Homeownership and New Zealand labour market flexibility: a spatial perspective*

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Abstract
Since the early 1990s, the proportion of New Zealand households living in owner occupied dwellings has declined markedly. Over the same period there has been a decline in the long-run rate of unemployment. Several demand, supply and institutional factors are responsible for the downward trend in unemployment, but this paper investigates the possible connection with homeownership. Andrew Oswald argued in a series of working papers in the 1990s that homeownership is detrimental to labour market flexibility because of transaction costs that home owners must incur when a job change necessitates a change of residence. An extensive theoretical and empirical literature on this hypothesis has emerged internationally, including in Australia. Using econometric models for panel data, we find evidence supporting the Oswald hypothesis – based on 1986, 1991, 1996 and 2001 census data for labour market areas. However, other contributions to this literature using regional data suffer potentially from misspecification due to a common absence of accounting for the influence of spatial autocorrelation and/or spatially lagged unemployment rates. We find strong support for the robustness of the Oswald hypothesis under the assumptions of spatial econometric models.

Keywords: Oswald's hypothesis, unemployment, homeownership, labour market flexibility, spatial modelling

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1. Introduction

Two decades ago New Zealand (NZ) was on a path of radical economic liberalisation that led to a significant restructuring and transformation of the economy. It was inevitable that such change would lead to massive job losses, particularly in the previously protected manufacturing sector, and a mismatch between job seekers and any jobs created in the transformation process. As can be seen from Figure 1, the unemployment rate peaked at 12% by 1991 and the NZ Government at that time responded with extending the economic reforms to the labour market through the introduction of the Employment Contracts Act (ECA) which promoted individual contracts and weakened the scope of collective bargaining and the power of trade unions. Subsequently, unemployment declined markedly and reviews of the reforms such as Evans et al. (1996) attributed this in part to the success of the ECA in enhancing labour market flexibility. A formal assessment of the impact of labour market reform is actually easier said than done (Gorter and Poot 1999) but there is little disagreement that the economic reforms, including the ECA, and external economic forces, such as globalisation, contributed to growing inequality, lesser social cohesion and increasing vulnerability of certain regions and population groups throughout the 1990s. This led to a political change of direction following the 1999 election of a left of centre coalition government and to various "corrections" to the reforms, including new labour relations legislation in the form of the Employment Agreements Act (EAA) that provided greater scope for collective bargaining and worker protection. The trend in the unemployment rate remained actually downward during this time of reintroduction of somewhat greater regulation of the labour market, as a result of buoyant economic conditions in recent years.

One trend that has coincided with the long-run decline in the unemployment rate since the early 1990s is a long-run decline in the rate of homeownership, at least in terms of owner-occupied dwellings. The number of persons owning one or more rental properties has actually increased, but the proportion of the NZ households living in owner-occupied dwellings has declined from a little less than 74 percent in 1986 and 1991, to 70.5 percent in 1996, 67.8 percent in 2001 and 66.9 percent in

2006. This is also shown in Figure 1.[3] There are several reasons for the decline in homeownership, but the main one being a decline in affordability of ownership due to rapidly rising house prices and relatively high interest rates. At the same time, real rents declined as landlords anticipated returns from capital gains rather than rental revenue. Growing inequality also put homeownership out of reach of those on low incomes.

In a series of working papers and a letter to the *Journal of Economic Perspectives* written in the late 1990s, Andrew Oswald (1996, 1997a, 1997b, 1999) argues that a high rate of homeownership increases the natural rate of unemployment because the transaction costs associated with relocation discourages workers from seeking employment outside their commuting area. Conversely, following this argument, the decline in homeownership observed in New Zealand since the 1980s would have increased geographic mobility and labour market flexibility, contributing to the decline in the long-term rate of unemployment.

There has not been any formal assessment in New Zealand of this possible link, despite Oswald's hypothesis having generated emprical studies in a number of other countries. Skilling (2004, p.19) refers to this hypothesis in a paper that advocates more widespread asset ownership among the New Zealand population, including of dwellings, but then downplays the possibility of homeownership having what he calls a "dark side" in terms of generating unemployment by referring to US evidence by Glaeser and Shapiro (2002) and Australian evidence by Flatau et al. (2003) that does not appear consistent with the Oswald hypothesis. Indirectly, some NZ econometric modelling by Maré and Timmins (2004) also contradicts the Oswald claim. Maré and Timmins estimate the responsiveness of the number of internal migrants to relative employment conditions in origin and destination regions and then interact this effect with home ownership rates. They find that responsiveness to relative employment performance is *greater* when more homes are owner-occupied, which is the opposite of what the Oswald hypothesis would suggest. However, their model analyses the spatial variation in mobility rates rather than unemployment rates per se.

The purpose of this paper is to investigate the Oswald hypothesis directly using a panel of observations on New Zealand labour market areas from 1986 to 2001.

[3] Homeownership rates are only available from the NZ Census of Population and Dwellings, so that a bivariate correlation with unemployment rates cannot be calculated. It should also be noted that there have been changes in the census questions on homeownership that may affect the intercensal comparison.

Having only access to grouped data at present, there are limitations to the extent to which the available data can test the hypothesis, but the uses of a panel ameliorates to some extent the missing variables bias that is likely to affect a purely cross-sectional analysis. Also, we will take the possible two-way causality between homeownership and unemployment into account by means of panel estimators that account for endogenous regressors. Furthermore, we will apply spatial econometric techniques to our panel data. This improves the efficiency and consistency of the estimation. The issue of spatial autocorrelation has actually not been considered earlier in this literature, despite the observation that there is considerable spatial dependence in unemployment rates (see e.g. Longhi et al. 2006 for German regions).

The next section provides a brief review of the international literature and its relevance in the NZ context. Section 3 discusses the results of a standard OLS specification of a model explaining the regional variation in unemployment rates. Section 4 then reports the results of the estimation of panel models that do not explicitly consider spatial dependence. Spatial panel models are reported in Section 5. The final section sums up and gives some suggestion for further NZ-based research.

2. Homeownership and unemployment: the issues

In a background paper written for a 1997 inaugural lecture, Andrew Oswald posits that the increase in homeownership in several European countries is an important cause of the upward trend in the unemployment rate in those countries (Oswald 1996). He argues that the primary reason is that homeowners are geographically less mobile and that an increase in the proportion of the population living in owner-occupied dwellings could therefore lead to less labour market flexibility and higher unemployment.

As the empirical evidence about this hypothesis to date has already been reviewed before (e.g., recently: Munch et al. 2006; Rouwendal and Nijkamp 2006), the review here can be brief and will identify some causes of apparently contradicting evidence.

There would be general agreement that geographic mobility involves costs and benefits and that as costs increase for given benefits mobility will therefore decrease. There would also be general agreement that there are significant transaction costs in the sale and purchase of a dwelling and owners may therefore be less inclined to look for employment opportunities outside the commuting range, as compared with renters. In addition, increasing duration of residence yields a nonpecuniary benefit in the form of attachment that tends to be greater for owners than renters as the former have a greater opportunity to modify the dwelling attributes (in terms of alterations, landscaping etc.) to suit individual tastes. These modifications are a type of location-fixed capital that is lost with a move.

Besides the plausible arguments why homeowners have lower migration rates (and are more likely to commute over longer distances) there is also plenty of empirical evidence that confirms that migration rates among homeowners are lower, all else being equal. For New Zealand, see e.g. Poot (1984, Chapt 7). The question is whether it is possible to identify an unbiased effect of ownership rates, via the mobility and job search effects, on the natural rate of unemployment.

Oswald (1996) simply considered bivariate correlations between unemployment rates and homeownership rates for (pooled) cross-sections of OECD countries, and regions in the US, UK, France, Italy and Sweden. He considers the evidence sufficiently robust to posit a stylized fact of a 1 percentage point increase in the rate of homeownership leading to a 0.2 percentage point increase in the unemployment rate. However, such an estimate is likely to be subject to omitted variable bias as there are various other determinants of a region's unemployment rate that are correlated with homeownership rates, such as the age structure and the average level of education of the population. The subsequent literature proceeded therefore along two lines: fully specified models of regional unemployment rates that include homeownership as a (possibly endogenous) covariate and micro-level research that investigates how homeownership can affect the likelihood of job quitting and search behaviour.

