Modelling Persons' Job Mobility and Location Choice Decisions for an Integrated Land Use and Transportation Modelling System

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Muhammad Ahsanul Habib, PhD
Assistant Professor
School of Planning, Dalhousie University
5410 Spring Garden Road, Halifax, NS, B3J2X4
Email: ahsan.habib@dal.ca

Eric J. Miller, PhD
Professor and Director
Cities Centre, University of Toronto
455 Spadina Ave., Suite 400
Toronto, ON, M5S 2G8, Canada
Email: miller@ecf.utoronto.ca

Bruce Mans
MPlan Candidate
School of Planning, Dalhousie University
5410 Spring Garden Road, Halifax, NS, B3J2X4
Email: bruce.mans@dal.ca

ABSTRACT

This paper presents a comprehensive modelling framework for representing individuals' continuous decisions of changing jobs over life courses. The key objective of the research is to develop disaggregate econometric models for employment transitions and location choice processes in order to implement persons' longitudinal job mobility behaviour within a dynamic microsimulation-based integrated urban modelling systems. The paper includes two behavioural model components: (1) job mobility model, (2) job location choice model. The models are empirically implemented by using a retrospective survey at the Greater Toronto and Hamilton Area (GTHA). The first component investigates timing of job mobility using competing risk duration modelling approaches for four different event types: switch a job, back to school, short term unemployment, and withdrawal from the labour force. The second component of job location choice is empirically estimated using discrete choice methodology. One of the features of the model is that it examines influence of current employment in making next job location decisions. Additionally, the paper investigates effects of both person-level and household-level attributes on location choice. A random parameter logit model is applied to account for panel heterogeneity effects. These models are expected to be implemented within Integrated Land Use, Transportation and Environment (ILUTE) modelling system, which is recently been updated with comparable disaggregate behavioural residential location models.

INTRODUCTION

The paper presents disaggregate econometric models for intra-urban job mobility decisions. Recent advancements in large-scale integrated urban models require comprehensive modelling frameworks to replicate behaviours of actors in an urban system. Job mobility and location choices are key decision processes that influence other long-term and short-term decisions, including travel. Traditionally, travel demand forecasting models uses exogenous employment forecasts, which completely ignores the dynamic nature of job mobility within an urban area. But workers continuously evaluate their decisions to change job, which warrants longitudinal modelling of this decision-making process in order to generate better forecasts of persons' employment locations in a given point in time.

This paper develops a two-step job mobility model, which is intended to be implemented within Integrated Land Use, Transportation and Environment (ILUTE) modelling system. It assumes that persons are the decision making units, and implements the modelling components using disaggregate employment history data. Mobility component takes a competing risk duration modelling approach in which four different termination event types are individually modelled: (1) Switch a job, (2) Back to school, (3) Short term unemployment, and (4) Withdrawal from the labour force.

On the other hand, location model component utilizes discrete choice modelling techniques. However it assumes a reference point in evaluating alternative job locations in terms of key variables, including commute times. The gains and losses are measured from the current job (common reference point) where gains are defined as the advantages gained from the alternative (for example, less auto travel time) and losses are defined as the disadvantages (for example, higher auto travel time) for each choice occasion. Unlike conventional location choice models, this formulation allows identification of asymmetric responses towards gains and losses, and hence examination of loss aversion attitudes in making job location decisions.

The rest of the paper is organized as follows: the next section briefly reviews the existing literature of job mobility and location choice research. It then discusses the data used in the empirical investigation followed by the description of the model structure used in the study. Finally, it provides discussion of the results of the competing risk mobility model and random parameter location choice model. The paper concludes with a summary of contributions and future research directions.

