.748	304
20%	0.872	0.789	0.763	361

Note: FT=full time employment; PT=part time employment; Out=out of the labour force.

Table 2: Unemployed base

	FT employment		PT employment		Out of labour force	
	(1)		(2)		(3)	
Intercept	1.673	(0.449)***	0.641	(0.451)	1.751	(0.460)***
Geographically weighted LHS variables	0.334	(0.056)***	0.205	(0.052)***	0.101	(0.061)*
Initial value	-0.561	(0.035)***	-0.647	(0.033)***	-0.621	(0.035) ***
Rental value	-0.001	(0.000)*	-0.001	(0.000)***	-0.000	(0.000)
Home ownership	-0.001	(0.002)	-0.001	(0.002)	0.001	(0.002)
Vehicle access	0.262	(0.391)	0.317	(0.391)	-0.262	(0.395)
Sex ratio	-0.000	(0.002)	0.000	(0.002)	0.000	(0.002)
Dependency ratio	-0.032	(0.152)	0.373	(0.155)**	0.614	(0.171)***
1-parent families	-0.012	(0.004)***	-0.013	(0.004)***	-0.012	(0.004)***
2-parent families	0.003	(0.002)	0.006	(0.002)***	0.001	(0.002)
Family	Control variable					
School qualifications	-0.004	(0.004)	-0.003	(0.004)	-0.000	(0.004)
Post-school qualification	0.010	(0.007)	0.020	(0.007)***	-0.007	(0.007)
Bachelors degree	0.037	(0.009)***	0.027	(0.009)***	0.019	(0.009)**
Post graduate qualification	-0.033	(0.016)**	-0.008	(0.016)	-0.015	(0.017)
No school qualifications	Control variable					
Overseas residence	-0.009	(0.005)**	-0.004	(0.005)	-0.009	(0.004)**
Pacific	-0.001	(0.002)	-0.002	(0.002)	-0.001	(0.002)
Maori	-0.005	(0.003)*	-0.009	(0.002)***	-0.007	(0.003)**
Asian	-0.008	(0.003)***	-0.010	(0.003)***	-0.001	(0.003)
European	*Control variable*					
Moran's I (residuals)	0.143***		0.116***		0.172***	
Chi^2	450.25***		569.78***		449.03***	
R^2	0.476		0.519		0.483	
Breusch-Pagen test for independence	668.818***					

Notes: *n* = 369. Standard errors in parentheses; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively; queen contiguity weight matrices employed.

