Abstract: Commuting is the manifestation of the spatial imbalance between the location of jobs and housing. This imbalance can limit the capacity of workers to take up certain jobs, due the constraints of information, time and income. There is evidence that workers in higher status occupations commute further whereas disadvantaged groups and some women face spatial entrapment due to competing family demands and employment in casual jobs with limited working hours. Extensive commuting imposes high social and economic costs from congestion and demands for the provision of adequate transport infrastructure which is generally under-utilised.

In this paper we analyse the determinants of commuting behaviour by occupation across NSW Statistical Local Areas. The extent to which the pattern of commuting is linked to measures of the spatial imbalance between residents and jobs, relative wages, occupational status and access to different forms of transportation is explored.

1. Introduction

Decisions about residential location are typically influenced by a wide range of factors, including housing affordability, proximity to work and amenities, including childcare, schools, recreational facilities and shopping, and access to the extended family and broader social networks. These decisions will be conditioned by the availability of both private and public forms of transportation, with the former being linked to the availability of household income. On the other hand, for secondary income earners residential location may well determine the locus of available job opportunities. Knowledge of these jobs will reflect the intensity of formal search activity and information secured via the operation of social networks (Stone et al, 2003).

Commuting is the manifestation of the spatial imbalance between the location of jobs and housing. This imbalance can limit the capacity of workers to take up certain jobs, due the constraints of time and income, in addition to imperfect information. There is a complex relationship between this spatial imbalance (urban form), mobility and individual accessibility. Home and work are not merely points in space but are interconnected by a complex web of economic and social relations (Kwan and Weber, 2003).

Kwan and Weber (2003) challenge whether commuting behaviour can be modelled in a satisfactory manner, emphasising that an individualistic approach must be taken to understand these interdependent relationships. This point is particularly apposite for women who are subject to different space-time constraints than men. However there is an extensive, mainly US literature, which analyses the determinants of commuting using spatially based aggregate or unit record data. The question of whether individuals exhibit idiosyncratic commuting behaviour is a statistical one, rather than one determined by case study evidence.

Kain (1968) started the longstanding debate about the causes of persistent intra-urban differences in unemployment rates by race (Horner, 2004: 69). Many authors emphasise the role of the spatial distributions of workers and jobs (the urban form), which in many areas
necessitates extensive commuting (eg. Kasarda, 1995; Shen, 2000). Shuttleworth and Lloyd (2005) also note that supply side characteristics, such as the endowment of skills, influence unemployment rates. In Australia disparities in rates of labour utilisation persist in regional areas (Mitchell and Carlson, 2001) and even within urban areas (ABS, 2001). The concentration of disadvantage within certain urban and regional areas is likely to exacerbate economic and social dysfunction (Gregory and Hunter, 1995) and is a major source of economic inefficiency.


In another strand of the literature, geographers have explored the efficiency of commuting patterns from the perspective of environmental sustainability, given the underlying spatial distribution of jobs and housing (see references in Horner and Murray, 2003:136). Extensive commuting imposes high social and economic costs through lengthy travel times resulting from peak-hour congestion, significant emission levels and demands for the provision of adequate transport infrastructure which is generally utilised inefficiently (Denniss and Watts, 2001). The extent to which the urban form influences commuting behaviour is important in determining the effectiveness of planning through the zoning of land for residential and industrial use, although it is acknowledged that planning decisions are influenced by a range of other considerations, including other forms of travel by residents, business access to transport infrastructure and the development of vertical and horizontal links between firms.

The spatial pattern of commuting which minimises the average commuting distance travelled (or commuting time) can be specified as the solution to a linear programming problem (White, 1988, Guiliano and Small, 1993; Horner and Murray, 2002, Horner 2002). A key question is whether either this pattern of commuting or job proximity, which measures the spatial competition for jobs, conditions actual commuting behaviour. Manning (2002) argues that commuting patterns are explained by thin labour markets, rather than a general equilibrium process, since workers have limited employment opportunities at any particular moment.

In this paper we analyse the average out-commuting distance by occupation across 180 Statistical Local Areas (SLAs) within NSW by drawing on the ABS Census Journey to Work data for 2001. In contrast to extant studies, we employ spatial econometric techniques and do not confine our study to urban areas. We utilise three alternative measures of spatial imbalance between residents and jobs, namely the minimum average distance commuted, the local aspatial (SLA) jobs to local employed residents ratio and a measure of job proximity (Shen, 2000). We also explore the extent to which access to motorised private transportation, the gender share of work journeys, the socioeconomic status of occupations, relative wage rates and the degree of remoteness condition these underlying commuting patterns. An understanding of the determinants of commuting behaviour will assist in the creation of targeted job creation strategies to address spatial concentrations of unemployment. We find that optimum commuting plays a dominant role in the determination of the average distance commuted, but these other factors are influential too.