The macro-level studies initially supported the Oswald hypothesis (see Pehkonen (1997) using Finish regional data; Partridge and Rickman (1997) using US state data; and Nickell and Layard (1999) using OECD country data), but subsequent studies are less conclusive (e.g. Flatau et al. 2002 using Australian data) or even reject the hypothesis (e.g., Green and Hendershott 2001, using US data).

One explanation for differences between macro studies is the extent to which the data are driven by cross-sectional (i.e. static) variation or by changes over time (such as the Fixed Effects or "within" estimator in panel data). Even without a formal meta-analysis, it is plausible that the latter type of data is likely to yield an on average larger effect, as was confirmed by Oswald's original study (1996, p. 15). The reason is that cross-sectional composition effects on the supply side, such as age and education, and labour demand effects (higher incomes in more prosperous regions) shift the regression coefficient in the opposite direction, suggesting an inverse relationship between a region's unemployment rate and the proportion of dwellings owner-occupied. In the New Zealand case, this is illustrated in Figure 2 that provides a cross-sectional scatter plot of unemployment rates and homeownership rates derived from recently released 2006 census data. Figure 2a displays a negatively sloped linear cross-sectional relationship across the 16 Regional Council regions. At the more refined spatial level of 73 Territorial Local Authorities, the inverse relationship remains but it is clear that the correlation is less. A map at this level would show that there is instead at this level significant spatial correlation: TLAs with high/low unemployment rates are likely to be surrounded by other TLAs with high/low unemployment rates and similarly for homeownership rates. Over time, all regions experienced qualitatively similar changes in homeownership rates and unemployment rates as displayed in Figure 1 at the national level (see Pool et al. 2005). Thus, results from regression modelling are likely to depend on, firstly, the extent to which the results are driven by cross-sectional versus time series variation and, secondly, the extent to which co-variates and the estimation technique is likely to account for omitted variable bias, simultaneity and spatial dependence. The New Zealand evidence in the subsequent section confirms this.

There is also a measurement issue with respect to homeownership that is important. Homeowners without mortgages have significant wealth and may search for jobs locally for longer than those whose mortgage repayment obligations lower their reservation wage (see e.g. Flatau et al. 2003 for Australian evidence and Goss and Phillips 1997 using US panel data). In addition, renters of public housing may lose their subsidy with migration and have therefore lower mobility than owners. Household structure matters too. Single persons are more likely to be in a rental (or 'flatting" situation) and therefore less likely to have job search constrained by the "tied stayer" phenomenon (where a potential wage gain from migration would be more than offset by an implied wage loss for the partner).

The micro level research that followed the earlier macro level studies of the Oswald hypothesis have been specifically focussed on such issues as the impact of the type of ownership and the structure of households on quits and job search behaviour.

These studies are also reviewed in Munch et al. (2006) and Rouwendal and Nijkamp (2006) and because the present paper is concerned with regional level macro data, we will not review these here. Rouwendal and Nijkamp (2006) conclude that the micro level studies almost unanimously reject the Oswald hypothesis. There is general empirical support for the idea that homeownership lowers geographic mobility but it does not logically follow that homeowners therefore experience longer unemployment spells. Instead, even controlling for human capital characteristics, homeowners appear to have higher exit rates from unemployment.

In conclusion, we note that there is some (but not uniform) support for the Oswald hypothesis at the macro level and yet the obvious explanation in terms of job search behaviour appears contradicted by micro level evidence. The questions is therefore (1) the extent to which the macro level evidence is spurious, or at least robust under a wide range of econometrics specifications, and (2) the need for a theoretical reconciliation of the macro and micro evidence. The latter has already been attempted by Dohmen (2005), but here we revisit the former issue with New Zealand data and specifically take account of spatial dependence, an issue that in the context of the Oswald hypothesis had not yet been considered before.

3. Cross-sectional results

The data for our analysis were obtained from the quinquennial New Zealand Census of Population and Dwellings 1986 to 2001. 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 & 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 & Papps, 2001; ONS & 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. By setting boundaries of commuting areas such that cross-boundary commuting is rare relative to within-boundary commuting, the resulting geographic areas reflect the theoretical idea of a self-contained local labour market better than administrative boundaries. This research yielded 140 LMAs for 1991 and 106 for 2001. However, 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 3. Table 1 describes the principle characteristics of the variables used in this analysis along with a brief definition of the variable. A feature that stands out from this table is the considerable heterogeneity that exists between LMAs on the variables of interest in this analysis. For instance the rate of unemployment in the LMA with the highest level of unemployment is on average 6 times that of that with the lowest in this period. Similarly the rate of homeownership is on average 28 percentage points higher in the LMA with the highest rate of home ownership than the lowest. Perhaps most strikingly the usually resident population of the LMA's ranges from a few thousands in the smallest to well over half a million in the largest.

The dependent variable in the regression analysis is the LMA unemployment rate. The explanatory variables are:

(i) the percentage of the LMA population in owner-occupied dwellings at the time of the previous census (lgpoprop_). The lag is introduced to avoid the problem of reverse causality. The Oswald hypothesis is that the coefficient of lgpoprop_ is positive (and likely to be around 0.2).

(ii) the predicted percentage employment growth over the pre-census intercensal period assuming each industry in the region grew at the national growth rate of that industry. This is a Bartik index that measures the impact of region's being endowed with nationally growing or declining industries. The coefficient is expected to be negative.

(iii) the percentage of the LMA population in single person households at the time of the previous census (lgpsphhlds). An increase is single person households is expected to increase labour supply and unemployment.

(iv) the percentage of the population aged 40 and over (midoldpopr). As labour turnover and unemployment rates are much higher for the young than for older workers, this variable is expected to have a negative coefficient.

(v) the percentage of the population of Maori ethnicity (maorir). Although the gap has decreased in recent years, Maori unemployment rates are much higher than unemployment rates among the Pakeha (European non-Maori) population. The coefficient is therefore expected to be positive.

(vi) the percentage of the population of Asian ethnicity (asianr). Note that multiple ethnicity is included in both Maori and Asian ethnicity measurement. Given that a relatively large number Asians are migrants and that particularly recent migrants experience a labour market disadvantage, the coefficient is also expected to be positive.

(vii) the percentage of the population in manual occupations. Given that economic restructuring has been particularly detrimental to manufacturing employment, a positive coefficient is expected.

(viii) pre-census intercensal net migration as a percentage of the end-of-period population. It has been commonly observed that, while unemployment obviously not a pull facto for migrants, net inward migration leads to greater labour amrket churning and therefore higher unemployment rates. The coefficient is therefore expected to be positive.

The results of a standard pooled OLS regression are shown in Table 2.[4]. As hypothesized by Oswald the coefficient of the homeownership rate is significant and positive. The estimated coefficient is 0.355 which is rather than more Oswald's suggested stylized fact of a coefficient of 0.2. The other coefficients are all statistically significant at the 5 percent level or better and have expected signs, except for the coefficient on manual that suggests that, all else being equal, unemployment

[4] All calculations referred to in this paper were conducted either using STATA or the freely available MatLab econometric toolbox by James Le Sage (available from http://www.spatial-econometrics.com/) and the Matlab spatial panel m files of J P Elhorst. An earlier version of these m files is included in the econometric toolbox however the latest version of these files is available from Elhorst's website http://www.rug.nl/economics/faculty/medewerkers/elhorstjp/software.

rates are lower in LMAs with a relatively large proportion of the population in manual occupations.

Table 2 also reports some diagnostics commonly used to identify misspecification in OLS cross-sectional models.[5] The Jarque-Berra test is far from significant indicating that we can have confidence that the OLS estimate errors are normally distributed. Similarly, the Breusch-Pagan statistic and robust White statistic give us no cause to reject the assumption of homoscedasticity.