Table 3: SUR with spatially-lagged variables: Unemployed base

	FT employment	PT employment	Out of labour force
	(1)	(2)	(3)
Intercept	1.684 (0.464)***	1.030 (0.455)**	1.722 (0.482)***
Dependent variables * queen weight matrix	0.431 (0.056)***	0.404 (0.054)***	0.268 (0.069)*
Initial value	-0.655 (0.036)***	-0.729 (0.033)***	-0.693 (0.037)***
Rental value	-0.001 (0.000)**	-0.001 (0.000)***	-0.001 (0.000)**
Home ownership	-0.001 (0.002)	0.001 (0.002)	0.003 (0.002)*
Vehicle access	-0.391 (0.404)	-0.482 (0.389)	-0.923 (0.422)**
Sex ratio	0.001 (0.002)	0.001 (0.002)	0.002 (0.002)
Dependency ratio	-0.222 (0.155)	0.039 (0.154)	0.444 (0.174)**
1-parent families	-0.011 (0.004)***	-0.015 (0.004)***	-0.012 (0.004)***
2-parent families	0.002 (0.002)	0.005 (0.002)**	0.001 (0.002)
Family		Control variable	
School qualifications	-0.004 (0.004)	-0.005 (0.004)	-0.002 (0.004)
Post-school qualification	0.015 (0.007)**	0.021 (0.006)***	-0.005 (0.007)
Bachelors degree	0.034 (0.009)***	0.024 (0.009)***	0.016 (0.009)*
Post graduate qualification	-0.028 (0.016)*	-0.004 (0.016)	-0.007 (0.017)
No school qualifications		Control variable	
Overseas residence	-0.014 (0.005)***	-0.012 (0.005)**	-0.012 (0.005)**
Pacific	-0.001 (0.002)	-0.000 (0.002)	-0.001 (0.002)
Maori	-0.004 (0.003)*	-0.006 (0.003)*	-0.005 (0.003)
Asian	-0.003 (0.003)	-0.001 (0.003)	0.003 (0.003)
Initial value * queen weight matrix	**0.213 (0.031)***	**0.281 (0.031)***	**0.236 (0.040)***
Rental value * queen weight matrix	**0.002 (0.001)**	**0.002 (0.001)**	**0.001 (0.001)**
Home ownership * queen weight matrix	0.005 (0.004)	0.005 (0.004)	0.002 (0.004)
Vehicle access * queen weight matrix	-0.150 (0.692)	-0.263 (0.681)	0.067 (0.719)
Sex ratio * queen weight matrix	0.004 (0.003)	0.005 (0.003)*	-0.000 (0.003)
Dependency ratio * queen weight matrix	0.090 (0.259)	0.105 (0.254)	0.016 (0.269)
1-parent families * queen weight matrix	-0.004 (0.008)	-0.001 (0.008)	-0.001 (0.008)
2-parent families * queen weight matrix	0.004 (0.005)	0.007 (0.004)	0.001 (0.005)
School qualifications * queen weight matrix	-0.005 (0.009)	-0.006 (0.008)	-0.006 (0.009)
Post-school qualification * queen weight matrix	-0.005 (0.014)	-0.014 (0.013)	-0.012 (0.014)
Bachelors degree * queen weight matrix	0.026 (0.019)	0.022 (0.019)	0.022 (0.020)
Post graduate qualification * queen weight matrix	-0.042 (0.034)	-0.031 (0.034)	-0.049 (0.036)
Overseas residence * queen weight matrix	-0.004 (0.011)	0.000 (0.010)	0.003 (0.011)
Pacific * queen weight matrix	0.002 (0.004)	-0.000 (0.004)	0.002 (0.004)
Maori * queen weight matrix	0.000 (0.007)	-0.004 (0.007)	-0.007 (0.007)
Asian * queen weight matrix	-0.001 (0.006)	-0.008 (0.006)	-0.006 (0.007)
European		*Control variable*	
Moran's I (residuals)	0.123***	0.074**	0.154***
Chi^2	566.31***	763.32***	531.45***
R^2	0.510	0.581	0.498
Breusch-Pagen test for independence		665.480***	

Notes: *n* = 369. Standard errors in parentheses; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively; queen contiguity weight matrices employed.