In the following section, the extant literature on commuting behaviour is reviewed. In Section 3, we model commuting behaviour of NSW workers in 2001. We then investigate commuting patterns by occupation and outline the variables and the econometric procedures. Results and conclusions follow in Sections 5 and 6.
2. Literature Review

The monocentric model assumed that employment was concentrated in the CBD with commuting occurring on a ray towards the CBD (Hamilton, 1982). Residential location was based on the trade-off between housing and commuting costs (Horner and Murray, 2002: 132). Hamilton found that the monocentric model greatly underestimated urban commuting but his method did not establish whether the assumptions of cost minimisation or monocentricity were contradicted (Giuliano and Small, 1993: 1487).

White (1988) took explicit account of the spatial location of workers and jobs, thereby dropping the assumption of monocentricity. He developed a linear programming problem to determine the minimum average commuting costs across areas within an urban conurbation, given the spatial distribution of workers and jobs. This Transportation Model can be specified as follows:

Let $x_{ij}$ denote the number of workers who commute from home in location $i$ to their workplace in location $j$ with associated costs, $C_{ij}$. These costs can take the form of imputed travel costs, which would include both specific travel costs and implicit costs reflecting travel time, or either the Euclidean travel distance or the shortest distance by major road between locations $i$ and $j$.

The total number of employees resident in location $i$ can be written as:

$$\bar{x}_i = \sum_j x_{ij} \quad j = 1, \ldots, n$$

Likewise the number of employees who work in location $j$ is:

$$\bar{x}_j = \sum_i x_{ij} \quad i = 1, \ldots, m$$

Then the Transportation Model (TM) can be depicted as the determination of the JTW matrix $Y = [y_{ij}]$ which minimises

$$T = \sum_{i,j} C_{ij} y_{ij} / E$$

subject to

$$\sum_j y_{ij} = \bar{x}_j$$

$$\sum_i y_{ij} = \bar{x}_i$$

and

$$y_{ij} \geq 0$$

where $E$ denotes the total number of employees.

If the actual average commuting distance is $T_a$, then the extent of excess commuting, $Z$ is defined as

$$Z = (T_a - T) / T_a$$

White (1988) found little excess commuting, but it was shown that these results were sensitive to the modifiable areal unit problem (MAUP) (Horner and Murray, 2002). Giuliano and Small (1993) examine the extent of excess in-commuting for the five county Los Angeles regions. Based on a fine disaggregation of origin and destination zones, they show that about two thirds of commuting in Los Angeles is excessive, which challenges the minimisation...
model. Commuting patterns are likely to reflect variations in household characteristics, preferences and local amenities (p.1485), as well as housing costs (p.1486).

Giuliano and Small apply the TM to each occupation separately, thus overcoming the major shortcoming of some applications of the TM which do not differentiate between different types of jobs. Giuliano and Small reject the claim that lower-paid workers are forced to undertake long commutes, due to the absence of suitable housing, finding that higher paid administration and technical staff have slightly longer commutes. Simpson (1992) found that highly skilled professional engaged in more spatially expansive and formal job search procedures compared to workers in lower occupational levels. Giuliano and Small (1993) also find a weak inverse relationship between the local worker job ratio and average commuting time and also a weak positive relationship between the actual and required commute, based on the solution to the TM (p.1497).

Giuliano and Small (1993: 1498) suggest that rapid job turnover and high moving costs may lead households to seek access to an array of future jobs. Also two income families and job heterogeneity may frustrate the minimisation of commuting costs for each partner. Non-work trips, other housing and neighbourhood characteristics and the impact of discrimination may also be important in the location decision.

A number of authors explore gender differences in the distance (or time spent) commuting with debate over whether women suffer spatial entrapment (see, for example, England, 1993 and Hanson and Pratt, 1995), due to the constraints of family responsibilities, limited hours of paid work and poor access to transport.

In their study of Tokyo commuting patterns, Merriman et al (1995) find that the percentage of excess commuting is much lower than Small and Song (1992) found in their study of the Los Angeles metropolitan area. As a consequence they caution against universal claims about the quantity of excess commuting, pointing to possible influences of urban structures and institutions on commuting patterns. Using simulations, they find that, even with the existing infrastructure, either the decentralisation of jobs or the centralisation of workers would lead to a substantial reduction in commuting time, with the latter having a greater impact (see also Horner and Murray, 2003).