However, there are several objections to the pooled OLS approach. Firstly OLS does not exploit the panel structure of the data; that is the repeated observations on the same regions over time. This is particularly serious in this case as not all factors determining differences in unemployment across regions are likely to be observed. As some of the omitted variables are likely to be correlated with the included variables, OLS will yield biased parameter estimates. Additionally the impact of a determinant of unemployment changing over time within a region may be different from the impact of the same determinant changing cross-sectionally relative to other regions. These shortcomings are widely known and covered in most econometric texts (see for example Stock and Watson (2003, Chapt 8), Verbeek (2004, Chapt 10) or for a more advanced treatment Baltagi (2005)).

The second difficultly with a pooled OLS approach relates to the potential presence of spatial dependence when using regional data. In the present application, spatial autocorrelation diagnostics show that this type of spatial dependence is indeed present (see Table 2).[6] The Moran I statistic is significant at the 1 percent level.[7]. This is further confirmed by the significance of Lagrange Multiplier tests of spatial autocorrelation. This causes problems for the OLS estimator as the presence of

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[5] The model diagnostics are those suggested in Anselin (2005, Chapt 22) and Arbia et al. (2005, pp., 17 -22)

[6] Spatial dependence takes two forms; spatial autocorrelation which is the presence of systematic spatial variation in a variable (Haining, 2001, 14763) or spatial heterogeneity which refers to changing structure or changing association across space or, more formally in a regression setting, structural instability in the form of non-constant error variances (heteroskedasticity) or model coefficients (variable coefficients, spatial regimes). The two are not mutually exclusive and may be observationally equivalent in a given set of cross sectional data (Anselin, 1999).

[7] Moran's *I* may be thought of as a translation of a non-spatial correlation coefficient, such as the Pearson's correlation coefficient, to a spatial context (O'Sullivan & Unwin, 2003, 197-201). Mathematically, the similarity is strong with both the Pearson's correlation coefficient and Moran's *I* having a covariance term as numerator and the sample variance as a denominator. Also like the correlation coefficient, the values of Moran's *I* range from close to +1 meaning strong positive spatial autocorrelation, to 0 meaning a random pattern, to close to -1 indicating strong negative spatial autocorrelation (Oliveau & Guilmoto, 2005)

correlated errors violates the Gauss-Markov assumption of uncorrelated random errors and more broadly the assumption of independence between observations. The consequences of ignoring the presence of spatial dependence in the data are non-trivial and unlike some other difficulties, such deviations from normality, are not often over come by simple transformations of the data. In the presence of spatial dependence (Rao, 1973) and Haining (1990; 2001) have found that OLS estimators are usually not optimal, while Underwood (1997) found that in the presence of positive spatial autocorrelation variance estimates are biased downward thereby increasing the likelihood of type 1 errors. Furthermore the presence of positive spatial autocorrelation that is not taken into account in regression analysis 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).

4. Non-spatial panel models

To improve on the estimates obtained by OLS we used several estimators for models of panel data.[8] The advantages of these models in dealing with pooled cross-section time-series data, such as we have here, is well established. Panel models can control for cross-sectional heterogeneity, are more informative than either pure time-series or cross-sectional models, present more variability and less collinearity, and can provide more efficient parameter estimates (Baltagi, 2005).

The standard test for differentiating between fixed and random effects in panel models is the Hausman specification test (Baltagi et al., 2003, p. 362). This test was performed and showed that the fixed effects model was the more appropriate in this instance (the results for the fixed effects estimator are shown in Table 3). It should be noted that the random effects specification would have been arguably inappropriate in any case in the present context because we are not concerned with a random draw of spatial units from a very large population but rather an exhaustive sampling (Nerlove

[8] Any standard econometrics text will include details of the derivation of these models; see for instance Stock and Watson (2003, Chapt 8), Verbeek (2004, Chapt 10) or for a more advanced treatment Baltagi (2005)).

& Balestra, 1996, p. 4) of LMAs in New Zealand and the effects that are in this particular sample.[9]

From the fixed effects results (see Table 3); the coefficient on the home ownership variable (lgpoprop) takes the expected sign, is statistically significant and has a magnitude similar to that found by Oswald (0.2) although it is around one third smaller than that obtained by the pooled OLS estimator (Table 2). Of the other variables only those for expected employment growth (pbgindlma), the proportion of the population aged 40 years and over (midoldpopr) and net-migration (netmig) remain significant at traditional levels. The estimate of rho (0.9333) suggests that a very high proportion of the unexplained variance in the unemployment rates comes from cross-sectional variation rather than time-series variation. The post estimation F test (F(57, 108)=18.44) indicates that there are significant individual (LMA) effects, underlining the inappropriateness of using a pooled OLS estimator.

As Baltagi et al. (2003, p. 362) point out however, the fixed and random effects estimators represent an 'all or nothing' choice between either assuming the exogeneity of all the regressors and the random individual effects (random effects) or assuming endogeneity of all the regressors and the individual effects (fixed effects). Taking an approach intermediate between these extremes, Hausman and Taylor (1981) proposed an estimator, based upon an instrumental variable approach which uses both the between and within variation of the strictly exogenous variables as instruments, and in which some of the regressors are correlated with the individual effects (Baltagi, 2005).

Table 4 shows the results for the Hausman Taylor estimator.[10]. Again the coefficient on the home ownership variable (lgpoprop) is of the correct sign, significant and intermediate between the estimates obtained by pooled OLS and Fixed effects estimators. Of the other variables included in the model all are significant with the exception of those for the proportion of single person households (lgpsphhlds_) and the average proportion of Asian persons (av_asian).

[9] This point, in the context of spatial panels, is discussed in more depth in Elhorst (2003; 2005)

[10] The variables for the proportion of the population who are Maori (maorir) or Asian (asianr) are dropped while two variables av_maori, the average proportion of the population who are Maori 1986-2001, and av_asian, the average proportion of the population who are Asian 1986-2001 are included time invariant exogenous variables.

5. Spatial models

Given that spatial dependence violates the assumptions required for optimality of the OLS estimator, a number of methods have been developed to account for such spatial dependence. Commonly this is done in one of two ways:[11] (1) spatial lag dependence - which pertains to spatial correlation in the dependent variable, or (2) spatial error dependence in which the error terms are spatially correlated (Anselin, 1988). 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)

$$y_i = g\left(\mathbf{y}_{J_i}, \theta\right) + \mathbf{x}_\mathbf{i}'\boldsymbol{\beta} + \varepsilon_i \qquad (1)$$

Where J_i includes all the neighbouring locations j of i (but of course $j \neq i$).While the function g can be in principle very general and non-linear, in practice it is usually a linearly weighted combination of the values of the dependent variable in the neighbouring locations, with the weights together forming the spatial weights matrix. This concept of a spatial weights matrix is central to many of the methods developed to deal with spatial data (Anselin et al., 2000, p. 231). The spatial weights matrix is a square matrix of dimension equal to the number of observations, with each row and column corresponding to a spatial unit. In its simplest form, an element w_{ij} of the weights matrix **W** is one if locations i and j are neighbours, and zero otherwise (the diagonal elements w_{ii} also equal zero). Commonly the weights matrix is row standardized so that weights add up to 1 when summing over j as this facilitates interpretation and comparison across models. A wide range of criteria may be used to specify the spatial weights matrix with Getis and Aldstadt (2004) identifying no fewer than 8 commonly used methods[12] and a plethora of lesser known or emergent approaches.[13] It should be noted that the construction of spatial weights matrices are not limited to geographic or Euclidean distance (Beck et al., 2005, 1; Leenders, 2002)

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

[12] Spatial contiguity, inverse distances raised to some power, length of shared borders divided by the perimeter, n^{th} nearest neighbours, ranked distances, constrained weights for an observation equal to some constant, all centroids within distance d and band width as the n^{th} nearest neighbours distance (Getis & Aldstadt, 2004, p. 91)

[13] 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)

but maybe constructed on the basis of any kind of spatial interaction, such as the flow of goods or persons or the regularity of air or train services between places. Indeed Conley (Conley & Topa, 2002) take this even further by constructing indexes of distance between areas based on sociological factors, such as ethnicity or occupational structure. A more detailed discussion of spatial weights matrices maybe found in Bavaud (1998).