LITERATURE REVIEW

Job mobility decision is one of the most important long-term decisions that persons make at different stages in life. Multidisciplinary research on job mobility is particularly extensive. Hofmeister (2006) reviewed relevant literature in the United States since 1995, and summarized key factors that affect spatial job mobility into three major categories: employment contexts, family and household contexts, and neighbourhood and community contexts. It concludes that although macro-level studies explaining job mobility patterns are abundant, modelling decision-making processes are not as prevalent in general. On the other hand, van Ommeren et al. (1999) proposes a search framework for job mobility, residential mobility and commuting. It is argued that cost and benefits of changing job depends on current job characteristics, personal and household characteristics as well as commuting distance (van Ommeren et al., 2000). Devin and Kiefer (1993) particularly emphasizes on non-wage characteristics (including journey to work time) to understand employment transitions. Individuals are often reluctant to give up the short traveling times between home and work in accepting a job offer (Van den Berg, 1992). Many economic models focuses on relationships between job mobility and commuting distances since a central part of theories of urban spatial structure have been derived from the linkages between home and work places (see Kain, 1962; Alonso, 1964; Muth, 1969). However, journey to work is not the only reason why individuals consider a move. In practice, the dispersal of job opportunities has created a much more complicated behavioural response towards mobility behaviour (Clark et al., 2003). Factors affecting job mobility includes: unemployment dynamics (Vickerman, 1984); changing labour market conditions (Reuschke, 2006); gender differences (Johnston-Anumonwo et al 1995; Wyly 1999); presence of children, relationship types, and life stages (Hofmeister, 2006). Since majority of job mobility models are empirically investigated at the national/regional scale, there is limited understanding of intra-urban job mobility behaviour.

Modelling work location has received relatively more attention from the transportation modellers. However, multidisciplinary contributions are limited compared to job mobility studies. Several disaggregate work location models are estimated in conjunction with the residential location choices (see Abraham and Hunt, 1997; Freedman and Kern, 1997, Waddell et al., 1993; Waddell et al., 2006; Waddell et al., 2007). Most of these models examine cross-sectional data. Therefore it is not possible to test linkages between previous and current job location choices. In addition, modelling employment transition decisions are often ignored in the cross-sectional studies. Therefore this paper investigates these two decision components together using a retrospective survey at the Greater Toronto and Hamilton Area (GTHA).

DATA

In order to estimate longitudinal job mobility and job location choice models, a detailed palette of datasets were required from a variety of sources. The retrospective data that includes persons' employment history came from the Residential Mobility Survey (RMS II), which was conducted in the Greater Toronto and Hamilton Area (GTHA) during the summer of 1998. RMS II was a mail-back survey and collected information from a random sample of 281 households. Haroun and Miller (2004) have validated the sample size against both Statistics Canada 1996 data and the Transportation Tomorrow Survey (TTS) 1996 data. They found fair consistency in representing the population within a few percentage points in terms of gender, tenure, household size, automobile ownership, and dwelling type.

For the purposes of this study, a 28-years (1970-1998) of longitudinal database is created with useful employment information, including employment status, industry type, occupation category, workplace locations, and mobility indicators. It also includes supplementary residential information including location, size, date of mobility, tenure, dwelling type, as well as socioeconomic characteristics such as age, gender, marital status, etc.

In addition to RMS II data, this study also includes valuable information from the Statistics Canada census data (1971-2001) and the Canadian Socio-Economic Information Management System (CANSIM II). The sources of data provided useful information regarding market indicators, unemployment rates, labour force participation rates, mortgage rates, etc. Finally, GIS data was also obtained from Desktop Mapping Technologies Inc. (DMTI), which includes spatial locations of CDB, regional centers, subway stations, commuter transit stops, highway exits, etc. Several variables are derived using GIS function in ArcGIS® 9.3. Finally, the zone-to-zone network level-of-service (LOS) data are generated from the GTAModel-based EMME/2 road and transit network models.

MODEL STRUCTURE

Job mobility model

This study investigates competing risk hazard-based duration models for four termination types: (1) Switch a job, (2) Back to school, (3) Short term unemployment, and (4) Withdrawal from the labour force. To account for these competing risks different hazard rates need to be specified for each type of event. Therefore, if a person is at risk of experiencing K events $(k = 1,2,3......,r)$, the hazard rate can be written as follows:

$$h_k(t, X) = \lim_{\Delta t \to 0} \frac{\Pr(t \le T \le t + \Delta t \mid T \ge t, X)}{\Delta t} \tag{1}$$