Shen (2000: 68) is critical of the commuting literature for drawing conclusions based on the analysis of large geographical areas, so that variations in commuting patterns particularly of the disadvantaged with severe transportation problems are hidden. He argues (2000: 71) that papers, including Giuliano and Small (1993), leaves major gaps in the understanding of urban transportation issues and the role of urban planning in influencing the jobs/workers balance. Consequently it is difficult to design programs to improve accessibility. He suggests that a complete model should include both socio-economic and land use/urban structure variables.

To explain average commutes, Shen (2000) adopts measures of job proximity, reflecting the availability of different modes of transport in each area, as a proxy for the underlying urban form, rather than minimum commute times which ignore multiple modes of transportation.

Shen (1998: 349) defines the job proximity of people living in location i as

\[ Z_i = \sum_j \bar{x}_j f(C_{ij}) / D_j \]  

(5)

where \( \bar{x}_j \) is the number of jobs in location j, and \( f(C_{ij}) \) denotes the impedance (decay) function. This measure is premised on all jobs being vacant at a point in time, rather than labour markets being thin (Manning, 2002).
The numerator measures the effective number of job opportunities in location j for residents of location i. \( D_j = \sum_k P_k f(C_{kj}) \) is the effective number of job seekers in location j, where \( P_k \) is the number of residents in location k who are seeking job opportunities, that is the employed plus the unemployed. Shen (1998) utilises an estimated negative exponential function of travel time between locations for the impedance function.

His measure is location specific in that it computes the effective competition for jobs in location j for residents of location i, summed over j. Shen (1998:363-364) shows that his measure of job proximity satisfies the following property:

\[
\sum_i (P_i / P) Z_i = X / P
\]

where \( X/P \) denotes the overall employment rate, that is

\[
X = \sum_j \bar{x}_j \quad \text{and} \quad P = \sum_i P_i
\]

(6)

In contrast to Giuliano and Small’s model, Shen’s accessibility measure does not differentiate between different occupations, however, so that an averaging process is being undertaken, with the only constraint on workers’ job access being location rather than skill or expertise.

Shen finds that socio-economic variables, as well as the urban spatial structure of the Boston metropolitan area and travel modes, influence average commute time. Policy should be designed to reduce commuters’ dependence on public transportation and improve employment accessibility, but also address the tendency for example for low income, less educated workers to travel short distances to work, which has implications for the spatial provision of services such as training and childcare.

Wang (2000) models commuting patterns in Chicago and finds that his gravity based measure of job accessibility explains more than 50% of the spatial variation of commute distances among the 7835 Traffic Analysis Zones.

Sultana (2002) explores the relationship between the job/residents (JR) imbalance and commuting time in Atlanta. She employs a spatial technique based on a 7 mile buffer around the centroid of each TA, rather than computing JR ratios for each TAZ. While a number of studies have challenged the imbalance hypothesis, (Sultana, 2002: 730), she finds that an area with an imbalanced JR is associated with long commutes, but the relationship is conditioned by house prices. In a study of 26 cities, Horner (2002) found a correlation between average commute length with the internal JR ratio. Horner (2004) notes that a severe J/H imbalance can be associated with social exclusion.

Shuttleworth and Lloyd (2005: 911) note that there is considerable agreement in the literature about the factors which influences the extent of commuting, but that social and locational factors are intertwined in a complex manner. Workers in better paid jobs often work in areas which are job poor which necessitate long commutes.

The early Australian literature explored the urban form of major cities. O’Connor (1978) examined the changes in the commuting patterns of Melbourne’s inner city residents based on the 1966 and 1971 Censuses. O’Connor and Maher (1979) explored changes in the spatial structure of the Melbourne metropolitan region, drawing on (non-exclusive) labour sheds which were based on Markov Chain analysis. Howe and O’Connor (1982) found differences in the commuting patterns of men and women in Melbourne, with there being a marked spatial-occupational association within the female workforce. Forster (1999) also examined
the trends in commuting patterns and noted the increased commuting into suburban centres, the greater use of the automobile and the rise in the average commuting distance traveled. The urban focus reflects the limited scope of JTW data, with published data limited to intra-urban SLAs until the 2001 Census. Trendle and Siu (2005) use a gravity model, differentiated by level of education to investigate commuting patterns on the Sunshine Coast. They find that more highly educated workers commute longer distances.

3. Modelling average commuting by residence and occupation

We model the determinants of the mean out-commuting distance by occupation across SLAs in NSW. Thus we are assuming that residential location is exogenous. We analyse overall commuting patterns for males and females to avoid imposing the current pattern of gender segregation by occupation and location in modelling commuting by gender.

