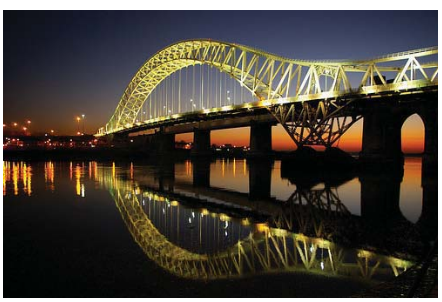
University Transportation Research Center - Region 2

Final Report

Conduct Urban Agglomeration with the Baton of Transportation

Performing Organization: Rensselaer Polytechnic Institute



December 2013

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The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

Research

The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

Education and Workforce Development

The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

Technology Transfer

UTRC's Technology Transfer Program goes beyond what might be considered "traditional" technology transfer activities. Its main objectives are (1) to increase the awareness and level of information concerning transportation issues facing Region 2; (2) to improve the knowledge base and approach to problem solving of the region's transportation workforce, from those operating the systems to those at the most senior level of managing the system; and by doing so, to improve the overall professional capability of the transportation workforce; (3) to stimulate discussion and debate concerning the integration of new technologies into our culture, our work and our transportation systems; (4) to provide the more traditional but extremely important job of disseminating research and project reports, studies, analysis and use of tools to the education, research and practicing community both nationally and internationally; and (5) to provide unbiased information and testimony to decision-makers concerning regional transportation issues consistent with the UTRC theme.

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16. Abstract

A key indicator of traffic activity patterns is commuting distance. Shorter commuting distances yield less traffic, fewer emissions, and lower energy consumption. This study develops a spatial error seemingly unrelated regression model to investigate commuting distance, and how various influential factors affect commuting distances in ten counties across the U.S. By integrating datasets from the Census Transportation Planning Product (CTPP) and Smart Location Database (SLD), this study acquires rich employment and residence information at the census block group (CBG) level. Patterns of commuting distance, characterized by mean and standard deviation, of three industry sectors are calculated. A set of jobs-residence metrics is created to represent the degree of matching between residence and employment. Variables characterizing the trip origins, such as income level and road network connectivity, are also controlled in the model. Results confirm that a high jobs-residence ratio is beneficial for commuting patterns. Short commuting distances are also associated with clustered industry sector distribution, and dense road networks with few intersections. In addition, sprawled regions should control car ownership to shorten commuting distances. Income and payment level have a county-specific effect, and related policies should be proposed on a case-by-case basis. Spatial autocorrelation is also found to be significant in many counties, confirming the need to consider spatial effects in commuting distance studies. This study contributes to the existing literature by providing valuable insights into the influence of a jobs-residence balance on commuting patterns, applying a more efficient econometric model, and comprehensively investigating multiple cases.

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Contents

1. Introduction

A key indicator of traffic activity patterns is commuting distance. Shorter commuting distances often correspond with less traffic, fewer emissions, and lower energy consumption. As a result, many programs are designed to shorten commuting distance: road network improvements, such as bridge and tunnel construction along major commuting corridors; and demand management interventions, such as road pricing. However, it is generally agreed that the most effective way to shorten commuting distance is by improving the jobs-residence balance, as commuting trips are essentially the results of home and workplace location choices. Over the years, many studies have been done on jobs-residence balance (Cervero, 1989, 1996; Levine, 1998), but there is still no consensus on how to evaluate "balance," and exactly what its effect is on commuting trip patterns (Wachs, Taylor, Levine, & Ong, 1993).

This study develops local and regional jobs-residence balance metrics by considering the degree of "matching" between employment positions and working-age residents. If an individual worker can find the "right" job near his/her residence, the commuting distance will be short. Otherwise, the worker will have to travel a longer distance to achieve the "right" match in the regional domain. The corresponding aggregate behavior is thus the evaluation of whether there are enough employment positions for the number of working-age residents. Essentially, these metrics evaluate equilibrium between labor force demand and supply. If the two sides match perfectly within a short distance, most residents will work locally and the average commuting distance will be short. Otherwise, residents will have to travel farther in their daily commutes. Jobs-residence balance not only influences the average commuting distance, but also its variability, which is an important factor often neglected in previous studies. Low commuting distance variability implies similar commuting behaviors, a high potential for car sharing, and for utilization of transportation services. Thus, this study analyzes both average and standard deviation of commuting distance simultaneously, using a seemingly unrelated regression (SUR) model. The SUR model captures the correlation among commuting trips of different industry sectors, and the correlation between average trip distance and distance variability. In addition, spatial units – in this study, census block group (CBG) – often exhibit different areas, shapes, and development patterns, which leads to heterogeneity. Besides, people often have similar commuting behavior when they live close to each other. A spatial error specification can accommodate the spatial correlation, and is incorporated into the SUR model.

To generate a thorough research overview, this study studies ten counties in the U.S. Counties were selected based on their variability of county forms, regional development patterns, and transportation services. The similarities and differences are analyzed, and general and county-specific policy implications are proposed.

The next section reviews the literature on jobs-residence balance and SUR models with spatial consideration. Model specification and data description are then presented, followed by results analysis and conclusions.

2. Literature Review

2.1 Jobs-Residence Balance and Commuting Pattern

Commuting pattern can be studied from a variety of perspectives and at different levels. At the disaggregate level, and from the perspective of a labor force, commuting distance can be considered as the result of household decisions, hence explained by household characteristics. For example, Rouwendal and Rieveld (1994) used a lognormal regression model to investigate commuting distance in the Netherlands. They found that commuting distance was related to household size, and the presence of a spouse. People who changed jobs frequently also tended to commute over a long distance. Wang and Chai (2009) applied a structural equation model to analyze commuting time, and found that the housing source system in China made a difference in commuting behavior. Still at the disaggregate level, but from the perspective of the job market, Van Ommeren et al. (1997) found that commuting distance was negatively related to the job arrival rate, and that people would accept a wide range of job and residence combinations as they search for better jobs and residences.

At the aggregate level, commuting distance is believed to be influenced by urban form and land use planning. Most studies found that improving the jobs-residence ratio reduced commuting distances. For example, Cervero and Duncan (2006) compared the effects of jobs-residence balance on work and shopping trips, and concluded that one of the most important approaches to reduce vehicle travel was by increasing jobs-residence ratio. Using a nonlinear optimization model, Horner and Murray (2003) found that jobs-residence balance could reduce congestion, emissions, and related externalities. Wang and Chai (2009) found that a high jobs-residence ratio shortened commuting trips, increased usage of non-motorized modes, and reduced travel. Sultana (2002) analyzed the Atlanta area, and concluded that the imbalance between job and residence locations was the most important determinant for the long commuting distances in that area. However, there is still no consensus regarding the effect of jobs-residence balance on commuting behavior. For example, Giuliano and Small (1993) found that policies aimed at changing the jobs-residence balance had only a minor effect on commuting. Peng (1997) formulated a set of nonlinear regression models and found that jobs-residence balance policy would have limited impact on vehicle miles traveled at the regional level.