The paper takes a latent survivour time approach to implement the competing risk model. Let's assume that the person i is at risk of k different kinds of events. Each event type has a corresponding duration $T_{1i}, T_{2i} ... T_{ki}$ associated with it, a corresponding hazard function $h_{ki}(t)$, and a corresponding survivor function $S_{ki}(t)$. Since it is only possible to observe the employment termination for an event k, which comes first (i.e. the shortest spell, $T_i = \min(T_{1i}, T_{2i} ... T_{ki})$), T_{ki} are essentially potential or latent failure times. Although latent, these unobserved failure times are assumed to exist and would be observed if time went on long enough without the employment spell fail due to some other type of event first. Therefore it is reasonable to assume that the duration times for different events are not exactly the same i.e. employment spells can't fail in two different ways at exactly the same time. Hence if the k various risks are conditionally independent, the contribution of each uncensored observation to the likelihood can be expressed as follows:

$$L_i = f_k(t_i, X_{ki}, \beta_k) \prod_{k \ne r} S_r(t_i | X_{ki}, \beta_r) \tag{2}$$

Here k denotes the k^{th} event and the r in the product term implies that the product is taken over the survivor times for all states except k. In other words, the contribution of a given observation with failure to risk k to the likelihood function is identical to its contribution in a model where only failures due to risk k to the likelihood function is identical to its contribution in a model where only failures due to risk k are observed and all other cases are treated as censored. Then the likelihood function becomes:

$$L = \prod_{i=1}^{N} f_k(t_i, X_{ki}, \beta_k) \prod_{k=1}^{r} S_k(t_i, X_{ki}, \beta_k) \tag{3}$$

Here β_k represents covariates for each type of failure. By providing a different set of coefficients for each type of failure, the latent survivor time approach captures heterogeneity across different types of events in terms of the covariates. However, since only one failure among the k possible outcomes is observed per person, the overall likelihood can be partitioned in terms of the number of units failing by each of the k outcomes.

$$L = \prod_{k=1}^{r} \prod_{i=1}^{N_k} f_k\left(t_i, X_{ki}, \beta_k\right) S_k\left(t_i, X_{ki}, \beta_j\right) \quad (4)$$

Assuming a censoring indicator δ_{ki} (such that δ_{ki} =1 if i failed due to k and 0 otherwise), the likelihood can be re-written as:

$$L = \prod_{k=1}^{r} \prod_{i=1}^{N_k} f_k\left(t_i, X_{ki}, \beta_k\right)^{\delta_{ki}} S_k\left(t_i, X_{ki}, \beta_j\right)^{1-\delta_{ki}} \quad (5)$$

This likelihood function is maximized in order to obtain parameter estimates. The paper examines parametric baseline hazards assuming Weibull and log-logistic distributions. In addition, it tests random effects (i.e. incorporating frailty component assuming a positive gamma distribution) within the alternative models. The goodness-of-fit of the models are evaluated based on the Akaike Information Criteria (AIC) where AIC = – 2 (Log likelihood) + 2(Number of Variables+ Number of Ancillary Parameters +1). The lower the value of the AIC the higher the goodness-of-fit of the corresponding model.

Job location choice model

Following reference-dependent residential location choice model structure in Habib and Miller (2009) the paper assumes the current job as the reference point to evaluate new location for a new job. As such, the utility of a job location i for a person j (who decides to change job location) in a particular occasion t is given by

$$U_{ijt/r} = \beta_0 + \beta_1 (Gain_{ijt} + \lambda Loss_{ijt}) + \beta_2 X_{ijt} + \varepsilon_{ijt} \quad (6)$$

Denoting $\gamma = \beta_1 \lambda$, the equation (2) can be rewritten in the following form:

$$U_{ijt/r} = \beta_0 + \beta_1 Gain_{ijt} + \gamma Loss_{ijt} + \beta_2 X_{ijt} + \varepsilon_{ijt} \quad (7)$$

where, $\beta_0, \beta_1, \beta_2$ and γ are the parameters to be estimated. $Gain_{ijt}$ refers to the amount of attribute value by which the alternative job location i exceeds that of current location for the person j at choice occasion t. And, $Loss_{ijt}$ refers to the amount of attribute value by which the location i is below than that of current location for the person j at choice occasion t. X_{ijt} denotes other attributes such as total employment, percentage of commercial land uses, etc.for the job location i at choice occasion t. The hypothesis of loss aversion is confirmed if the ratio of the loss and gain coefficient in equation (3) is greater than one (i.e. $\gamma / \beta_1 > 1$).