In matrix notation then, simplifying g through the use of the spatial weights matrix **W**, we have the spatial lag model, what has been called the 'mixed regressive, spatial autoregressive model' (Anselin, 1988):

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{2}$$

with ρ being the spatial autoregressive coefficient[14] and $\boldsymbol{\varepsilon}$ an independently and identically distributed (i.i.d.) error term.

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),[15] we have;

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

where y is a vector of observations on the dependent variable, **W** is again the spatial weights matrix, **X** is a matrix of observations on the explanatory variables, $\boldsymbol{\varepsilon}$ is a vector of spatially autocorrelated error terms, **u** a vector of i.i.d. errors, and λ and $\boldsymbol{\beta}$ are parameters (Anselin, 2001, 2005, forthcoming).

It is important, however, to be clear that the above approaches are not merely clever exercises in matrix algebra designed to overcome some shortcoming in the

[14] 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_{J_i}.

[15] 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).

OLS estimator but that they instead attempt to model actual spatial processes. In the case of cross sectional spatial lag models, the specification of the model is typically conceived of as a formal representation of the equilibrium outcome of processes of social and spatial interaction in which the dependent variable for one agent is jointly determined with that of neighbouring agents (Anselin, forthcoming; Anselin et al., forthcoming). In the spatial error model it is assumed that some shocks or unknown effects that are not explicitly modelled spill over across the units of observation and induce spatial correlation in the error terms. Anselin (forthcoming) cites the example (Dubin, 1988) of hedonic house price models in which it is often assumed that neighbourhood effects that are extremely difficult to quantify are shared by houses in similar locations and hence give rise to spatial correlated error terms.

The extension of these, and other, spatial models to a panel setting has become increasingly common, motivated perhaps by the desire to capture both spatial effects and to retain the advantages panel models enjoy over cross sectional estimators. However, despite a considerable amount of theoretical development a number of controversies remain, such as the appropriateness of the random effects specification in spatial settings (Elhorst 2003; 2005), and, at least until recently, a dearth of software available to run these models on.[16]

In this paper we will consider two models, the fixed-effects spatial lag model and the fixed-effects spatial error model. The random-effects model is not considered as it would be inappropriate, as noted earlier, given that we are concerned with an exhaustive sampling of LMAs in New Zealand and the effects that are contained in this particular sample.

Extension of the cross sectional spatial lag model of equation (2) to a panel is relatively straight forward (Anselin et al., forthcoming). Starting with the cross section spatial weights matrix $\mathbf{W}_N$ where the subscript N denotes the number of cross-sectional units, and the weights are assumed constant over time, the full weights matrix for a panel of T time periods becomes;

$$\mathbf{W}_{NT} = \mathbf{I}_T \otimes \mathbf{W}_N \qquad (4)$$

[16] The spatial tool box in Matlab now provides excellent software for these models.

where I_T is an identity matrix of dimension T. From this it follows that for the spatially lagged dependent variable we have:

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

in which $\mathbf{y}_{NT}$ now refers to the column vector in which the observations of each cross-section are stacked, i.e. $\mathbf{y}_{NT}' = (\mathbf{y}_1', \mathbf{y}_2', ..., \mathbf{y}_T')$ and $\mathbf{y}_t'$ the cross-section of N observations at time t. The specification of the spatial panel lag model is then

$$\mathbf{y}_{NT} = \rho(\mathbf{I}_T \otimes \mathbf{W}_N)\mathbf{y}_{NT} + X_{NT}\boldsymbol{\beta} + \varepsilon_{NT} \tag{6}$$

with ρ again being the spatial autoregressive coefficient.

The extension to the spatial error model is again straightforward, i.e. now we have similar to (3):

$$\mathbf{y}_{NT} = \mathbf{X}_{NT}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{NT} \text{ with } \boldsymbol{\varepsilon}_{NT} = \lambda(\mathbf{I}_T \otimes \mathbf{W}_N)\boldsymbol{\varepsilon}_{NT} + \mathbf{u}_{NT} \tag{7}$$

The estimation of (6) and (7) is done by maximum likelihood methods that are discussed in e.g. Elhorst (2003) and Anselin et al. (forthcoming). Below we report the results for the spatial lag and spatial error panel models of unemployment rates in New Zealnd LMAs, but first we briefly discuss the construction of the spatial weights matrix used in our analysis.

As is obvious from the specification of the spatial panel models, the construction of the spatial weights matrix is a central issue. For this paper we have chosen to use a spatial weights matrix based upon the reciprocal of the square of travel times between the largest urban areas in each LMA. We believe that this approach is justifiable on the basis of common practice, the properties of transport cost function, gravity models, and on the broader ground that, as Tobler (1970, p. 236) points out , “Everything is related to everything else, but near things are more related than distant things” . The inverse square relation, of course, by according more weight to near neighbours than those more distant goes someway toward quantifying such a relation.

Table 5 shows the results for the spatial lag model under a number of different specifications, a pooled model with spatially lagged dependent variable and no fixed effects (SLDV), a pooled model with spatially lagged dependent variable and spatial fixed effects (SLDVSFE), a pooled model with spatially lagged dependent variable and time period fixed effects (SLDVTFE) and, lastly, a pooled model with spatially lagged dependent variable, spatial and time period fixed effects (SLDVSTFE).

Under all specifications of the spatial lag model investigated here the home ownership variable (lgpoprop_) is highly significant with parameter estimates ranging from 0.32 in the SLDV model to 0.21 for the SLDVSTFE model. We therefore conclude that there is robust evidence for a macro-level relationship between homeownership and regional unemployment rates in New Zealand.

Given that models of columns (1), (2) and (3) are nested in the model of column (4), the choice of the best model is easily done by taking account of the standard result that twice the difference in loglikelihood has a chi square distribution with degrees of freedom equal to the number of parameter restrictions. Using this criterion, it is obvious that the SLDVSFE model of column (2) is the preferred model. The hypothesis of zero time fixed effects cannot be rejected and the inclusion of such effects also leads to the incorrect conclusion of insignificance of the spatial lag.

Considering only the spatial panel lag models, and comparing these to the standard fixed effects and Hausman Taylor estimator, the spatial lag model yields parameter estimates some 5-11 percent lower than the standard fixed effects model and 17-23 percent lower than the Hausman Taylor estimator. Hence some of the variation in regional unemployment rates is incorrectly attributed to the explanatory variables rather than to the presence of some spatial spillover effect of unemployment across regions.

As noted above, after time period fixed effects are introduced, the spatial autoregressive coefficient (ρ) ceases to be significant under either SLDVTFE or SLDVSTFE. As time period fixed effects control for omitted variables that are constant between regions but vary over time this would suggest that while there is cross sectional spatial dependence that can not be accounted for by spatial fixed effects, over time there are no national effects that are not captured by any of the included explanatory variables.

On the whole, the economic variables in the SLDVSFE model perform as expected, with the percentage of manual workers which had an unexpected sign in the earlier model now no longer significant.

Table 6 shows the results for the spatial error model under 4 specifications analogous to those undertaken for the spatial lag model, i.e. a pooled model with spatial error autocorrelation and no fixed effects (SEM), a pooled model with spatial error autocorrelation and spatial fixed effects (SEMSFE), a pooled model with spatial error autocorrelation and time period fixed effects (SEMTFE) and a pooled model with spatial error autocorrelation, spatial fixed effects and time period fixed effects (SEMSTFE).

As with the spatial lag models in the spatial error models the home ownership variable (lgpoprop_) is highly significant under all specifications considered. However, the range of parameter estimates for the home ownership variable is considerably less, ranging from around 0.24 in SEMSFE to 0.215 in SEMSTFE , than in the spatial lag models. Of the other variables we find again that net migration (net_mig) and the proportion of persons aged 40 and over (midoldpopr) are significant across all specifications of the spatial error model considered.