Table 4: PT base

	FT employment		Unemployment		Out of labour force	
	(1)		(2)		(3)	
Intercept	1.103	(0.265)***	0.562	(0.452)	-1.026	(0.316)***
Geographically weighted LHS variables	0.293	(0.083)***	0.187	(0.071)***	0.208	(0.069)***
Initial value	-0.618	(0.033)***	-0.820	(0.051)***	-0.621	(0.048)***
Rental value	0.001	(0.000)***	-0.001	(0.000)***	-0.001	(0.000)***
Home ownership	-0.002	(0.001)	-0.001	(0.002)	-0.002	(0.001)
Vehicle access	0.208	(0.224)	0.440	(0.391)	0.578	(0.264)**
Sex ratio	-0.000	(0.001)	0.001	(0.002)	-0.000	(0.001)
Dependency ratio	-0.405	(0.092)***	0.484	(0.157)***	-0.291	(0.120)**
1-parent families	0.000	(0.002)	-0.016	(0.004)***	-0.001	(0.003)
2-parent families	-0.003	(0.001)**	0.007	(0.002)***	0.005	(0.002)***
Family	Control variable					
School qualifications	-0.003	(0.003)	-0.000	(0.004)	-0.004	(0.003)
Post-school qualification	-0.003	(0.004)	0.022	(0.007)***	0.025	(0.004)***
Bachelors degree	0.012	(0.005)**	0.029	(0.009)***	0.007	(0.006)
Post graduate qualification	-0.027	(0.009)***	-0.005	(0.016)	-0.009	(0.011)
No school qualifications	Control variable					
Overseas residence	-0.008	(0.003)***	-0.010	(0.005)**	0.005	(0.003)
Pacific	0.001	(0.001)	-0.004	(0.002)**	-0.000	(0.001)
Maori	0.003	(0.002)*	-0.013	(0.003)***	-0.002	(0.002)
Asian	0.003	(0.002)	-0.010	(0.003)***	-0.008	(0.002)***
European	*Control variable*					
Moran's I (residuals)						
Chi^2	479.99***		443.23***		480.23***	
R^2	0.548		0.538		0.571	
Breusch-Pagen test for independence	87.500***					

Notes: *n* = 369. Standard errors in parentheses; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively; queen contiguity weight matrices employed.

Table 5: SUR with spatially-lagged variables: PT base

	FT employment	Unemployment	Out of labour force
	(1)	(2)	(3)
Intercept	0.570 (0.246)**	0.829 (0.454)*	-0.861 (0.328)***
Dependent variables * queen weight matrix	0.492 (0.080)***	0.248 (0.073)***	0.213 (0.070)***
Initial value	-0.779 (0.034)***	-0.876 (0.050)***	-0.627 (0.049)***
Rental value	0.000 (0.000)**	-0.001 (0.000)***	-0.001 (0.000)***
Home ownership	0.000 (0.001)	0.001 (0.002)	-0.001 (0.001)
Vehicle access	-0.142 (0.202)	-0.162 (0.356)	0.349 (0.276)
Sex ratio	0.001 (0.001)	0.002 (0.002)	0.000 (0.001)
Dependency ratio	-0.258 (0.082)***	0.229 (0.157)	-0.362 (0.126)***
1-parent families	0.003 (0.002)*	-0.016 (0.004)***	-0.001 (0.003)
2-parent families	-0.003 (0.001)**	0.005 (0.002)**	0.005 (0.002)***
Family		Control variable	
School qualifications	-0.002 (0.002)	-0.001 (0.004)	-0.003 (0.003)
Post-school qualification	-0.001 (0.003)	0.024 (0.006)***	0.024 (0.004)***
Bachelors degree	0.010 (0.004)**	0.029 (0.008)***	0.008 (0.006)
Post graduate qualification	-0.023 (0.008)***	-0.000 (0.016)	0.010 (0.011)
No school qualifications		Control variable	
Overseas residence	-0.004 (0.002)	-0.017 (0.005)***	0.003 (0.004)
Pacific	-0.000 (0.001)	-0.001 (0.002)	0.000 (0.001)
Maori	0.001 (0.002)	-0.010 (0.003)***	-0.001 (0.002)
Asian	-0.001 (0.002)	-0.002 (0.003)	-0.007 (0.002)***
Initial value * queen weight matrix	0.465 (0.046)***	0.210 (0.039)***	0.049 (0.025)*
Rental value * queen weight matrix	0.000 (0.000)	0.002 (0.001)**	0.000 (0.000)
Home ownership * queen weight matrix	-0.001 (0.002)	0.004 (0.004)	0.005 (0.003)*
Vehicle access * queen weight matrix	0.061 (0.355)	-1.078 (0.680)	-1.447 (0.462)***
Sex ratio * queen weight matrix	-0.001 (0.002)	0.004 (0.003)	0.005 (0.002)**
Dependency ratio * queen weight matrix	0.033 (0.133)	0.172 (0.253)	0.030 (0.172)
1-parent families * queen weight matrix	-0.005 (0.004)	-0.003 (0.008)	-0.002 (0.005)
2-parent families * queen weight matrix	-0.002 (0.002)	0.006 (0.005)	0.005 (0.003)
School qualifications * queen weight matrix	0.002 (0.004)	-0.005 (0.008)	0.003 (0.006)
Post-school qualification * queen weight matrix	0.011 (0.007)	-0.013 (0.013)	0.002 (0.009)
Bachelors degree * queen weight matrix	0.004 (0.010)	0.025 (0.019)	0.008 (0.013)
Post graduate qualification * queen weight matrix	-0.012 (0.018)	-0.038 (0.033)	0.002 (0.023)
Overseas residence * queen weight matrix	-0.003 (0.005)	0.002 (0.010)	-0.001 (0.007)
Pacific * queen weight matrix	0.003 (0.002)	0.000 (0.004)	-0.000 (0.002)
Maori * queen weight matrix	0.004 (0.003)	-0.003 (0.007)	0.007 (0.005)
Asian * queen weight matrix	0.006 (0.003)*	-0.009 (0.006)	-0.001 (0.004)
European		*Control variable*	
Moran's I (residuals)			
Chi^2	741.38***	563.65***	529.69***
R^2	0.670	0.602	0.596
Breusch-Pagen test for independence		47.323***	