Collectively denote $Gain_{ijt}$, $Loss_{ijt}$ and X_{ijt} as Z_{ijt} and all the corresponding coefficients as β. Now, assuming ε_{ijt} as independently and identically distributed (iid) the choice probability of the decision-maker j choosing job location i in the choice occasion t can be expressed in multinomial logit form (McFadden, 1978):

$$P_{ijt} = e^{\beta_j Z_{ijt}} / \sum_{i=1}^{k} e^{\beta_j Z_{ijt}} \quad (8)$$

To incorporate panel effects of the dataset this paper examines a random parameter logit model where the choice probabilities are obtained through the integrals of standard logit probabilities over a probability density of parameters. It assumes all random parameters to be normally distributed (i.e. $\beta \sim N(\mu, \nu)$).

For the random parameter model, conditional on β_j, the choice probability of the person j for a single choice occasion choosing job location i (denoted simply as y_j) can be written as:

$$g(y_j \mid \beta_j) = e^{\beta_j Z_{ij}} / \sum_{i=1}^{k} e^{\beta_j Z_{ij}} \quad (9)$$

The unconditional probability is obtained by integrating $g(y_j \mid \beta_j)$ over all values of β_j weighted by the density of β_j as shown in the equation (6):

$$P_j(y_j \mid \mu,\nu) = \int g(y_j \mid \beta_j) f(\beta_j \mid \mu,\nu) d\nu \quad (10)$$

where $f(.)$ is the density function assumed to be normal as stated above. Hence the unconditional log likelihood function is given by:

$$L(\mu,\nu) = \sum_{j=1}^{J} \ln \int g(y_j \mid \beta_j) f(\beta_j \mid \mu,\nu) d\nu \quad (11)$$

Since this likelihood function is a multivariate integral that cannot be evaluated in closed form, the integral of the choice probabilities is approximated by Monte Carlo simulation (Train, 2003). For each decision-maker, taking draws from $f(\beta_j \mid \mu,\nu)$ the conditional choice probability $g(y_j \mid \beta_j)$ is calculated for each draw. This process is repeated for R times. Finally, the integration over $f(\beta_j \mid \mu,\nu)$ is approximated by averaging the R draws. Hence the resulting simulated log-likelihood function can be expressed as:

$$LL_s = \sum_{j=1}^{J} \ln \frac{1}{R} \sum_{r=1}^{R} \hat{P}_j(y_j \mid \mu,\nu) \quad (12)$$

where $\hat{P}_j$ is the simulated probability of the person j choosing job location i, and μ and ν are parameters to be estimated.

This simulated log-likelihood function is maximized to obtain parameter estimates. Under weak regularity conditions the maximum simulated log-likelihood estimator is consistent, asymptotically efficient and asymptotically normal (Hajivassiliou and Ruud, 1994; McFadden and Train, 2000). The study uses 150 random draws to estimate the parameters. In addition to the estimation of a random parameter model, this research also estimates a conventional logit location choice model for comparison purposes.

RESULT DISCUSSIONS

Job mobility models

Table 1 shows the results of the Weibull model for job mobility. Several socioeconomic variables are first tested in the model. Age is found to have a significant influence on the probability of job mobility. Younger persons are generally more likely to change jobs frequently than older persons. The model also confirms that the probability of job mobility amongst males is significantly lower than their female counterparts. Results also indicate a strong correlation between job mobility and length of education. Job mobility events are typically more frequent among people with more total years of education. Finally, the model also reveal that employment duration periods tend to be longer for workers during their first spell of employment, and get shorter for preceding jobs. The model also indicates that workers of different industries have different job mobility rates. Among the industries that are tested, the business, recreation, and sales/services industries featured the highest rates of mobility respectively.

The model also suggests that labourers tended to decrease their commuting distances when switching jobs. Commuting stress may also be responsible for high employment turnover rates for workplaces that are located further from highway exits. The model reveals that as employment firms increase in distance from highway exits, they also will experience higher job mobility. On the other hand, results found that workplaces in dense retail areas also experience higher employment turnover than in areas with low retail density.

Several household characteristics are also statistically significant for job mobility. First, a direct correlation exists between residential tenure and job tenure. As the duration period of living in the same house increases, the likelihood of job mobility decreases. Results also reveal that people living in single detached homes are less likely to be active in the job market. Job mobility also increases when additional workers are added to a household. The potential reason for this trend is most likely related to the increased stability of a household when multiple persons earn additional income. As seen with other variables, with additional stability comes more flexibility to test out the job market. Additionally, people residing in census tracts with higher average housing values also experience increasing rates of job mobility.