With the introduction of fixed effects, either spatial or temporal, to the spatial error model the spatial auto regressive parameter (spat.aut) ceases to be significant. Comparing the SEMSFE model to the standard fixed effects estimator we find that the estimates are nearly identical. The similarity of the standard fixed effects and SEMSFE model is not surprising given the insignificant spatial auto regressive parameter (spat.aut) in the latter.

With respect to the home ownership variable, the Hausman Taylor parameter estimates are considerably higher than either the SEMFE, SEMTFE or SEMSFTE results. The Hausman Taylor estimator has given consistently higher estimates of the parameter on the home ownership variable (lgpoprop) than either the standard fixed effects or spatial models, giving rise to some concern over whether appropriate instruments (exogenous variables) had been identified..

The issue arises of which of the general spatial models, lag or error, is most appropriate in this instance. One may take one of a number of approaches to this. Firstly a purely technical approach might be taken in which model selection is made on the basis of some formal test, usually a Lagrange multiplier or Rao Score test (Anselin et al., forthcoming). Secondly the choice as to which model is appropriate might be based on an *a priori* theoretical consideration such as whether we consider the relationship between the unemployment rate in a given region and its neighbours to arise from interaction, through trade or migration for instance, (the lag model) or through spillovers arising from specific shocks (the error model). Thirdly, and lastly, Arbia et al.(2005, p. 26) take a pragmatic approach to differentiate between lag and error models basically by asking the question whether or not the parameter estimates differ appreciably from those obtained by a classical fixed effects approach.

Our preference is for the lag model, particularly the SLDVSFE variant, is based on the second and third of these considerations. The object of this paper speaks to long term structural relations as opposed to transient shocks hence our interest is in models of interaction such as those that are implicit in the lag approach. There would also appear to be little to gain from adopting the spatial error approach, as opposed to the classic fixed-effects model, as, at worst, the parameter estimates on the home ownership variable (lgpoprop) are virtually indistinguishable from the fixed-effects model.

6. Conclusions

This paper provides the macro-level evidence of a relationship between homeownership and unemployment in New Zealand. Given that New Zealand experienced a notable decline in the proportion of the population in owner-occupied dwellings at the same time as the rate of unemployment has been on a downward trend, a study of whether a link between these two trends is either spurious or instead robust to well-specified econometric models is clearly of scientific interest as well as of policy significance.

We use pooled data on 58 Labour Market Areas observed at the times of the 1986, 1991, 1996 and 2001 population census and formulate the panel models that this type of data permits. We find that the homeownership rate has a positive and significant effect on the regional unemployment rate in a standard OLS specification, but that that this effect remains significant across a wide range of specifications that account for departures from the standard linear model. These include the use of regional fixed or random effects, endogeneity of the homeownership variable and the presence of spatial dependence. All estimates are of the order of 0.2 to 0.3, and the statistically most satisfactory model yields a coefficient of 0.2164 which is very close to Oswald's suggested stylized fact of an increase in homeownership of 1 percentage point leading to an increase in the unemployment rate of 0.2 percentage points.

The question thus arises why the macro evidence in the literature that has tended to be supportive of the Oswald hypothesis in several countries (but not in others) appears inconsistent with the micro evidence, which has been reviewed by Rouwendal and Nijkmap (2006) and which finds a near unanimous rejection of the hypothesis.

While a formal reconciliation of this apparently contradicting evidence at macro and micro levels is beyond the scope of the present paper, we suggest that the key issue may be the differences in job-market related characteristics of home owners and renters that in aggregate yield general (dis)equilibrium effects of decreases in homeownership leading to a more flexible labour market and lower unemployment. People with better labour market outcomes are more likely to be home owners. However, when housing affordability declines, as it did in New Zealand during the last decade and a half, the younger workers among these find themselves less able to purchase and have consequently greater mobility. The international literature does confirm this greater geographical mobility. However, these "potential owners turned renters" may have a lower risk of unemployment (given their human capital characteristics) than those who are the traditional long-term renters. The greater geographical mobility of these "new renters" lowers pressure on the *local* labour market and therefore permits the existing renters a greater proportion of hires in the improving labour market, lowering the local unemployment rate. Thus, one possible reconciliation of the micro and macro evidence is that it is not that home owners have necessarily longer unemployment spells (their unemployment rate will be low at the macro level) but their lower geographic mobility creates greater competition for jobs in the local labour market, thus lowering employment opportunities for the local renters. This type of "dual labour market" interpretation would be consistent with both the macro and micro evidence.

The fact that geographical mobility of owners is more costly than that of renters, ceteris paribus, is not disputed. What matters is the extent to which this affects job search behaviour. Little is know on this in New Zealand, but in future research we plan to investigate this by considering both longitudinal micro data as well as direct evidence by introducing appropriate questions in Computer-Aided Telephone Interviews of a random sample of workers in one or more LMAs.

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Table 1 Data Descriptives

	Year	Net Migration[1]	Population[2]	Home Ownership[3]	Single Person Household[4]	Over 40 Population[5]	Maori Population[6]	Asian Population[7]	Manual Employment[8]	Bartik Index[9]	Unemployment[10]
Label		**'net_mig'**		**'lgpoprop'**	**'lgpsphhlds'**	**'midoldpopr'**	**'maorir'**	**'asianr'**	**'manualr'**	**'pbgindlma'**	**unemprate**
Mean	1986	N/A	56260	71.56	18.05	34.21	15.10	0.74	13.28	N/A	6.74
Median	1986	N/A	22749	72.45	18.17	33.91	12.09	0.53	13.39	N/A	6.67
S.D	1986	N/A	93409	5.77	2.19	3.64	10.51	0.67	2.06	N/A	1.80
Max	1986	N/A	514890	80.15	22.34	42.49	51.63	3.63	18.56	N/A	13.60
Min	1986	N/A	3360	47.99	13.51	23.13	2.79	0.09	8.30	N/A	2.33
Mean	1991	-1.87	58168	72.52	20.14	37.31	16.19	1.19	11.60	-7.96	10.38
Median	1991	-1.99	22002	73.29	20.27	37.03	12.54	0.78	11.58	-8.39	10.02
S.D	1991	7.11	99385	5.43	2.02	3.87	11.39	1.21	1.60	1.89	2.86
Max	1991	21.75	552591	81.14	24.69	46.25	57.16	5.73	14.67	-0.72	21.07
Min	1991	-22.07	3273	51.18	15.32	27.13	3.17	0.23	7.24	-11.98	6.00
Mean	1996	-1.74	62383	70.03	21.08	39.97	18.39	1.66	13.23	14.94	7.51
Median	1996	-2.29	23634	70.63	21.03	39.49	15.17	0.98	13.13	14.34	7.07
S.D	1996	8.76	111061	4.96	2.00	4.03	11.32	1.82	1.68	2.90	2.87
Max	1996	41.14	629432	79.15	25.36	48.46	56.06	9.00	17.75	22.21	18.98
Min	1996	-17.06	3516	51.39	16.03	29.98	4.64	0.40	8.48	9.41	2.33
Mean	2001	-2.41	64433	69.78	24.46	44.36	18.25	2.08	13.94	4.06	7.00
Median	2001	-2.40	23519	70.50	24.60	44.44	15.09	1.18	13.63	3.98	6.36
S.D	2001	6.56	119230.1	4.35	2.14	4.47	11.46	2.45	1.98	1.90	2.88
Max	2001	16.47	680547	77.80	28.79	55.70	57.88	12.84	18.58	9.40	17.99
Min	2001	-19.64	3483	55.12	17.79	36.34	4.47	0.41	9.34	0.36	2.51