In addition to disagreement on the effect of jobs-residence balance, also under debate are proper metrics for evaluating jobs-residence balance. The simplistic form to evaluate jobs-residence balance is the ratio of jobs to housing units. For example, Cervero (1989) used the ratio of number of employees to number of households to indicate jobs-residence balance. In a later study for 23 San Francisco Bay Area cities, Cervero proposed a ratio of jobs to employed residents (1996). More complex metrics are derived from land use and people's income/expenditure perspectives. For example, Frank (1994) built a relationship between residential and industrial land use. Hamilton (1991) investigated the contrast of workers earning and cost of housing. These jobs-residence metrics are usually developed on large spatial units, such as counties, boroughs, or cities. However, commuting distance and jobs-residence balance ratio could vary significantly within large spatial units. Simple reliance on these broad metrics makes it impossible to further investigate heterogeneity within the unit.

2.2 SUR with Spatial Consideration

Zellner (1962) first proposed the SUR model to deal with correlated regression equations, and it has been used since for many studies in the transportation field. Albalate and Bel (2010) used a SUR model to investigate the effect of tourism on public transportation in European cities. Anselin (1988b) extended the SUR model with spatial consideration by incorporating spatial autocorrelation into the error terms. Elhorst (2003) provided a comprehensive study on the specification and estimation of spatial panel data models. The spatial correlation term can be either a spatially lagged term or a spatial error autocorrelation term. Wang and Kockelman (2007) developed a spatially and temporally autocorrelated SUR model to study China's traffic crash problem, with two equations and two time periods. Zhou and Kockelman (2009) incorporated two spatial processes into a SUR model to predict households and employment distribution in Austin, TX. Baltagi and Bresson (2011) generalized the model by incorporating spatial effects via spatial lagged dependent variables to investigate housing prices in Paris, France.

3. Methodologies

3.1 Model Specification

This study analyzes both average and standard deviation of commuting distance for three employment types. Thus, a 6-equation seemingly unrelated regression (SUR) model is built to capture correlations among them. SUR model assumes that serial correlation exists in the error term. Let $g(g = 1...G)$ denote equation number. The SUR can be specified in matrix denotation as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_G \end{bmatrix} = \begin{bmatrix} X_1 & 0 & 0 & 0 \\ 0 & X_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & X_G \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_G \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_G \end{bmatrix} \tag{1}$$

where y_g is a $(N \times 1)$ vector representing the average or standard deviation of commuting distance, where N is the number of CBGs. X_g is a $(N \times K)$ matrix indicating the influential factors such as jobs-residence ratio. β_g is a $(K \times 1)$ vector of the estimable coefficients. The error terms have mean **0,** and a variance-covariance matrix where the off-diagonal elements $\sigma_{gh} \neq 0$.

CBGs, the spatial unit in this study, usually have different sizes and development patterns. Beside, people living closer often have similar commuting behavior. These spatial heterogeneities and autocorrelations may be partly captured by the measurement errors and may result in heteroskedasticity (Anselin, 1988a). A spatial error regression is able to capture the spatial interaction in the error term (Lesage & Pace, 2008). For each equation, use u as the heteroskedasticity error term and ε denotes the idiosyncratic term, then u can be written as

$$u = \rho W u + \varepsilon \tag{2}$$

After rearrangement,

$$u = \left(I - \rho W\right)^{-1} \varepsilon \tag{3}$$

where I is an identical matrix, and ρ is the estimable spatial parameter with a range of [0,1], indicating the magnitude of spatial interaction. W is a row-standardized spatial proximity weight matrix with dimension $(N \times N)$, with each element as a decay function of network distance between centroids of two CBGs. The distance decay function is

$$w_{ij} = d_{ij}^{-0.3} \times \exp\left(-0.07 \times d_{ij}\right) \tag{4}$$

for two centroids of i and j. Such a decay function curve is calibrated in the report "Travel Estimation Techniques for Urban Planning" (NCHRP Report 365, Transportation Research Board, 1998).

For a spatial error SUR model consisting of G equations, the final model can be specified in matrix form as

$$y_g = X_g \beta_g + (I_N - \rho_g W)^{-1} \varepsilon_g = X_g \beta_g + H^{-1} \varepsilon_g \tag{5}$$

3.2 Model Estimation

The parameters that need to be jointly estimated are β_g, Σ, and ρ_g. Given that they are intertwined in the model specification and log-likelihood function, this study uses an estimation method that combines feasible generalized least square (FGLS) and maximum likelihood estimation (MLE).

In the FGLS process, the β is firstly estimated by ordinary least square (OLS), and then the residual ε_g corresponding to each equation g is calculated. Next, the matrix Σ is estimated by

$$\hat{\Sigma} = [\hat{\sigma}_{gh}] = \mathrm{cov}\left(\hat{\varepsilon}_g, \hat{\varepsilon}_h\right) \tag{6}$$

SUR model presumes that error terms are identical within one equation, but not cross equations. Thus, the variance-covariance matrix of error terms can be expressed as $\Omega = H^{-1}{}'(\Sigma \otimes I_N) H^{-1}$, where $\otimes$ denotes the Kronecker product. Then, FGLS re-estimates the value of β based on $\hat{\Sigma}$ by (Hayashi, 2001)

$$\hat{\beta} = (X'\Omega^{-1}X)X'\Omega^{-1}Y \tag{7}$$

In the MLE process, ρ_g is estimated by maximizing the log-likelihood function of the spatial error SUR model with the estimated values of β and Σ from FGLS. As $y \sim MVN(X\beta, H^{-1}{}'(\Sigma \otimes I_N) H^{-1})$, after some basic math manipulation, the log-likelihood function can be written as (Wang & Kockelman, 2007)

$$L = -\frac{NG}{2}\ln(2\pi) + \ln\left|H\right| - \frac{N}{2}\ln\left|\Sigma\right| - \frac{1}{2}\left[H(y - X\beta)\right]'\left(\Sigma^{-1} \otimes I_N\right)\left[H(y - X\beta)\right] \qquad (8)$$

The FGLS and MLE processes are iterated until convergence to obtain the final estimates of all parameters. In this study, the estimation process is coded in MATLAB. A validation test of the code is executed first, and a satisfactory validation result is obtained.