Economic variables may also impact job mobility events. The model tested the significance of interest rates on job mobility and found a positive correlation. High interest rates increase higher rates of job mobility, potentially due to the high amount of employment opportunities available in the market.

The results for mobility associated with returning back to school suggest that people under the age of 35 are more likely to return to school. The under 25 age cohort show an even more likelihood of exiting to the work force to continue their education. Similarly, the model also revealed that if a person is the child of the household head (perhaps living at parents' home), he/she is also more likely to return to school. Furthermore, household characteristics may also play a role in determining the likelihood of returning to school. For example, the model finds that as the number of job within a household increase, so too does the probability of returning to school. Finally, gender is also revealed as a significant factor, as females are shown to be more likely to return to school than males.

Some interesting work-related variables may also be associated with return to school events, as indicated by the model. Workers in the sales and services industry, for example, are more likely to return, while skilled workers are comparatively less likely to return. This is possibly explained by the fact that people in these positions most likely already have received adequate training, negated the need to return to school. In addition, it is found that person born in the GTHA are less likely to return to school than people who are born outside of the region, including other areas in the province, other provinces altogether, and other countries.

Regarding short-term unemployment event, age and gender are statistically significant variable in determining the likelihood of becoming unemployed. People within the age cohort of 41-55 have been found to be less prone to unemployment when compared with other age cohort. Specifically, employees aged between 46 and 50 have the highest probability of avoiding unemployment.

Additionally, workers employed in the sales and services industry are significantly more likely to become unemployed than other industries. In terms of occupation type, professionals are less likely to become unemployed. Finally, the model also found that renters are also more likely to be unemployed than home owners.

The final model that deals with complete withdrawal from the labour force (for example, become home-makers). Persons between the ages of 26 and 35 are more likely to withdrawal themselves from the workforce. The model also indicates that women with children frequently withdraw themselves from the labour force. Similarly effect is found for the people who belong to the households with more than one worker. Results also reveal that people with more education are also less likely to withdraw from workforce. Interestingly, employees working in the business industry are also significantly higher duration of work compared to workers of other industries. Finally, the model suggest that when unemployment rates are high, workers are more likely to withdrawal from the workforce permanently.

Job location choice model

Table 2 shows the parameter estimates of the job location model. The goodness-of-fit (adjusted Rho-square) of the random parameter model is 0.399. The model suggests that the higher the *gains* in auto commute travel time (i.e. decrease in peak period auto travel time from the current job to the next) increase the probability of choosing the alternative. Similar effect is also observed for the transit travel time. On the other hand, the higher the *losses* in commute travel times (i.e. increase in the travel time) the lower the probability of choosing the alternative. However, both *loss* parameters exhibit statistically significant standard deviations.

Both level-of-service parameters show loss aversion attitudes of the decision-makers. The ratio of the coefficients of the *loss* and *gain* for auto and transit travel time are 7.64 and 4.28 respectively, which are significantly higher than one. That means asymmetric evaluation of *gains* and *losses* exists, and individuals are very sensitive to the *losses* compared to equal amounts of *gains*.

The result also reveals that the higher the number of employment in a zone, the higher the probability of choosing the alternative. Both percentage of commercial land use and percentage of industrial land use also have positive impacts. Similarly, higher density of population increases the likelihood of choosing the alternative.

CONCLUSION

The paper presents comprehensive modelling framework for job mobility and location choice processes. Mobility decisions are implemented using a competing risk model. The results suggest that Weibul model with gamma shared frailty component describes termination probability best for each event type. On the other hand, random parameter model exhibits better model fit compared to traditional logit model. One of the key features of the location choice model is that it tests loss aversion attitudes. The study reveals that asymmetric evaluation of *gains* and *losses* exist. Particularly, workers are very sensitive to the losses in auto and transit travel times in choosing alternative location. These models are expected to be implemented within Integrated Land Use, Transportation and Environment (ILUTE) modelling system, which is recently been updated with comparable disaggregate behavioural residential mobility and (re) location choice models.