Notes: *n* = 369. Standard errors in parentheses; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively; queen contiguity weight matrices employed.

Table 6: Out of labour force base

	FT employment	PT employment	Unemployment
	(1)	(2)	(3)
Intercept	0.245 (0.317)	-1.099 (0.309)***	-0.483 (0.427)*
Geographically weighted LHS variables	0.323 (0.061)***	0.259 (0.060)***	0.453 (0.033)***
Initial value	-0.389 (0.032)***	-0.651 (0.039)***	0.031 (0.042)
Rental value	-0.000 (0.000)	-0.001 (0.000)***	-0.001 (0.000)***
Home ownership	0.000 (0.001)	-0.002 (0.001)*	-0.002 (0.002)
Vehicle access	0.076 (0.285)	0.623 (0.261)**	1.054 (0.366)***
Sex ratio	0.000 (0.001)	-0.000 (0.001)	0.001 (0.002)
Dependency ratio	-0.237 (0.124)*	-0.342 (0.114)***	0.052 (0.164)
1-parent families	-0.003 (0.003)	-0.001 (0.003)	0.007 (0.004)*
2-parent families	0.000 (0.002)	0.005 (0.002)***	0.005 (0.002)**
Family		Control variable	
School qualifications	-0.004 (0.003)	-0.003 (0.003)	-0.001 (0.004)
Post-school qualification	0.011 (0.005)**	0.025 (0.004)***	-0.028 (0.006)***
Bachelors degree	0.014 (0.006)**	0.008 (0.006)	0.060 (0.008)***
Post graduate qualification	-0.004 (0.012)	0.008 (0.011)	-0.083 (0.015)***
No school qualifications		Control variable	
Overseas residence	0.000 (0.003)	0.004 (0.003)	-0.006 (0.004)
Pacific	0.001 (0.001)	-0.000 (0.001)	-0.002 (0.002)
Maori	0.002 (0.002)	-0.002 (0.002)	-0.005 (0.003)*
Asian	-0.005 (0.002)**	-0.009 (0.002)***	-0.002 (0.003)
European		*Control variable*	
Moran's I (residuals)			
Chi^2	349.70***	599.11***	519.38***
R^2	0.433	0.573	0.582
Breusch-Pagen test for independence		248.027***	

Notes: *n* = 369. Standard errors in parentheses; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively; queen contiguity weight matrices employed.