4. Data Description

Ten counties across the United States, representative of diversified population density, transportation services and development patterns, are analyzed in this study. For example, New York County, NY and San Francisco County, CA are examples of high population density, while the populations of Dallas County, TX and Duval County, FL are sprawled. Multnomah County, OR and New York County, NY provide multiple commuting modes, while people in Albany County, NY and Shawnee County, KS generally have to rely on private automobiles. Figure 1 is a map showing the ten counties' locations, and Table 1 lists county names, number of CBGs, and basic characteristics.

The commuting pattern data comes from the Census Transportation Planning Product (CTPP) (U.S. Census Bureau, 2010), which contains a Longitudinal Employer-Household Dynamics (LEHD) dataset from 2010. Its Origin-Destination (OD) data file provides number of commuters between each OD pair at census block level for three employment types. The employment is classified as:

1. Jobs in good producing industry sectors;
2. Jobs in trade, transportation, and utilities industry sectors;
3. Jobs in all other services industry sectors.

As different industry sectors require workers with different educational backgrounds, experiences, and skills, workers' commuting patterns would most likely differ. For example, type 1 workers often have specific technical skills, and tend to keep working for the same company for a long time, but type 3 workers may be more flexible, have a wider variety of potential employers, and may change jobs more frequently. This study investigates the industry sectors separately. The data at the level of spatial unit (CBG) in this study are grouped from the census block level data in the OD files. Then, the average and standard deviation of commuting trips of the three employment types originating from CBGs are derived.

The demographic, employment, and built environment data of each CBG come from Smart Location Database (SLD), a product of the Environmental Protection Agency (2013). However, commuting pattern is affected by factors not only within the CBG, but also in the surrounding area. People usually search for jobs in the regional domain as long as they can accept the commuting distance. Therefore, the SLD data is further derived to regional metrics, capturing factors in the surrounding areas. Regional factors are a set of distance-weighted metrics, where the weights are a function of network distance, as shown in equation (4). As the function value approaches zero, when the distance reaches 45 miles, this study uses 45 miles as the threshold on deriving regional metrics. Table 2 lists all variables used in this study with their definitions, and Table 3 reports the mean and standard deviation of variables of the ten counties.

It is worth noting that network distance, instead of Euclidean distance, is used throughout the study. Network distance is a more behaviorally-consistent measurement of distance in transportation field, as people travel following certain routes. For a more accurate investigation, this study uses ArcGIS to derive network distance in calculations of commuting distance, regional metrics, and spatial proximity matrix.

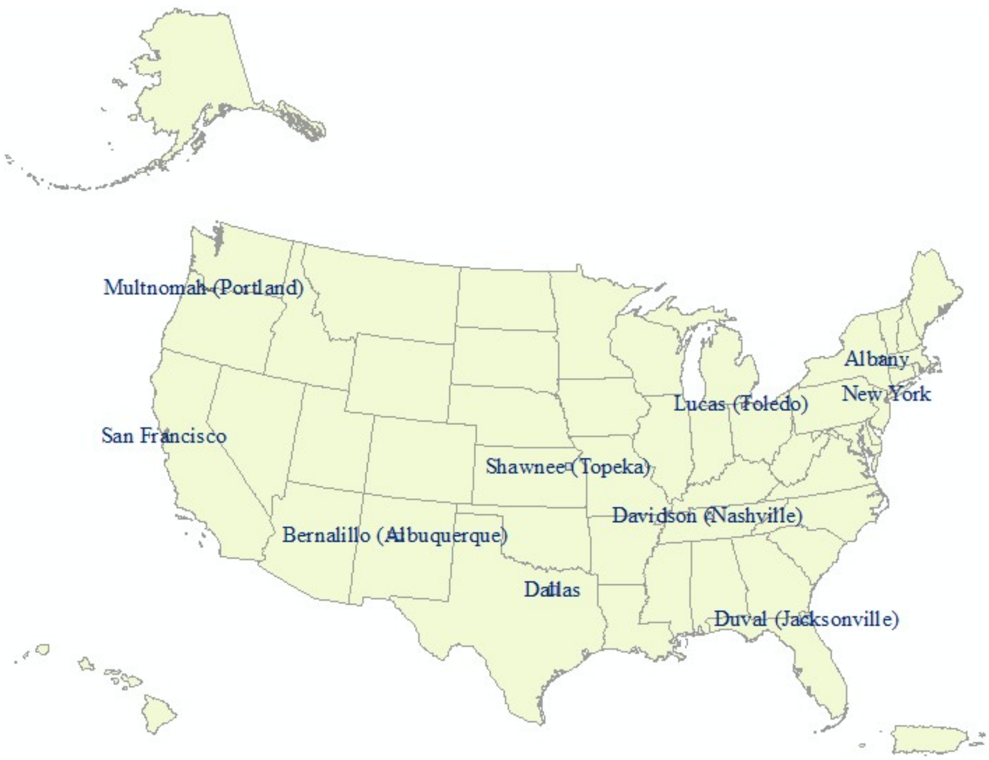

Figure 1. Map of ten counties analyzed

Table 1. Information of the ten selected counties, summarized from Smart Location Database (Environmental Protection Agency, 2013)

County Name	State	Number of CBGs	Major Characteristics
Albany	New York	235	Mid-size sprawled area; Political center of New York State; Regional transportation hub
Bernalillo	New Mexico	433	Dense downtown Albuquerque city against sparse rural area
Dallas	Texas	1664	Large-size sprawled city; Regional center of economic, technology, and transportation
Duval	Florida	489	Its center city, Jacksonville, is the largest in Florida in population and area
Davidson	Tennessee	472	Mid-size sprawled area; Center of politics, transportation
New York	New York	1080	Dense area with multiple transportation modes; Center of finance, transportation, etc.
Multnomah	Oregon	521	Multiple well-developed commuting modes
San Francisco	California	574	Dense area with hills; Multiple urban renewal projects
Lucas	Ohio	397	At the corner of three States (Ohio, Michigan, and Indiana)
Shawnee	Kansas	135	Satellite city of Kansas City

Table 2. Variable names and definitions, summarized from Census Transportation Product (U.S. Census Bureau, 2010) and Smart Location Database (Environmental Protection Agency, 2013)