A prime determinant of the mean commuting distance will be a variable representing spatial imbalance. Three variables are utilised: (i) the minimum average commute (MC) which is based on the solution of the TM across the 180 SLAs for each occupation; (ii) the Jobs to Resident (JR) employment ratio for each occupation and SLA; and (iii) Job Proximity (JP), based on Shen (2000). The first measure should have a positive coefficient, whereas the other two should yield a negative coefficient in the commuting model. Since unemployment rates are not available by SLA and occupation, an occupation specific measure of JP cannot be constructed, so a unique JP value is used for each SLA.

Since male and female commutes are combined, we include the male share of residents’ employment by occupation as an independent variable to pick up any gender influence on commuting distance, which is independent of the spatial distribution of housing and jobs. This variable should have a positive coefficient.

The focus on out-commuting does not lend itself to modelling housing affordability and hence residential location, since residential location is taken as given. Part-time employment would tend to mitigate against long distance commuting due to its high implied relative direct and indirect cost. Unfortunately the ABS Census profiles of residents do not report the breakdown of employment by gender, occupation and part-time and full-time status.

The socio-economic status of the ASCO 2nd Edition occupations (SS) draws on the path analytic approach of Ganzeboom et al (1992) and was devised by Jones and McMillan (2001). This variable is not designed to reflect the differential spatial imbalance between residents and jobs for each occupation, which is already captured by one of the three variables but rather to capture different behaviour by different occupational groups, given the extant spatial imbalance.

The 2001 Census has rather limited socio-economic data that is relevant for this empirical work. We argue that access to different modes of public and private transportation will influence the capacity of individuals to commute long distances. Consequently we measure the percentage of households that do not have access to private motorised transport. An increase in this variable would be expected to have a negative effect on the average commute. We chose not to include a measure of educational attainment for each SLA, because all the major occupations are being analysed separately within the modelling framework, so individuals’ training and skills which qualify them for a particular occupation are being taken into account.

The preferred employment location will reflect the relative wage. Using the spatial weight matrix described below, a relative wage variable (RW) was created by dividing an estimated residents’ wage by occupation (see below) by the spatially weighted average occupational wage. It would be expected that local employment would be more attractive and hence
commuting would be lower, ceteris paribus, the higher the relative wage. This variable is a crude proxy for the relative wage, however, because the numerator is based on the estimated wages of local residents obtained in different locations, rather than the average wage associated with local employment. However, if residents predominate in local employment, then the numerator and denominator will represent the local and spatially weighted wage. This measure also fails to take account of the direct and indirect cost of commuting.

Finally locational dummy variables were utilised based on the ABS classification of 2001 SLAs by the ASGC Remoteness measure. Five categories of remoteness are employed: Major City, Inner Regional (IR), Outer Regional (OR), Remote and Very Remote (RV), where the last two are combined. A non-metro category is defined by the exclusion of Major City. Some SLAs are recorded under more than one category, so they are represented in both categories. While the availability of private motorised transport plays a key role in patterns of commuting, it does not identify the availability of public transport which is of particular significance in metropolitan areas. This could be picked up by the locational dummies.

4. The data and econometric estimation

4.1 The variables
There are 198 SLAs in NSW of which 18 were removed from the sample, because a study of commuting patterns (Watts et al, 2005) showed that they exhibited a high level of interaction with SLAs in adjacent states. Six of these SLAs straddled state borders (see Appendix 1). Thus there are 1620 observations across 9 occupations.

The straight line distances between the centroids of the SLAs were computed. The 2001 Journey to Work data include trips in excess of 200km, however, which cannot be associated with daily commuting. We used 200km as the maximum one way commute.

Intra-SLA commuting was based on the assumption that the SLAs were circular (Horner and Murray, 2002). The average commute of a resident would be the radius, which was incorporated into the calculation. About 10% of Census respondents did not specify their place of work. However a proportionate reassignment of these data across the SLA work locations would leave the average commute unchanged. The impact of assigning observations of residence and work locations for which occupation was unknown across occupations would be minimal and was ignored.

The dependent variable, CO, is the simple weighted average overall commute by SLA of residence and ASCO Edition 2 occupation. There are no Advanced Clerical & Service Workers recorded for Unincorporated NSW Far West, so the average commute across the remaining 8 occupations was used.