1/	Net migration	(net_mig)	Net migration calculated by census survivorship method – see Baxendine et al (2005) for details
2/	Population		The census usually resident population
3/	Home Ownership	(lgpoprop)	The proportion of owner occupied dwellings in LMA
4/	Single Person Household	(lgpsphhlds)	The proportion of single person households in LMA
5/	Over 40 Population	(midoldpopr)	The proportion of the population age 40 years and over
6/	Maori Population	(maorir)	The proportion of an LMA's population who are classed as Maori
7/	Asian Population	(asianr)	The proportion of an LMA's population who are classed as Asian
8/	Manual Employment	(manualr)	The proportion of the LMA's employment in manual occupations
9/	Bartik Index	(pbgindlma)	Predicted growth in employment * 100
10/	Unemployment	(unemprate)	Those age 15 and over who are unemployed as a percentage of the labour force

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Table 2 Ordinary Least Squares Estimates

R-squared	0.7511		
Rbar-squared	0.7391		
sigma^2	2.7024		
Durbin-Watson	1.6734		
Nobs, Nvars	174, 9		

Variable	Coefficient	t-statistic	t-probability
lgpoprop_	0.3550	11.9160	0.0000
pbgindlma	-0.1417	-8.7483	0.0000
lgpsphhlds_	0.3207	3.7498	0.0002
midoldpopr	-0.4030	-7.8480	0.0000
maorir	0.2395	16.7167	0.0000
asianr	0.2298	2.2465	0.0260
manualr	-0.1992	-2.5438	0.0119
net_mig	0.1288	6.3071	0.0000
constant	-9.3260	-4.1108	0.0001

Test on normality of errors			
Jarque-Bera	3.181	Chi-sq (2)	P-value = 0.2038
Diagnostics for homoscedasticity			
Breusch-Pagan	11.84	Chi-sq (8)	P-value = 0.1583
White	45.48	Chi-sq (44)	P-value = 0.4102

Spatial Auto Correlation Diagnostics			
Moran I-test for spatial autocorrelation in residuals			
Moran I	0.1172		
Moran I-statistic	2.8696		
Marginal probability	0.0041		
LM error tests for autocorrelation in residuals			
LM value	5.2582		
Marginal probability	0.0218		
chi(1) .01 value	17.6110		
LM error tests for autocorrelation in SAR model residuals			
LM value	13.9980		
Marginal probability	0.0002		
chi(1) .01 value	6.6350		

Table 3 Fixed Effects Estimates

```
Fixed-effects (within) regression               Number of obs      =       174
Group variable (i): lma                         Number of groups   =        58

R-sq:  within  = 0.9051                         Obs per group: min =         3
       between = 0.3565                                        avg =       3.0
       overall = 0.4730                                        max =         3

                                                F(8,108)           =    128.69
corr(u_i, Xb)  = 0.1389                         Prob > F           =    0.0000

------------------------------------------------------------------------------
   unemprate |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   pbgindlma |  -.0934861   .0099337    -9.41   0.000    -.1131765   -.0737957
   lgpoprop_ |   .2373762   .0493266     4.81   0.000     .1396022    .3351502
      maorir |   .0617004   .0648956     0.95   0.344    -.0669339    .1903347
      asianr |   .0636248   .0952925     0.67   0.506    -.1252613     .252511
 lgpsphhlds_ |   .0827596   .0973051     0.85   0.397     -.110116    .2756352
     manualr |  -.0343912   .0612447    -0.56   0.576    -.1557888    .0870064
  midoldpopr |  -.4089754   .0573612    -7.13   0.000    -.5226754   -.2952755
     net_mig |   .0512736   .0189786     2.70   0.008     .0136548    .0888924
       _cons |   4.706234   4.046869     1.16   0.247    -3.315363    12.72783
-------------+----------------------------------------------------------------
     sigma_u |  2.3201436
     sigma_e |  .62017334
         rho |  .93331549   (fraction of variance due to u_i)
```