Variables Name	Definition
Dependent Variables	
Type_1_Avg	Average commuting distance of type 1 jobs
Type_2_Avg	Average commuting distance of type 2 jobs
Type_3_Avg	Average commuting distance of type 3 jobs
Type_1_Std	Standard deviation of commuting distance of type 1 jobs
Type_2_Std	Standard deviation of commuting distance of type 2 jobs
Type_3_Std	Standard deviation of commuting distance of type 3 jobs
Independent Variables	
Job_Pop_L_Type_1	Local ratio of type 1 Jobs and working population
Job_Pop_L_Type_2	Local ratio of type 2 Jobs and working population
Job_Pop_L_Type_3	Local ratio of type 3 Jobs and working population
Job_Pop_R_Type_1	Regional type 1 Jobs-residence ratio, weighted by distance decay function
Job_Pop_R_Type_2	Regional type 2 Jobs-residence ratio, weighted by distance decay function
Job_Pop_R_Type_3	Regional type 3 Jobs-residence ratio, weighted by distance decay function
Car_Owner0	Percent of household with zero cars
Car_Owner2p	Percent of household with more than two cars
LowInc	Percent of low income working population in CBG
LowPay	Percent of low payment jobs in CBG
Mix_L	Local Employment diversity entropy
Mix_R	Regional Employment diversity entropy weighted by distance decay function
NetDnst_L	Local network density (miles/acre)
NetDnst_R	Regional network density weighted by distance decay function (miles/acre)
Inter_L	Local intersection density (Number of intersections/acre)
Inter_R	Regional intersection density weighted by distance decay function (Number of intersections/acre)

Table 3. Summary statistics of variables, summarized from Census Transportation Planning Product (U.S. Census Bureau, 2010) and Smart Location Database (Environmental Protection Agency, 2013)

Population Density	**High**						**Low**											
Counties	New York		Multnomah		San Francisco		Albany		Bernalillo		Dallas		Duval		Davidson		Lucas		Shawnee	
Variables Name	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Dependent Variables																				
Type_1_Avg	7.32	2.91	10.57	2.15	18.30	4.71	14.17	4.18	9.05	4.03	18.47	3.86	12.02	3.12	21.53	4.35	10.58	3.25	9.49	2.64
Type_2_Avg	6.12	1.99	9.46	2.75	12.01	2.37	12.90	4.04	8.77	3.95	20.32	3.54	12.66	2.75	21.47	3.22	11.65	3.05	9.54	2.66
Type_3_Avg	4.58	1.70	8.06	2.76	9.24	1.35	12.13	3.61	8.03	4.08	18.50	3.21	11.52	2.95	18.55	2.90	8.50	2.07	6.63	2.81
Type_1_Std	6.46	2.73	7.87	2.10	16.08	2.57	9.87	2.50	6.26	3.15	13.92	4.32	8.21	1.99	17.43	3.15	10.94	4.28	7.90	1.89
Type_2_Std	6.30	1.39	7.38	2.22	13.44	1.99	9.31	1.71	6.28	2.59	15.12	3.57	8.34	1.55	18.06	2.00	13.89	4.27	9.73	2.22
Type_3_Std	4.68	0.67	7.09	2.07	11.61	1.35	8.29	1.49	5.81	2.54	13.17	2.63	7.38	0.99	16.57	1.58	9.89	2.42	6.50	1.07
Independent Variables																				
Job_Pop_L_Type_1	98.93	188.14	92.84	156.67	128.04	202.71	74.93	160.13	96.21	174.61	80.09	170.57	91.14	181.84	77.69	181.59	46.67	116.18	67.08	138.06
Job_Pop_L_Type_2	54.38	120.13	68.23	160.24	76.85	142.64	65.41	139.80	74.56	158.10	68.30	166.01	64.93	167.92	56.31	149.68	41.08	94.22	66.36	160.93
Job_Pop_L_Type_3	10.90	41.18	9.79	24.80	8.08	9.29	13.36	33.03	25.17	68.97	33.52	84.67	20.71	76.19	36.88	102.65	18.88	49.73	26.80	80.61
Job_Pop_R_Type_1	0.12	0.01	0.18	0.01	0.12	0.01	0.11	0.004	0.17	0.02	0.28	0.02	0.14	0.02	0.19	0.01	0.28	0.03	0.17	0.02
Job_Pop_R_Type_2	0.35	0.03	0.27	0.02	0.29	0.03	0.25	0.01	0.28	0.02	0.40	0.02	0.37	0.03	0.34	0.02	0.30	0.01	0.25	0.02
Job_Pop_R_Type_3	1.50	0.20	0.88	0.11	1.28	0.19	0.92	0.07	1.04	0.14	1.18	0.10	0.99	0.12	1.06	0.10	0.87	0.05	1.11	0.16
Car_Owner0	0.77	0.14	0.12	0.14	0.25	0.22	0.13	0.16	0.06	0.08	0.08	0.11	0.09	0.11	0.08	0.12	0.11	0.13	0.08	0.11
Car_Owner2p	0.03	0.04	0.50	0.19	0.34	0.20	0.49	0.22	0.58	0.19	0.54	0.22	0.51	0.20	0.51	0.21	0.51	0.20	0.56	0.22
LowInc	0.19	0.07	0.23	0.04	0.20	0.06	0.25	0.05	0.26	0.05	0.23	0.05	0.26	0.05	0.25	0.06	0.31	0.06	0.29	0.05
LowPay	0.28	0.15	0.31	0.12	0.37	0.17	0.33	0.17	0.34	0.17	0.30	0.19	0.35	0.16	0.31	0.19	0.36	0.23	0.35	0.18
Mix_L	0.55	0.26	0.58	0.25	0.50	0.27	0.50	0.28	0.46	0.30	0.39	0.32	0.51	0.28	0.39	0.30	0.38	0.31	0.46	0.30
Mix_R	0.30	0.01	0.50	0.01	0.38	0.01	0.42	0.01	0.40	0.01	0.32	0.01	0.47	0.03	0.33	0.01	0.28	0.02	0.35	0.02
NetDnst_L	31.39	13.25	24.67	8.77	30.67	7.89	16.28	9.62	19.24	7.35	19.20	6.39	16.23	7.02	14.37	6.76	17.02	7.11	15.28	7.15
NetDnst_R	15.75	0.60	17.80	0.78	17.53	0.42	8.96	0.25	13.56	0.48	10.17	0.23	12.43	0.45	7.17	0.23	6.70	0.17	8.89	0.33
Inter_L	91.80	113.47	158.01	82.15	190.94	115.29	69.24	56.02	604.69	248.80	75.70	44.88	70.59	49.20	64.51	89.77	75.37	48.45	69.30	44.80
Inter_R	57.20	1.35	107.45	6.68	99.73	3.68	36.33	1.47	60.82	2.65	39.41	0.68	52.15	3.00	29.83	1.46	27.45	1.07	37.44	1.67

5. Results Analysis

The commuting pattern data was analyzed using a spatial error SUR model. Table 4 shows the full estimation results for Albany County, NY. The Albany data is also analyzed using a standard linear regression, a standard SUR, and a spatial error regression. Among all the models, the spatial error SUR model is the best, indicated by the non-zeros values at off-diagonal elements in Σ, significant spatial parameters ρ and the largest log-likelihood values. Table 5 and 6 show estimation results for the other nine counties in a simplified version that only reports the estimated values of β and ρ with significant levels in asterisk. The estimation results reveal important, interesting insights on commuting pattern.