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Table 1: Parameter estimation results of competing risk mobility models

Switch a Job

Variables	Weibull model gamma shared frailty		log-logistic model gamma shared frailty	
	Coef.	*t*-statistics	Coef.	*t*-statistics
Constant	2.8420700	5.31	2.812693	4.74
age	0.0277249	3.57	0.0220476	2.73
pmale	0.4193863	3.00	0.4259332	2.99
toschool	-0.0398999	-1.67	-0.041683	-1.58
firstjid	0.5123992	3.76	0.6154073	4.50
business	-0.3339741	-2.14	-0.324678	-2.01
recreation	-0.9161202	-2.16	-0.819427	-1.96
salesservice	-0.5378780	-2.94	-0.487036	-2.62
retden5	-0.1598892	-1.64	-0.193691	-1.95
displabourer	-0.0052694	-1.81	-0.004144	-1.37
jhiexit	-1.4701120	-1.86	-1.305652	-1.68
jobinc	-0.4129843	-2.90	-0.497672	-3.37
duration	0.0172241	1.63	0.0148758	1.30
dsingdet	0.2848223	2.14	0.2864625	2.06
avgdwval	-0.0000017	-2.56	-1.64E-06	-2.40
intrate	-0.0540821	-3.17	-0.063046	-3.31

Back to School

Variables	Weibull model gamma shared frailty		log-logistic model gamma shared frailty	
	Coef.	*t*-statistics	Coef.	*t*-statistics
Constant	7.2120640	5.48	7.042791	4.85
under25	-2.7077350	-2.80	-2.803069	-2.83
age2635	-1.6208170	-1.80	-1.59739	-1.82
pmale	0.9179163	1.69	0.9137999	1.62
numdemp	-0.4103123	-1.59	-0.418876	-1.55
pchildren	-1.1671730	-1.81	-0.967921	-1.34
salesservice	-0.6600700	-1.23	-0.663441	-1.20
pskilled	0.9752650	1.19	0.9327008	1.15
currentcity	1.1319790	1.38	1.315493	1.48

Unemployed (short-term)

Variables	Weibull, gamma shared frailty		log-logistic gamma shared frailty	
	Coef.	*t*-stat.	Coef.	*t*-stat.
Constant	5.2537670	6.84	5.093306	6.40
age4145	0.7419811	1.46	0.7604538	1.51
age4650	1.1558530	1.68	1.145279	1.68
age5155	1.0512640	1.47	1.04434	1.46
pfemale	-0.4373759	-1.43	-0.489037	-1.62
pprofessio~l	0.9241452	1.78	0.8829718	1.72
salesservice	-0.7872297	-2.41	-0.766073	-2.32
jobchange	-0.5582394	-2.44	-0.564899	-2.30
ljregcen	0.3202375	2.27	0.3000726	2.14
dumrent	-0.6131005	-1.98	-0.585414	-1.88
intrate	0.0811260	1.64	0.0794061	1.59

Withdrawal from the labour force				
Variables	Weibull, gamma shared frailty		log-logistic gamma shared frailty	
	Coef.	*t*-stat.	Coef.	*t*-stat.
Constant	6.9149690	5.85	6.657982	5.28
age2630	-0.7314645	-1.21	-0.638396	-1.02
age3135	-0.5977797	-1.18	-0.583886	-1.11
fewithchild	-1.6405160	-3.47	-1.61435	-3.29
multiplewo~r	-1.3074800	-1.56	-1.242309	-1.54
pseccom	0.2086431	1.64	0.2064222	1.62
business	1.1808730	1.50	1.153283	1.48
unemprt	-0.0458127	-2.26	-0.042886	-1.98

Table 2: Parameter estimation results of job location choice model

	Multinomial logit		**Random parameter logit**	
Variables	Coefficient	t-statistics	Coefficient	t-statistics
Gain parameters (β_1)				
Gain (decrease) in auto commute travel time	0.02241	1.27	0.01731701	0.81
Gain (decrease) in transit commute travel time	0.01590	2.32	0.01730457	2.12
Loss parameters (γ)				
Loss (increase) in auto commute travel time	-0.07383	-5.72	-0.13233888	-3.47
Loss (increase) in transit commute travel time	-0.04791	-10.16	-0.07411988	-5.88
CT characteristics				
Total emploment	0.00018	2.18	0.00024133	2.14
Percentage of commercial land uses	0.03922	3.81	0.05059385	4.18
Percentage of industrial land uses	0.01775	3.99	0.0207052	3.74
Density of population	0.00028	1.20	0.000471158	1.55
Standard deviation of the random parameters				
Loss (increase) in auto commute travel time			0.1171746	2.94
Loss (increase) in transit commute travel time			0.05642715	4.24