We solved the Transportation Model over the 180 SLAs for each occupation using an evaluation version of Premium Solver Platform Version 6.5 from Frontline Systems. The software works with Microsoft Excel. The large number of unknowns (32,400) necessitated the use of Mosek Solver Engine, which readily provided integer solutions. The extent of excess commuting lies within a range of 25-49% (Table 1).
**Table 1: Average Actual & Minimised Commutes by Occupation (km), 2001**

<table>
<thead>
<tr>
<th>Occup. Status</th>
<th>TOT</th>
<th>MA</th>
<th>PR</th>
<th>AP</th>
<th>TR</th>
<th>AC</th>
<th>CS</th>
<th>IP</th>
<th>EC</th>
<th>LR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual (km)</td>
<td>19.49</td>
<td>23.07</td>
<td>18.22</td>
<td>19.36</td>
<td>21.00</td>
<td>18.36</td>
<td>18.69</td>
<td>20.75</td>
<td>17.00</td>
<td>23.73</td>
</tr>
<tr>
<td>Min (km)</td>
<td>14.20</td>
<td>16.90</td>
<td>12.26</td>
<td>14.16</td>
<td>15.24</td>
<td>14.64</td>
<td>14.16</td>
<td>15.19</td>
<td>13.36</td>
<td>16.00</td>
</tr>
<tr>
<td>Excess (%)</td>
<td>27.14</td>
<td>36.51</td>
<td>48.61</td>
<td>36.72</td>
<td>27.43</td>
<td>25.41</td>
<td>32.00</td>
<td>36.60</td>
<td>27.25</td>
<td>48.31</td>
</tr>
</tbody>
</table>


Notes: TOT denotes total employment; MA is Managers & Administrators; PR is Professionals; AP is Associate Professionals; TR is Tradespersons & Related Workers; AC is Advanced Clerical & Service Workers; CS is Intermediate Clerical Sales & Service Workers, IP is Intermediate Production & Transport Workers; EC is Elementary Clerical, Sales & Service Workers; and LR are Labourers & Related Workers.

There is no systematic relationship between (minimum) commuting distance and occupational status. While managerial employees have quite long average commutes, professional employment is more localised, whereas Tradespersons and Labourers have relatively long commutes.
Figure 1: Average Out-Commuting in NSW, 2001
A negative exponential function of straight line distance was employed for the impedance function, which underpins the calculation of job proximity. A gravity function was estimated:

\[ x_{ij} = k(x_i)^\alpha (x_j)^\beta \exp(-\gamma d_{ij}) \]  

(8)

where \( d_{ij} \) is the distance between locations i and j. This yielded an estimate of -0.0265 for \( \gamma \).

In Figure 1 average out-commutes by occupation are plotted as a function of the distance from Inner Sydney. The polycentric pattern of employment implies that average out-commuting does not rise linearly with distance from Sydney. In addition, there are is some variance in average commuting distances across the occupations.

Since the SLA distance matrix is integral to the construction of the dependent variable, a row standardised weight matrix based on first order contiguity, rather than distance, was employed in the spatial econometric estimation to avoid high correlation between the dependent and independent variables. The spatial weight matrix was defined as the Kronecker product of a 9*9 identity matrix and the 180*180 spatial weight matrix to accommodate the nine observations per SLA. The first-order contiguity structure for the 180 SLAs is shown in Figure 2.

Drawing on the ABS Census Basic Community Profile (B29), we measure the percentage of households in each SLA which did not have access to a motor vehicle (NMV) and NVS, the percentage of households without access to either a motor vehicle or a scooter. These variables are SLA specific.

The ABS has published an experimental series of wages by major occupation across the SLAs since 2000/2001 based on Australian Taxation Office data (Cat.5673.0), but the ASCO Edition 1 occupational classification is employed up to and including 2001/02. The ABS publication 6310.0 provides average weekly wages for all jobs by major occupation for August 2001 under the ASCO new classification. These occupational wage relativities were used to calculate an SLA specific adjustment coefficient to apply to average weekly wages by occupation, so that the total wage bill in the particular SLA coincided with that provided in the ATO statistics. The estimated average wage by occupation and SLA was used in the relative wage measure, described above. All variables were normalised by subtracting their means and dividing by their standard errors. Failing to scale the variables could cause problems of singularity in the estimation procedure.
4.2 Econometric estimation

When sample data has a locational component, there are two problems, namely spatial dependence between the observations and spatial heterogeneity (LeSage, 1998). Inter-SLA commuting will promote spatial dependence between adjacent SLAs. As a consequence, ordinary least squares estimation is likely to be blighted by spatial correlation, which can take two forms, namely spatial lag and spatial error. The former is associated with the dependent variable being correlated with nearby observations of the dependent variable. Ignoring this form of serial correlation leads to inconsistent, biased estimators. The latter entails the correlation of errors with those of nearby observations, but ignoring this form of autocorrelation does not affect the consistency of the estimators, only their efficiency (Anselin, 1988).