Regional jobs-residence ratios mostly have significant negative coefficients, indicating that a high ratio would contribute to short commuting trips and small distance variability. Among the estimated coefficients of employment types and counties, job type 1 in San Francisco County has the largest absolute value of -140.479. With a 1% increase of jobs-residence ratio, the average trip distance would decrease approximately 1.4 miles with other factors constant in San Francisco. People most practically start searching for jobs within their living community, and then expand the search regionally. A high ratio implies that people are able to find jobs easily, and will likely work locally. From a demand and supply perspective, job markets with more positions would increase the possibility of people finding an ideal job within a short distance. Thus, an active job market with sufficient job positions is very helpful in reducing commuting distance and its variability. In addition, the three employment types have different sensitivities towards jobs-residence balance. With a 1% increase of the ratio, the average trip distance would reduce by 0.46, 0.24, and 0.04 miles for the three employment types, respectively. Among the three types, goods producing jobs are affected by jobs-residence balance to the largest extent. Regions with a lot of goods producing companies should strongly consider the jobs-residence balance.

Commuting trips distance and its variability would increase when there are more two-plus car ownership households in sprawled regions, such as Dallas County. Higher car ownership in a spread-out area implies more chances of mobility, as people are able to access jobs farther away. Therefore, for a better commuting pattern, sprawled regions need to control or limit car ownership by providing more available commuting modes, increasing toll charges, and levying fuel surcharges. On the other hand, in dense regions, commuting trip distance and its variability would decrease when there are more zero-car ownership households. This correlation is supported by the significantly positive coefficients in the cases of New York County, Multnomah County (Portland, OR), and San Francisco County. Such a phenomenon can be explained by the availability of public transportation in these regions. Trains and subways are important, even dominant, commuting modes in these regions. People can be still of high mobility without cars, as long as other transportation modes are available.

The percentage of low income workers and the percentage of low payment jobs have dual direction effects on commuting patterns in different counties. In other words, the impact of income and payment is inconclusive, and should be analyzed region-specifically. For example, Dallas has significantly positive coefficients in all equations, indicating the better commuting pattern is related to high income workers and high payment jobs. However, low income good producing workers in San Francisco also tend to commute short distances.

Clustered industry sector distribution is beneficial for short commuting in most counties (except Multnomah County), because the coefficients of regional employment diversity entropy are significant and negative. The extreme case appears in Albany County's employment type 3, where the coefficient of 143.060 indicates that the commuting trip distance would increase approximately 1.43 miles when the diversity entropy increases 1%. The effect of employment diversity on variability is inconsistent in the ten counties, and should be analyzed on a case-by-case basis. When same industry sectors concentrate, workers with corresponding skills would reside close to the industry center, finding convenience and comfort in terms of commuting and neighboring environment. This proximity to the industry sector center is also good for information exchange, colleague communication, and shared services. Therefore, clustering industry sectors is highly recommended for regions characterized by long commuting distances.

Dense road networks are good for commuting patterns, as indicated by the negative coefficients in most average and standard deviation equations. This may be due to the fact that people often start accessing jobs along roadways, and dense road networks provide high accessibility for jobs close to residences. Among the counties studied, Albany is the most sensitive to road network density. The coefficients of -17.308, -25.567, and -26.774 in the three employment-type equations of average distance are the largest of those in the ten counties. With one additional mile of roads per acre, the average commuting distance would decrease by 17.308, 25.567, and

26.774, respectively, in Albany. Albany stands out because it is an auto-oriented county with good road systems. Once a denser network is constructed, more employment positions would be exposed to the public, jobs which people would be able to access easily. Intersection density, on the other hand, has an opposite effect on commuting patterns. A region with more intersections means higher potential chances for travelers to reach surrounding road networks, and results in extended commuting trips. In addition, more intersections may lead to potential traffic congestions. Traffic lights or stop signs at intersections have to be established, and they delay smooth traffic flows. Thus, an ideal road network would have high road density with fewer intersections.

The spatial error parameters are significant in most average distance equations. Among the counties studied, Dallas has the largest estimated values in all three employment-type equations. Thus, high spatial correlations are confirmed in Dallas County. Dallas County is a typical sprawled region in the U.S., with a sparse distribution of residents. The similarities between residents living close to one another are much larger than those living far away. Overall, the significant spatial error parameters in this study indicate the need to consider spatial effects in analyzing commuting pattern. Such a parameter helps to reduce the effects of missing explanatory variables, measurement errors, etc. Future studies should carefully consider the role of spatial specification in analyzing commuting patterns.

In summary, good commuting patterns can benefit from a high jobs-residence ratio, clustered industry sector distributions, and dense road networks with few intersections. Car ownership should be controlled in spread-out regions to shorten commuting distances. Proportions of low income workers and low payment jobs do not have a consistent impact in the ten counties studied, and these factors should be considered on a case-by-case basis. The model specification with SUR and spatial error is necessary when analyzing commuting pattern issues, as it improves the model's goodness-of-fit.