Table 7: SUR with spatially-lagged variables: Out of labour force base

	FT employment	PT employment	Unemployment
	(1)	(2)	(3)
Intercept	0.205 (0.318)	-0.961 (0.316)***	0.631 (0.447)
Dependent variables * queen weight matrix	0.472 (0.065)***	0.352 (0.066)***	0.453 (0.033)***
Initial value	-0.432 (0.033)***	-0.664 (0.041)***	0.032 (0.042)
Rental value	-0.000 (0.000)	-0.002 (0.000)***	-0.001 (0.000)**
Home ownership	0.001 (0.001)	-0.002 (0.001)	-0.001 (0.002)
Vehicle access	-0.171 (0.279)	0.356 (0.264)	1.099 (0.390)***
Sex ratio	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.002)
Dependency ratio	-0.218 (0.121)*	-0.354 (0.114)***	0.057 (0.168)
1-parent families	-0.002 (0.003)	-0.001 (0.003)	0.008 (0.004)**
2-parent families	0.000 (0.002)	0.005 (0.002)***	0.004 (0.002)**
Family		Control variable	
School qualifications	-0.003 (0.003)	-0.003 (0.003)	-0.001 (0.004)
Post-school qualification	0.015 (0.005)***	0.025 (0.004)***	-0.027 (0.006)***
Bachelors degree	0.012 (0.006)**	0.008 (0.006)	0.062 (0.008)***
Post graduate qualification	-0.005 (0.011)	0.008 (0.011)	-0.087 (0.015)***
No school qualifications		Control variable	
Overseas residence	-0.000 (0.003)	0.003 (0.003)	-0.005 (0.004)
Pacific	0.002 (0.001)	-0.000 (0.001)	-0.003 (0.002)
Maori	0.000 (0.002)	-0.002 (0.002)	-0.006 (0.003)*
Asian	-0.003 (0.002)	-0.007 (0.002)***	-0.003 (0.003)
Initial value * queen weight matrix	0.248 (0.041)***	0.158 (0.038)***	0.014 (0.039)
Rental value * queen weight matrix	0.000 (0.001)	0.000 (0.000)	-0.000 (0.001)
Home ownership * queen weight matrix	0.001 (0.003)	0.004 (0.003)	-0.001 (0.004)
Vehicle access * queen weight matrix	-0.977 (0.475)**	-1.400 (0.458)***	1.018 (0.658)
Sex ratio * queen weight matrix	0.003 (0.002)	0.005 (0.002)***	0.000 (0.003)
Dependency ratio * queen weight matrix	0.051 (0.178)	0.069 (0.171)	-0.268 (0.245)
1-parent families * queen weight matrix	-0.006 (0.006)	-0.001 (0.005)	0.013 (0.008)*
2-parent families * queen weight matrix	0.005 (0.003)	0.006 (0.003)*	-0.001 (0.005)
School qualifications * queen weight matrix	0.000 (0.006)	0.001 (0.006)	-0.005 (0.008)
Post-school qualification * queen weight matrix	0.009 (0.009)	0.000 (0.009)	-0.023 (0.013)
Bachelors degree * queen weight matrix	0.010 (0.013)	0.005 (0.013)	0.009 (0.018)
Post graduate qualification * queen weight matrix	-0.000 (0.024)	0.005 (0.023)	-0.043 (0.032)*
Overseas residence * queen weight matrix	-0.007 (0.007)	-0.003 (0.007)	-0.003 (0.010)
Pacific * queen weight matrix	0.002 (0.002)	-0.001 (0.002)	-0.002 (0.003)
Maori * queen weight matrix	0.008 (0.005)*	0.003 (0.006)	-0.019 (0.006)***
Asian * queen weight matrix	0.004 (0.004)	-0.001 (0.004)	-0.001 (0.006)
European		*Control variable*	
Moran's I (residuals)			
Chi^2	428.03***	649.84***	560.52***
R^2	0.502	0.604	0.600
Breusch-Pagen test for independence		241.090***	

Notes: *n* = 369. Standard errors in parentheses; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively; queen contiguity weight matrices employed.