The most general model (SAC) incorporates both a spatial lag ($\rho W_1 y$) and spatially correlated residuals.

\[
y = \rho W_1 y + X\beta + u
\]

\[
u = \lambda W_2 u + \varepsilon
\]

where $\varepsilon$ is normally distributed and $W_1$ and $W_2$ denote the weight matrices.

If the residuals are not spatially correlated ($\lambda=0$), then the spatial autoregressive (SAR) model is defined. On the other hand, the spatial error model (SEM) is obtained if the spatial lag parameter ($\rho$) is zero. The reader is referred to Mitchell and Bill (2004) for a detailed outline of these models.

Lesage (1998) outlines a range of spatial autocorrelation tests, namely Moran I-statistic, Likelihood ratio, Wald and Lagrange, which were employed. Also a spatial error LM test of the SAR residuals was used to test whether the inclusion of the spatial lag term removed the spatial dependence of the residuals.

5. The results

The results using JR and JP are shown in Table 3. All the OLS specifications were blighted by spatial correlation of the residuals, which was revealed by all the diagnostic tests of which the Moran and Wald are reported. The parameter estimates were little affected by the adoption of a spatial model.

The JR variable was generally insignificant and sometimes incorrectly signed, with the inclusion of the different control variables under OLS and the spatial specifications. A quadratic term in JR did not improve the specification, so this variable was discarded.

On the other hand, both JP and MC (minimum commute) were highly significant (see Tables 3 and 4) and were always correctly signed. Regressions with MC always had a significantly higher degree of explanatory power.

The male share (MS) was significant and correctly signed in the presence of MC. When significant, the control variables, socioeconomic status (SS) and the percentage of households without access to motor vehicle or scooter (NVS) took the correct sign, but contributed little to the explanatory power of the regression. Location variables RV and IR were both significant, but if the non-metropolitan variable was included by itself, it was insignificant.

The inclusion of both the MC and JP yields significant coefficients for OLS and the spatial specifications, but the vehicle access variable becomes insignificant (see Table 4). The Job Proximity variable measures spatial job competition, and has a correlation of -0.5 with the optimal commute, so the inclusion of both can be justified.
The LM SAR test revealed correlated residuals and the general spatial model (SAC) yielded a negative value for $\lambda$, the spatial error coefficient. The preferred model is the spatial error model with both spatial imbalance variables which has a marginally lower $R^2$ and lower value of the log likelihood function than the SAC (column 7, Table 4). All variables are significant and correctly signed, except the vehicle access variable. These results are not markedly affected by the exclusion of the relative wage variable.