Table 4 Hausman Taylor Estimates

```
Number of obs      =       174
Group variable (i): lma                             Number of groups   =        58

Psuedo r square 0.8442                              Obs per group: min =         3
                                                                   avg =         3
                                                                   max =         3
Random effects u_i ~ i.i.d.                         Wald chi2(7)       =   1149.08
                                                    Prob > chi2        =    0.0000
------------------------------------------------------------------------------
   unemprate |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
TVexogenous  |
   pbgindlma |   -.096847   .0066235   -14.62   0.000    -.1098288   -.0838652
  lgpsphhlds_ |   .1004122   .0759445     1.32   0.186    -.0484363    .2492608
  midoldpopr |  -.3541805   .0396445    -8.93   0.000    -.4318823   -.2764788
     net_mig |   .0541606    .015573     3.48   0.001     .0236382    .0846831
TVendogenous |
   lgpoprop_ |   .2748128   .0328597     8.36   0.000     .2104089    .3392167
TIexogenous  |
    av_maori |   .2138981    .024113     8.87   0.000     .1666375    .2611586
    av_asian |   .2343003   .1713876     1.37   0.172    -.1016132    .5702137
             |
       _cons |  -3.636332   3.014722    -1.21   0.228    -9.545078    2.272413
-------------+----------------------------------------------------------------
     sigma_u |   1.801856
     sigma_e |  .60337172
         rho |  .89917381   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table 5 Spatial panel – lagged dependent variable

	Model							
	1		2		3		4	
R-squared	0.7714		0.9779		0.7995		0.9780	
Rbar-squared	0.7589		0.9643		0.7859		0.9638	
sigma^2	2.3535		0.2275		2.0643		0.2263	
Log-likelihood	-322.8635		-119.1725		-310.2452		-118.3763	
Variable	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig
'lgpoprop_'	0.3224	0.0000	0.2164	0.0000	0.2260	0.0000	0.2118	0.0000
'pbgindlma'	-0.1075	0.0000	-0.0728	0.0000	0.0355	0.6009	-0.0424	0.1559
'lgpsphhlds_'	0.3906	0.0000	0.0893	0.2329	0.3453	0.0000	0.1050	0.1730
'midoldpopr'	-0.3821	0.0000	-0.3455	0.0000	-0.1392	0.0313	-0.3208	0.0000
'maorir'	0.2215	0.0000	0.0795	0.1170	0.2516	0.0000	0.0907	0.1056
'asianr'	0.2319	0.0153	0.1042	0.1663	0.3920	0.0003	0.1431	0.1287
'manualr'	-0.0866	0.2577	-0.0101	0.8324	0.0404	0.6023	-0.0036	0.9403