Table 4. Results of Albany County, NY using the spatial error SUR model

	(1) Type_1_Avg		(2) Type_2_Avg		(3) Type_3_Avg		(4) Type_1_Std		(5) Type_2_Std		(6) Type_3_Std	
	Coef	t_stat	Coef	t_stat	Coef	t_stat	Coef	t_stat	Coef	t_stat	Coef	t_stat
Job_Pop_L	0.002	1.62	0.001	0.76	-0.0002	-0.11	0.002	1.74	-0.0002	-0.27	-0.001	-0.71
Job_Pop_R	-30.136	-0.44	-37.742	-2.64	-7.134	-5.87	-44.998	-0.73	-2.096	-0.14	1.811	1.70
Car_Owner0	-0.087	-0.04	3.935	2.26	1.147	0.85	-2.081	-1.26	2.194	1.83	-1.351	-1.94
Car_Owner2p	0.846	0.51	1.658	1.30	1.062	1.08	-0.260	-0.21	0.915	1.05	-0.264	-0.52
LowInc	-12.981	-2.13	-6.043	-1.27	-2.241	-0.61	-15.237	-3.37	-9.208	-2.85	1.940	1.02
LowPay	0.663	0.54	0.797	0.84	-0.187	-0.25	-0.298	-0.33	0.357	0.55	-0.511	-1.34
Mix_L	1.047	1.41	-0.322	-0.55	-0.303	-0.66	0.713	1.29	-0.591	-1.45	-0.087	-0.35
Mix_R	95.698	4.06	127.710	6.34	143.060	8.88	8.159	0.47	12.123	0.98	49.231	6.03
NetDnst_L	-0.124	-2.33	-0.049	-1.17	-0.029	-0.89	-0.010	-0.25	0.044	1.55	0.044	2.66
NetDnst_R	-17.308	-6.86	-25.567	-11.13	-26.774	-16.21	8.115	4.35	0.733	0.46	-3.981	-5.05
Inter_L	0.016	2.15	0.001	0.16	0.002	0.37	0.006	1.02	-0.004	-0.91	-0.001	-0.48
Inter_R	1.356	3.20	2.761	7.62	3.113	11.64	-1.086	-3.38	0.095	0.41	1.128	9.28
Constant	85.825	6.21	97.858	9.15	85.520	10.19	-18.057	-1.71	-4.023	-0.60	-20.096	-4.85
Spatial rho	0.071	0.09	0.796	5.23	0.774	4.55	0	0	0	0	0	0
Sigma	9.11											
	3.16	5.52					Log likelihood at Null					-98280
	2.66	3.33	3.33				Log likelihood					-2548
	3.52	-0.02	-0.07	5.02			Log likelihood in standard linear regression					-2846
	0.01	1.71	0.08	0.26	2.58		Log likelihood in standard SUR					-2840
	-0.37	0.13	0.47	0.05	0.20	0.89	Log likelihood in spatial error regression					-2562

Table 5. Estimation results of average commuting distance in the other nine counties

		High Population Density			Low Population Density						
		New York	Multnomah	San Francisco	Albany	Bernalillo	Dallas	Duval	Davidson	Lucas	Shawnee
Eq (1)	Job_Pop_L	-0.0002	0.0004	0.001*	0.002	-0.0004	0.0001	0.0004	-0.001	0.001	-0.001
	Job_Pop_R	-60.987***	-28.081***	-140.479***	-30.136	-48.837***	-16.290***	-95.326***	1.857	-54.054*	-50.461***
	Car_Owner0	1.455**	2.945***	7.358***	-0.087	-0.935	-0.247	1.699	0.947	4.952***	2.111
	Car_Owner2p	2.173	1.928***	-1.223	0.846	0.331	1.367***	-0.055	0.809	2.847***	0.666
	LowInc	-3.196**	1.502	-32.350***	-12.981**	-0.970	6.310***	-1.223	-22.525***	2.489	-0.405
	LowPay	-0.670	0.262	-1.734*	0.663	0.056	2.242***	-1.066*	-0.584	0.442	1.386*
	Mix_L	-0.377	-0.496	-0.926	1.047	-0.361	-0.148	-0.061	-0.013	0.095	-0.206
	Mix_R	191.370***	-35.940**	-35.937	95.698	92.191***	-3.715	28.147***	85.517**	44.416**	81.047***
	NetDnst_L	-0.005	-0.012	-0.046	-0.124**	-0.109***	-0.188***	-0.105***	-0.130***	-0.072*	-0.157**
	NetDnst_R	-7.032***	-0.753	0.107	-17.308***	-7.360***	-7.024***	-6.716***	-10.538***	-8.795***	-12.438***
	Inter_L	0.002**	-0.001	-0.002	0.016**	0.0003	-0.004	0.003	0.010***	0.005	0.026**
	Inter_R	0.592***	-0.010	0.103	1.356***	0.471*	1.184***	0.867***	1.389***	0.818	1.865**
	Constant	34.233***	46.872***	44.213*	85.825***	53.726***	50.060***	52.778***	33.976***	47.504***	30.020***
	Spatial rho	0	0.388	0.513	0.071	0.323	0.977***	0.461	0.469	0.597*	0.209
Eq (2)	Job_Pop_L	0.0005*	0.0001	0.002***	0.001	-0.0003	0.001***	0.0003	-0.001*	0.00003	-0.0001
	Job_Pop_R	-14.421***	-27.490***	-22.277***	-37.742***	-31.118***	-7.538**	-38.350***	-12.907*	-42.503***	-5.464
	Car_Owner0	-0.162	1.448*	2.670***	3.935**	-1.889	-0.918	0.206	-2.303	-0.487	3.636*
	Car_Owner2p	-0.759	1.280**	1.559*	1.658	0.644	2.478***	0.207	0.242	0.576	1.605
	LowInc	2.009***	9.297***	-1.381	-6.043	-3.542	12.548***	-2.781	-1.256	3.931	13.982***
	LowPay	-0.276	0.610	-0.547	0.797	0.307	2.521***	-0.829*	0.548	-1.114*	0.465
	Mix_L	-0.439***	0.046	-0.445	-0.322	-0.455	-0.442*	0.019	-0.135	-0.132	-0.188
	Mix_R	8.761	-42.304**	42.272	127.710***	91.295***	7.868	53.613***	28.715	48.840**	70.478***
	NetDnst_L	-0.006*	-0.015	0.008	-0.049	-0.108***	-0.132***	-0.100***	-0.226***	-0.110**	-0.149**
	NetDnst_R	-2.515***	-5.442***	-1.509	-25.567***	-7.474***	-1.700	-6.806***	-7.800***	-12.968***	-4.853
	Inter_L	0.001	-0.0003	-0.002	0.001	-0.00002	-0.011***	-0.008**	0.012***	0.003	0.019*
	Inter_R	0.388***	0.391***	0.006	2.761	0.532**	-0.206	0.978***	0.720**	2.093***	0.208
	Constant	26.134***	89.902***	27.602*	97.858***	52.837***	44.763***	38.187***	53.731***	40.868***	17.078**
	Spatial rho	0.833***	0.889***	0.650**	0.796***	0.393	0.968***	0.746***	0.776***	0.711***	0
Eq (3)	Job_Pop_L	0.001*	0.00001	0.004	-0.0002	-0.001	0.001*	0.001	-0.0004	0.003**	0.0004
	Job_Pop_R	-2.770***	-8.365***	-2.929***	-7.134***	-6.525***	-2.646***	-11.303***	-0.573	-15.420***	-1.125
	Car_Owner0	0.063	1.813**	2.196***	1.147	-2.035	-0.974	0.549	-1.200	2.842***	1.628
	Car_Owner2p	0.115	1.420***	1.779***	1.062	-0.005	2.772***	0.280	-0.271	1.766***	0.868
	LowInc	-0.042	8.096***	-5.904***	-2.241	-5.218	14.468***	-1.180	6.082***	7.809***	6.632
	LowPay	-0.110	-0.143	-0.030	-0.187	0.399	2.619***	-0.971**	-0.096	-0.684**	0.499
	Mix_L	-0.050	-0.105	0.128	-0.303	-0.223	-0.314	0.001	0.113	0.062	-0.007
	Mix_R	-37.247***	-64.150***	-20.338	143.060***	82.493***	56.828***	30.697***	53.463***	86.689***	82.927***
	NetDnst_L	-0.001	-0.028*	0.003	-0.029	-0.105***	-0.143***	-0.144***	-0.125***	-0.068***	-0.146***
	NetDnst_R	-2.039***	-4.275***	-2.237***	-26.774***	-6.759***	-6.771***	-4.419***	-15.530***	-13.468***	-4.021*
	Inter_L	-0.0003*	-0.001	-0.001	0.002	0.000	-0.012***	0.004	0.002*	0.008***	0.017***
	Inter_R	0.601***	0.320***	0.221**	3.113***	0.341	0.956***	0.480***	1.037***	2.207***	-0.095
	Constant	17.708***	87.075***	37.876***	85.520***	56.150***	32.835***	40.748***	82.503***	24.390***	16.352***
	Spatial rho	0.935***	0.281	0.873***	0.774***	0.355	0.988***	0.857***	0.855***	0.928***	0.602*