Table 3: NSW Commuting behaviour by occupation and SLA, 2001

<table>
<thead>
<tr>
<th></th>
<th>JR</th>
<th>JP</th>
<th>OLS</th>
<th>SAR</th>
<th>SEM</th>
<th>SAC</th>
<th>OLS</th>
<th>SAR</th>
<th>SEM</th>
<th>SAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>JR</td>
<td>0.039**</td>
<td>-0.428***</td>
<td>0.027*</td>
<td>0.027*</td>
<td>-0.301***</td>
<td>0.017</td>
<td>0.017</td>
<td>-0.485***</td>
<td>-0.278***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.060)</td>
<td>(24.33)</td>
<td>(1.76)</td>
<td>(1.76)</td>
<td>(18.79)</td>
<td>(1.19)</td>
<td>(1.19)</td>
<td>(22.32)</td>
<td>(17.67)</td>
<td></td>
</tr>
<tr>
<td>JP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MS</td>
<td>0.004</td>
<td>0.004</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.009</td>
<td>0.000</td>
<td>0.000</td>
<td>0.008</td>
<td>0.008</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.253)</td>
<td>(0.98)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.64)</td>
<td>(1.42)</td>
<td>(1.42)</td>
<td>(0.39)</td>
<td>(0.75)</td>
<td></td>
</tr>
<tr>
<td>NVS</td>
<td>-0.244***</td>
<td>-0.409***</td>
<td>-0.155***</td>
<td>-0.155***</td>
<td>-0.038***</td>
<td>-0.240***</td>
<td>-0.240***</td>
<td>-0.090***</td>
<td>-0.029***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(12.14)</td>
<td>(3.00)</td>
<td>(9.29)</td>
<td>(9.29)</td>
<td>(2.61)</td>
<td>(11.09)</td>
<td>(11.09)</td>
<td>(4.92)</td>
<td>(2.15)</td>
<td></td>
</tr>
<tr>
<td>SS</td>
<td>0.021</td>
<td>0.022</td>
<td>0.012</td>
<td>0.012</td>
<td>0.020</td>
<td>0.015</td>
<td>0.015</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.28)</td>
<td>(1.60)</td>
<td>(0.88)</td>
<td>(0.88)</td>
<td>(1.20)</td>
<td>(0.47)</td>
<td>(0.47)</td>
<td>(0.79)</td>
<td>(1.23)</td>
<td></td>
</tr>
<tr>
<td>RW</td>
<td>-0.142***</td>
<td>-0.052***</td>
<td>-0.170***</td>
<td>-0.170***</td>
<td>-0.101***</td>
<td>-0.173***</td>
<td>-0.173***</td>
<td>-0.103***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(8.62)</td>
<td>(3.58)</td>
<td>(12.60)</td>
<td>(12.60)</td>
<td>(7.72)</td>
<td>(12.32)</td>
<td>(12.32)</td>
<td>(6.65)</td>
<td>(7.81)</td>
<td></td>
</tr>
<tr>
<td>RVR</td>
<td>0.712***</td>
<td>0.610***</td>
<td>0.455***</td>
<td>0.455***</td>
<td>0.443***</td>
<td>0.410***</td>
<td>0.410***</td>
<td>0.434***</td>
<td>0.431***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(41.38)</td>
<td>(39.85)</td>
<td>(26.65)</td>
<td>(26.65)</td>
<td>(27.83)</td>
<td>(22.82)</td>
<td>(22.82)</td>
<td>(35.69)</td>
<td>(27.75)</td>
<td></td>
</tr>
<tr>
<td>IR</td>
<td>0.063***</td>
<td>-0.057***</td>
<td>0.042***</td>
<td>0.042***</td>
<td>-0.037**</td>
<td>0.067***</td>
<td>0.067***</td>
<td>-0.056***</td>
<td>-0.030**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.44)</td>
<td>(3.48)</td>
<td>(2.82)</td>
<td>(2.82)</td>
<td>(2.55)</td>
<td>(5.00)</td>
<td>(5.00)</td>
<td>(3.68)</td>
<td>(2.10)</td>
<td></td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.456</td>
<td>0.351***</td>
<td>0.573***</td>
<td>0.573***</td>
<td>0.397***</td>
<td>0.573***</td>
<td>0.573***</td>
<td>0.397***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.585***</td>
<td>-0.277***</td>
<td>0.518***</td>
<td>0.518***</td>
<td>-0.090***</td>
<td>-0.277***</td>
<td>-0.277***</td>
<td>-0.090***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(26.74)</td>
<td>(16.96)</td>
<td>(17.30)</td>
<td>(17.30)</td>
<td>(9.38)</td>
<td>(17.30)</td>
<td>(17.30)</td>
<td>(9.38)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.574</td>
<td>0.688</td>
<td>0.655</td>
<td>0.655</td>
<td>0.722</td>
<td>0.702</td>
<td>0.702</td>
<td>0.760</td>
<td>0.760</td>
<td></td>
</tr>
<tr>
<td>Moran</td>
<td>0.00***</td>
<td></td>
<td>0.00***</td>
<td>0.00***</td>
<td></td>
<td>0.00***</td>
<td>0.00***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wald</td>
<td>0.00***</td>
<td></td>
<td>0.00***</td>
<td>0.00***</td>
<td></td>
<td>0.00***</td>
<td>0.00***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LM</td>
<td>0.00***</td>
<td></td>
<td>0.00***</td>
<td>0.00***</td>
<td></td>
<td>0.00***</td>
<td>0.00***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAR</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: MC denotes the minimum commute; JP is Job Proximity; MS is male share of commutes; NVS denotes the percentage of households with no motor vehicle or scooter; SS is the socioeconomic status of the major ASCO Division 2 occupations; RW is the relative wage; and RVR and IR are locational dummies
<table>
<thead>
<tr>
<th></th>
<th>MC</th>
<th>MC/JP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>SAR</td>
</tr>
<tr>
<td>MC</td>
<td>0.921***</td>
<td>0.875***</td>
</tr>
<tr>
<td></td>
<td>(89.72)</td>
<td>(71.14)</td>
</tr>
<tr>
<td>JP</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MS</td>
<td>0.024***</td>
<td>0.022***</td>
</tr>
<tr>
<td></td>
<td>(3.49)</td>
<td>(3.30)</td>
</tr>
<tr>
<td>NVS</td>
<td>-0.019***</td>
<td>-0.016**</td>
</tr>
<tr>
<td></td>
<td>(2.61)</td>
<td>(2.19)</td>
</tr>
<tr>
<td>SS</td>
<td>0.019***</td>
<td>0.017***</td>
</tr>
<tr>
<td></td>
<td>(2.78)</td>
<td>(2.61)</td>
</tr>
<tr>
<td>RW</td>
<td>-0.045***</td>
<td>-0.054***</td>
</tr>
<tr>
<td></td>
<td>(6.57)</td>
<td>(7.93)</td>
</tr>
<tr>
<td>RVR</td>
<td>0.049***</td>
<td>0.040***</td>
</tr>
<tr>
<td></td>
<td>(4.82)</td>
<td>(3.94)</td>
</tr>
<tr>
<td>IR</td>
<td>0.034***</td>
<td>0.032***</td>
</tr>
<tr>
<td></td>
<td>(4.60)</td>
<td>(4.39)</td>
</tr>
<tr>
<td>ρ</td>
<td>0.076***</td>
<td>0.074***</td>
</tr>
<tr>
<td></td>
<td>(6.77)</td>
<td>(3.40)</td>
</tr>
<tr>
<td>λ</td>
<td>0.105***</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(9.52)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>$\bar{R}^2$</td>
<td>0.929</td>
<td>0.930</td>
</tr>
<tr>
<td>Moran</td>
<td>0.00***</td>
<td></td>
</tr>
<tr>
<td>Wald</td>
<td>0.00***</td>
<td></td>
</tr>
<tr>
<td>LM</td>
<td>0.00***</td>
<td></td>
</tr>
<tr>
<td>SAR</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** See Table 3.