'net_mig'	0.1107	0.0000	0.0441	0.0029	0.0485	0.0362	0.0390	0.0136
W*dep.var.	0.2729	0.0043	0.2350	0.0078	0.1210	0.1389	0.1950	0.0517
'constant'	-12.6832	0.0000	-		-		-	

Model

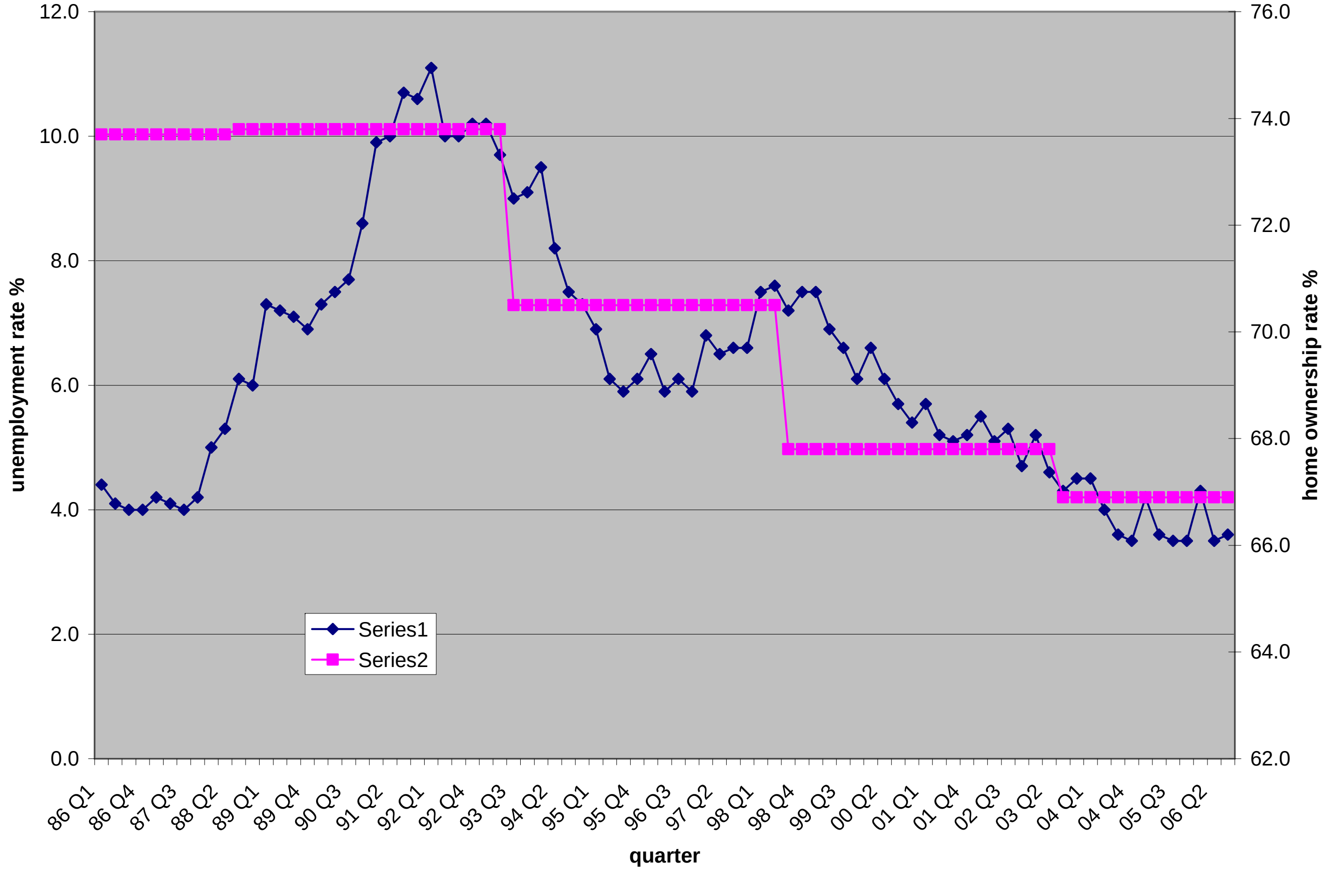
1	Pooled model with spatially lagged dependent variable and no fixed effects
2	Pooled model with spatially lagged dependent variable and spatial fixed effects
3	Pooled model with spatially lagged dependent variable and time period fixed effects
4	Pooled model with spatially lagged dependent variable, spatial and time period fixed effects

Table 6 Spatial error model results

	Model							
	1		2		3		4	
R-squared	0.7940		0.9768		0.7974		0.9775	
Rbar-squared	0.7840		0.9629		0.7850		0.9632	
sigma^2	2.1215		0.2386		2.0858		0.2320	
Log-likelihood	-318.5762		-122.2527		-311.0804		-119.9339	
Variable								
'lgpoprop_'	0.2342	0.0000	0.2377	0.0000	0.2269	0.0000	0.2152	0.0000
'pbgindlma'	-0.0197	0.7525	-0.0933	0.0000	0.0423	0.5445	-0.0428	0.1723
'lgpsphhlds_'	0.4043	0.0000	0.0817	0.2868	0.3315	0.0000	0.1102	0.1560
'midoldpopr'	-0.1887	0.0029	-0.4071	0.0000	-0.1292	0.0447	-0.3260	0.0000
'maorir'	0.2540	0.0000	1.1576	0.2470	0.2601	0.0000	0.0889	0.1200
'asianr'	0.4055	0.0005	0.8327	0.4050	0.4035	0.0003	0.1589	0.0990
'manualr'	0.0417	0.5933	-0.6670	0.5048	0.0243	0.7526	-0.0079	0.8715
'net_mig'	0.0556	0.0136	3.4208	0.0006	0.0465	0.0467	0.0391	0.0146
spat.aut.	0.8940	0.0000	0.0550	0.8220	0.2340	0.2805	0.1990	0.3717
'constant'	-14.4755	0.0000	-		-		-	

Model	
1	Pooled model with spatial error autocorrelation, no fixed effects
2	Pooled model with spatial error autocorrelation and spatial fixed effects
3	Pooled model with spatial error autocorrelation and time period fixed effects
4	Pooled model with spatially lagged dependent variable, spatial and time period fixed effects

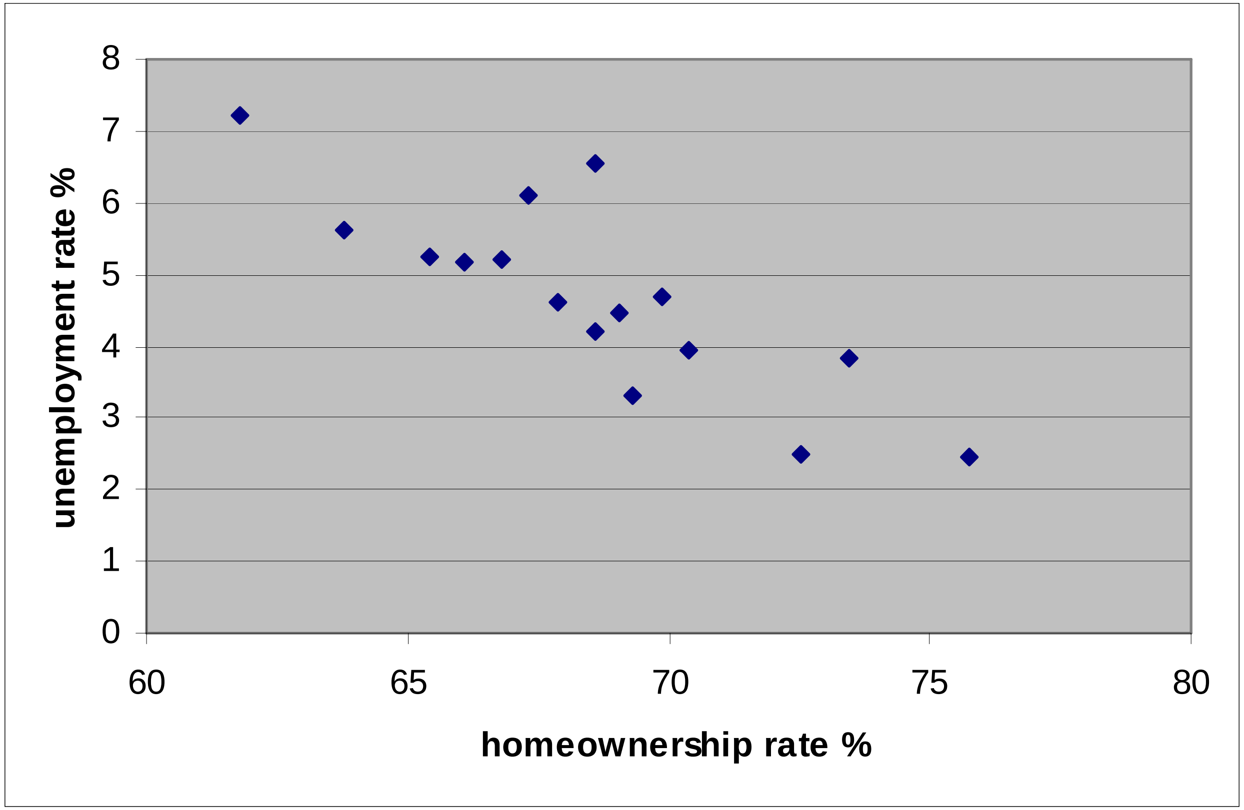
Figure 1 New Zealand unemployment rate and home ownership rate 1986-2006



Source: Statistics New Zealand, *Household Labour Force Survey*

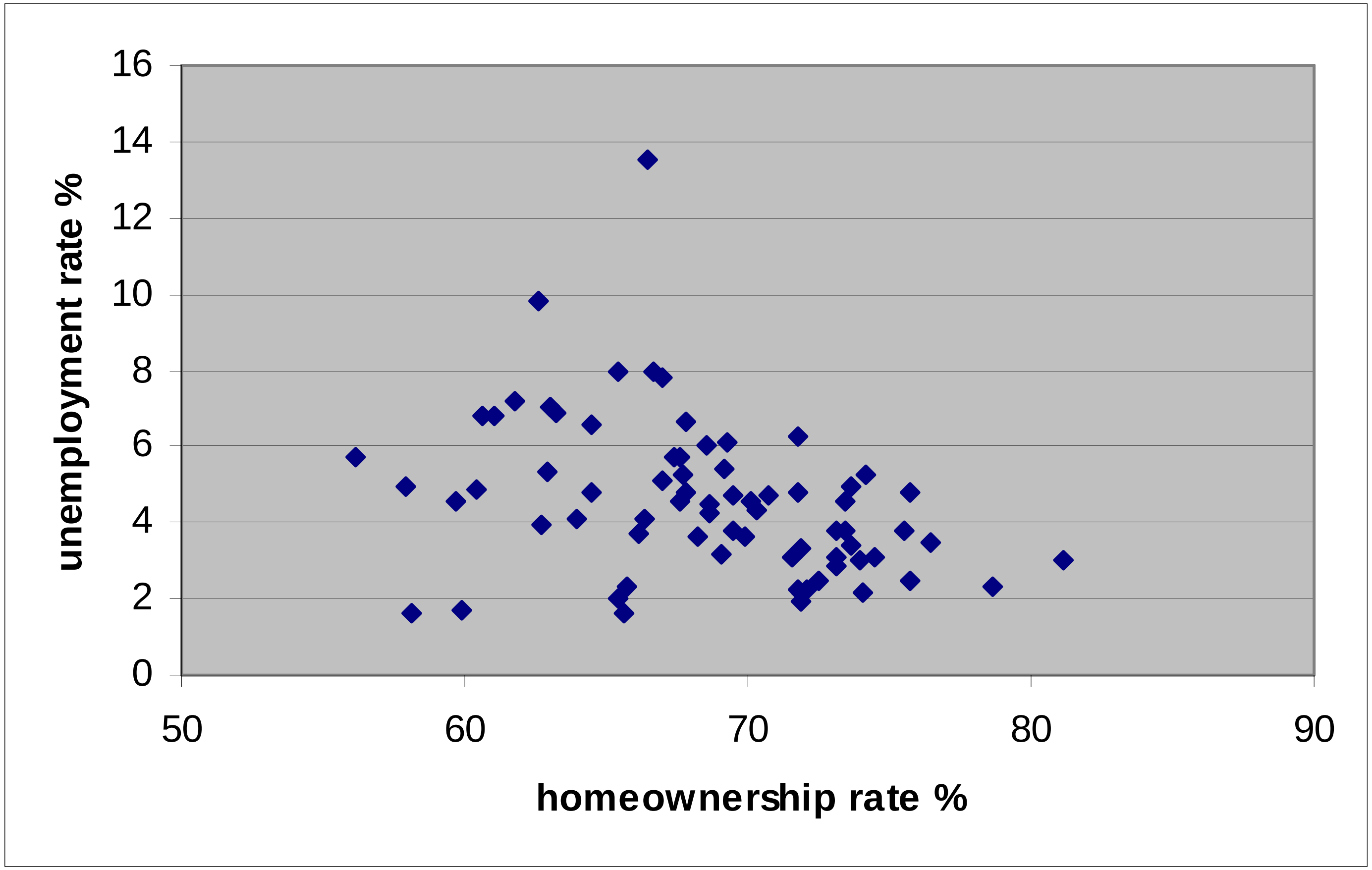
Figure 2 Home ownership and unemployment rates: 2006 census

(a) 16 Regional Council regions



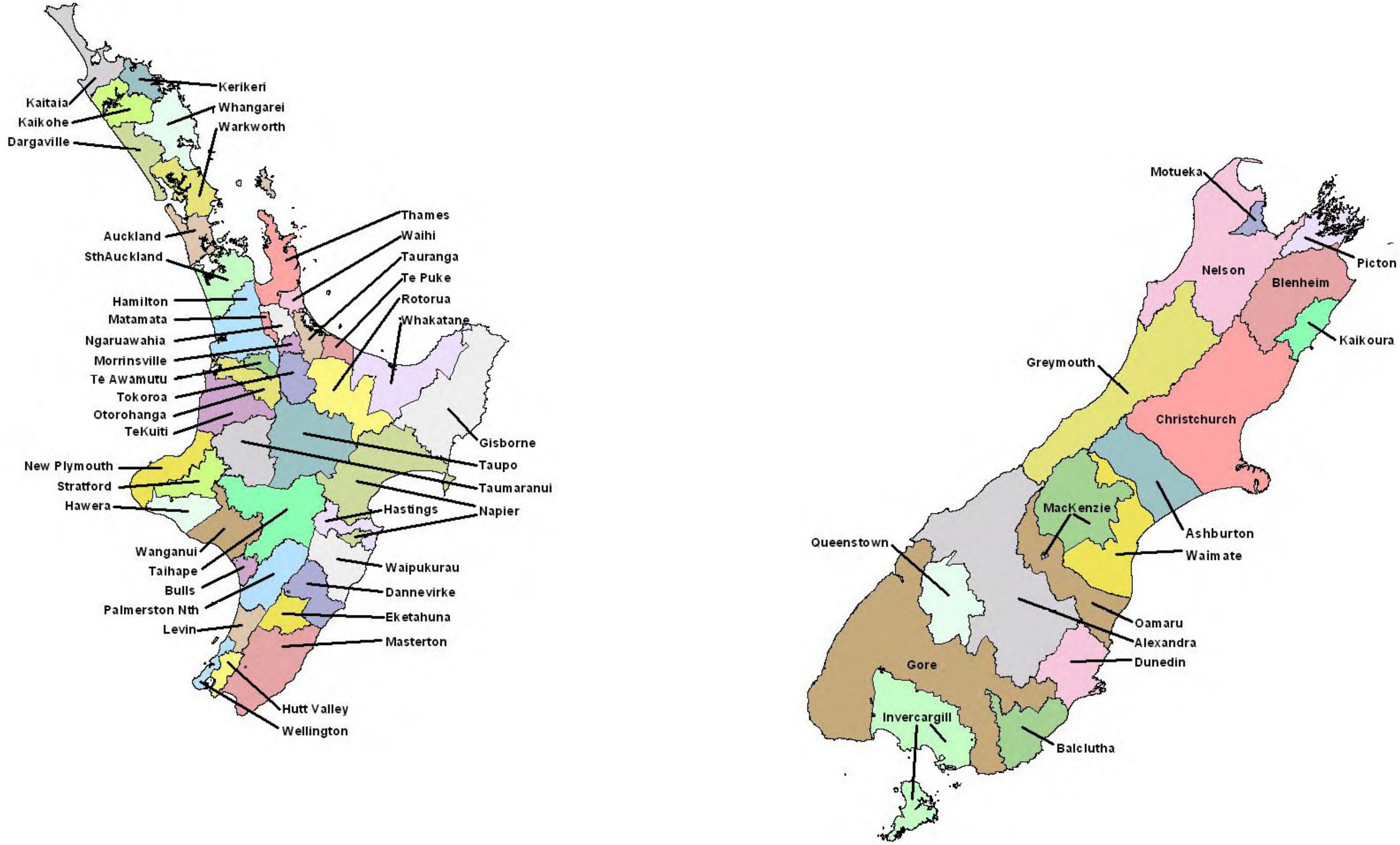
Source: Statistics New Zealand, *Census of Population and Dwellings 1986-2001*

(b) 73 Territorial Authority regions



Source: Statistics New Zealand, *Census of Population and Dwellings 1986-2001*

Figure 3 New Zealand Labour Market Area Boundaries – 58 Labour Market Areas



Source: Maré and Timmins (2004)