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Estimation results of standard deviation of commuting distance in the other nine counties

		High Population Density			Low Population Density						
		New York	Multnomah	San Francisco	Albany	Bernalillo	Dallas	Duval	Davidson	Lucas	Shawnee
Eq (1)	Job_Pop_L	0.0001	-0.0004	0.0004	0.002*	0.001	0.001	0.0004	-0.001	0.003*	-0.001
	Job_Pop_R	-3.063	-6.790	-44.704***	-44.998	-7.905	37.673***	-11.589	23.212	-29.737**	-7.390
	Car_Owner0	2.120***	2.592***	3.178***	-2.081	-3.057	0.693	0.236	2.264	3.992	1.749
	Car_Owner2p	2.110	2.109***	-0.175	-0.260	-1.931*	-0.441	-0.144	1.149	2.122	-0.008
	LowInc	-2.872*	5.479*	-10.591***	-15.239***	3.300	4.926**	3.246	-10.729***	-3.524	-5.515
	LowPay	-0.294	-0.783	-1.326**	-0.298	0.015	-0.438	-1.169**	-0.531	0.482	-0.446
	Mix_L	-0.120	-0.003	0.260	0.713	-0.659	0.634*	0.309	0.490	1.418*	-0.490
	Mix_R	157.656***	-48.845***	-15.113	8.159	71.851***	-13.824	22.843**	-41.364	-72.824**	1.512
	NetDnst_L	-0.009	0.033	-0.019	-0.010	-0.083***	-0.140***	-0.027	0.046	-0.033	0.052
	NetDnst_R	-2.679**	-4.876***	-0.918	8.115***	-2.538*	6.444***	-3.677***	-3.054	7.144	-0.726
	Inter_L	0.002*	-0.004*	-0.001	0.006	0.0004	0.011***	0.002	-0.006**	-0.001	-0.004
	Inter_R	-0.093	0.540***	0.255	-1.086***	0.010	-1.410***	0.613***	0.578	-1.702	0.224
	Constant	6.289	59.432***	20.217	-18.057*	14.684***	-1.573	12.571***	32.896***	37.786**	8.092
	Spatial rho	0	0.706***	0	0	0	0	0	0.586*	0	0
Eq (2)	Job_Pop_L	0.001	-0.0002	0.001**	-0.0002	-0.001	0.001*	0.0002	-0.001	-0.00001	0.0005
	Job_Pop_R	-4.905	0.112	-16.785***	-2.096	-16.403**	23.679***	-9.669**	4.156	-20.920	27.378
	Car_Owner0	0.699**	-0.837	1.366**	2.194*	-3.399*	1.773*	-1.331*	0.065	-2.614	-0.091
	Car_Owner2p	-0.258	0.011	0.017	0.915	-1.468*	0.738	-0.260	0.233	-0.346	0.471
	LowInc	1.117	12.897***	-0.027	-9.208***	0.988	8.869***	-1.247	-0.109	6.944	6.041
	LowPay	-0.021	-0.237	-0.474	0.357	-0.237	0.423	-0.541	0.315	-1.171	-0.224
	Mix_L	-0.139	0.252	-0.104	-0.591	-0.837**	-0.101	0.298	0.210	-0.130	0.070
	Mix_R	107.566***	-11.350	50.624**	12.123	61.082***	0.994	32.880***	10.447	-54.059	33.172
	NetDnst_L	-0.003	0.002	0.008	0.044	-0.083***	-0.052***	-0.004	0.033	-0.123*	0.056
	NetDnst_R	-1.498***	-3.046**	0.510	0.733	-3.243***	6.991***	-3.106***	-5.679***	2.983	-3.035
	Inter_L	0.000	-0.0003	-0.001	-0.004	-0.0001	-0.003	-0.011***	-0.005***	0.005	-0.004
	Inter_R	0.035	0.244*	0.040	0.095	0.297*	-1.555***	0.674***	0.705***	-0.190	0.532
	Constant	-3.217	38.035***	-14.261	-4.023	15.346***	-6.129***	1.400	32.538***	20.934	-4.257
	Spatial rho	0	0	0	0	0	0	0.675***	0.508	0	0
Eq (3)	Job_Pop_L	-0.0004	0.002	0.004	-0.0014	-0.002*	0.0004	-0.0002	-0.001	0.004*	-0.0003
	Job_Pop_R	-0.261	-2.509*	-1.996***	1.811*	-1.124	6.915***	-2.272***	1.011	1.818	2.805**
	Car_Owner0	0.365**	0.431	2.032***	-1.351*	-2.119	0.127	-0.829	-0.599	1.436	0.100
	Car_Owner2p	1.157**	0.612	0.673	-0.264	-2.584***	1.042***	-1.105***	-1.057**	1.635*	-0.845
	LowInc	1.783***	10.904***	-4.751***	1.940	0.738	12.333***	-0.729	8.134***	12.764***	3.757
	LowPay	-0.036	-1.016	0.146	-0.511	-0.774	0.955***	-0.190	-0.664**	-1.456***	0.175
	Mix_L	-0.016	0.059	0.122	-0.087	-0.806**	0.259	0.308*	0.142	0.852*	0.357
	Mix_R	9.351	-29.032**	82.736***	49.231***	50.445***	54.812***	17.746***	23.676*	33.055	26.823**
	NetDnst_L	0.001	0.030	0.006	0.044***	-0.071***	-0.062***	-0.009	0.006	-0.057	0.014
	NetDnst_R	0.083	-2.594**	-1.891**	-3.981***	-3.368***	-3.074***	-2.164***	-8.915***	-5.033*	0.397
	Inter_L	0.000	-0.004**	-0.001*	-0.001	-0.000003	-0.002	0.000	-0.001	0.008	0.005
	Inter_R	0.017	0.221*	0.250***	1.128***	0.193	0.580**	0.395***	1.022***	1.348***	-0.203
	Constant	-0.665	43.424***	-9.062	-20.096***	24.202***	-6.734	8.537***	39.956***	-8.831	-3.374
	Spatial rho	0.631**	0.448	0.473	0	0	0	0.863***	0.892***	0	0