### 6. Conclusion

In this paper we find the typical results found in the extant literature, namely that men commute further than women and that workers in more prestigious occupations commute further on average, after taking account of spatial imbalance. At this level of spatial disaggregation, the minimum commute based on the TM solution is highly significant in the determination of average commuting distance, but that does not imply that the actual commute closely tracks the minimum commute, as is demonstrated in Table 1. On the other hand, the simple Jobs to Residents variable performs poorly, in
contrast to some US studies. Isolating cause and effect is difficult given the ecological approach which is adopted (Shuttleworth and Lloyd, 2005).

Also the analysis is confined to commuting distance which is not simply related to commuting time or cost when a mixture of urban and regional SLAs are under consideration. Data on travel cost will enhance the empirical work, along with more detailed socio-economic data, which will better guarantee that the distinct behaviour of particular groups is not hidden. In addition, an analysis based on more spatially disaggregated urban data will allow further investigation of whether the optimal commuting pattern strongly influences actual commuting behaviour. A single equation model has been estimated which takes residential location as given. The specification of a simultaneous model is worthy of consideration.

Watts (2003) showed that the spatial imbalance of workers and jobs has an influence on the job accessibility of residents in urban areas and hence their capacity to secure jobs, which in turn, impacts on the spatial distribution of unemployment. An understanding of the determination of commuting patterns assumes considerable importance in both the design of a job creation policy, because the location of additional jobs will strongly influence who actually takes them up (see also Immergluk, 1998), as well as the development of sustainable transportation systems.

References


Australian Bureau of Statistics (2001b) Employee Earnings, Benefits and Trade Union Membership Australia, August, Cat. 6310.0.


438


Appendix 1

The following 8 SLAs straddle the state borders with Queensland, and ACT: Cooma-Monaro (A) (ACT), Gunning (ACT), Queanbeyan (ACT), Tweed (A) - Pt A (Queensland), Tweed (A) - Pt B (Queensland), Yarrowlumla (A) - Pt A (ACT), Yarrowlumla (A) - Pt B (ACT) and Yass (A) (ACT). In addition, in a separate analysis based on total JTW data for the whole of Australia (Watts, et al, 2005), SLAs were grouped into Local Labour markets based on an algorithm developed by Coombes et al (1986). With the exception of Cooma-Monaro (singleton LLM) and Gunning (grouped with NSW SLAs), the above SLAs were all grouped with SLAs from other states, signifying signifying inter-action through in- and out-commuting. Consequently commuting to and from these 6 SLAs was not formally considered, given the likely distortion from ignoring the flows of commuters to and from inter-state SLAs. In addition the following SLAs, which were located close to state borders, also were grouped with inter-state SLAs: Albury (C), Balranald (A), Berrigan (A), Corowa (A), Culcairn (A), Holbrook (A), Hume (A), Murray (A), Tallaganda (A), Wakool (A) and Wentworth (A). These also were removed from the sample. A further check was carried out on all SLAs by contrasting intra-NSW JTW, across all occupations, with total commuting, both within and outside NSW. In many cases, the NSW totals exceeded those associated with Australia as a whole.

---

1 The author is Deputy Director, Centre of Full Employment and Equity and Associate Professor in Economics at The University of Newcastle, Australia.