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

6. Conclusions

Short commuting distances reduce traffic congestion and energy consumption, and improve air quality. This study comprehensively studies the commuting patterns of ten counties across America, using a spatial error SUR model. All ten cases confirm the benefit of a high jobs-residence ratio, clustered industry sector distribution, and dense road networks with few intersections. Among these factors, the jobs-residents ratio provides the most definite and effective way to shorten commuting distance. Other factors, such as car ownership and income and payment level differ in their effect on commuting patterns in the ten cases studied. Collectively, to create a good commuting pattern, regional agencies need to offer an active economic market, keep the same industry sectors together, and construct well-designed road networks. Region-specific policies should be proposed based on regional characteristics such as population density and urban form.

The spatial error SUR model demonstrated in this study greatly contributes to the existing literature in commuting patterns and transportation research. Many phenomena in the transportation field involve multiple equations correlation, and spatial dependency; the methodology developed in this study can be applied to solve such problems in a statistically rigorous and efficient way.

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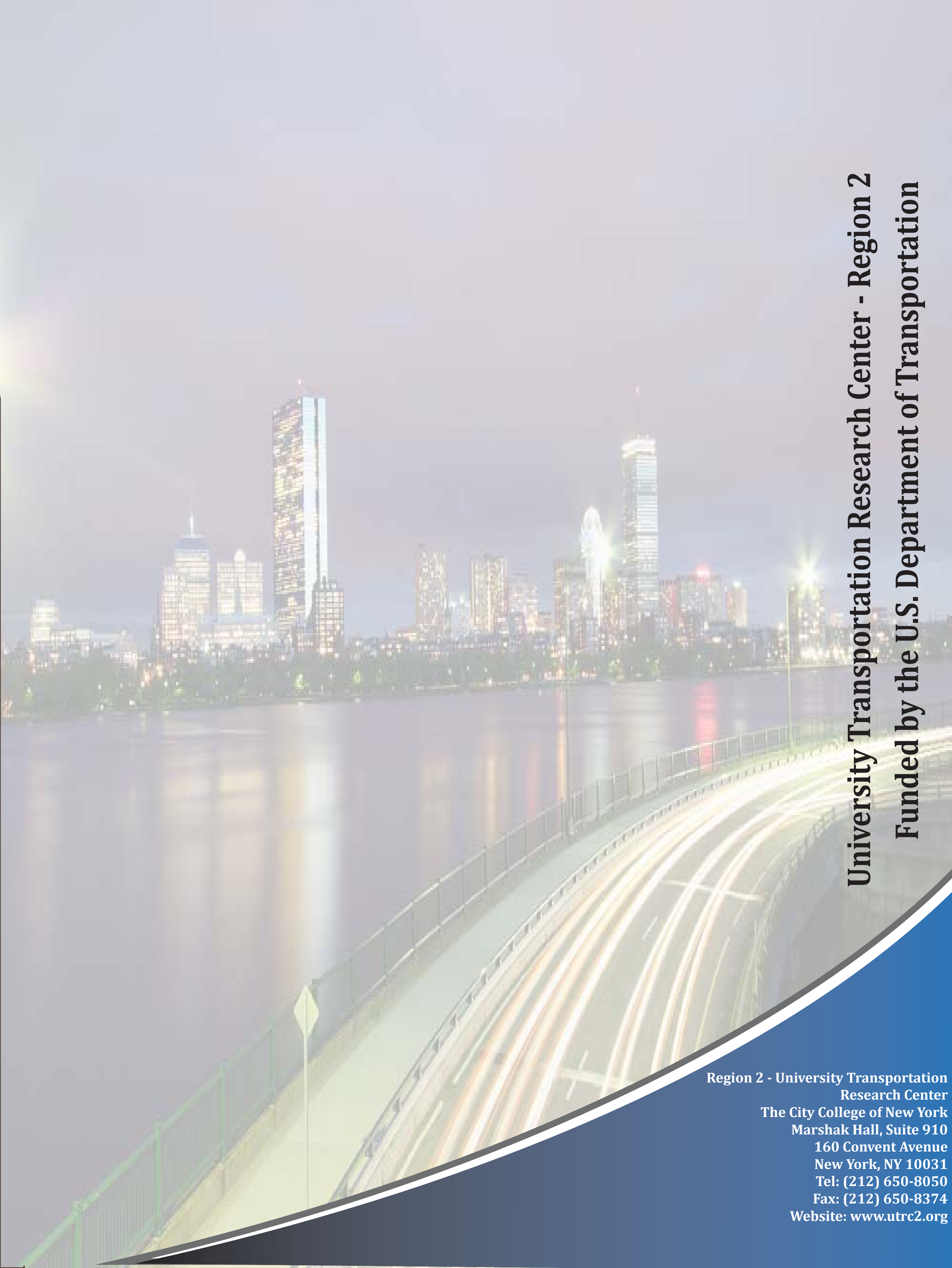

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