EMPIRICAL EXAMINATION OF NEIGHBORHOOD CONTEXT OF INDIVIDUAL TRAVEL BEHAVIORS

Abstract
In recent years, recognition of the importance of neighborhood context has produced a growing body of geographic research. When making their activity-travel decisions, individuals are restricted in different ways. In particular, individual choice behavior is often influenced by a neighborhood environment and a built environment. This study using the 2010 household trip survey demonstrated the effectiveness of incorporating multilevel mechanisms in various contexts of activity–travel behavior by comparing with traditional models. The analysis shows that one individual's activity participation patterns with respect to mode choice, trip count, trip distance, and trip time, under a variety of spatio-temporal constraints, tend to be affected by shared characteristics of neighborhoods. The results also imply that neighborhood travel behaviors are significantly influenced by neighborhood characteristics requiring policy makers to consider not only individual characteristics but surrounding environment.

Key words: trip behavior, trip survey, multilevel, neighborhood, context

Introduction

In recent years, recognition of the importance of neighborhood context has produced a growing body of research (Antipova et al., 2011; Badland et al., 2009; Frank et al., 2010; Van Dyck et al., 2010). It is well known that individual choice behavior is often influenced by neighborhood environment, and in some cases choices are made jointly by a built environment. Individuals are restricted in different ways when making their activity-travel decisions. More and more studies have been showing interest in studying neighborhood environment in various contexts of activity–travel behavior and confirmed the effectiveness of incorporating multi-level mechanisms by comparing with traditional models (Mercado, 2009; Schwanen et al., 2004). Although the importance of neighborhood influence is widely recognized in transportation planning, most of the research efforts to date have accommodated individual-neighborhood interaction effects by using average characteristics as explanatory variables in individual-level models.

Many previous studies have confirmed the relationship between land use and household vehicular travel. The empirical analysis of previous research also supports the hypothesis that changing land use can be a potential way to decrease the household vehicular travel distance and use of automobiles. With gasoline hustling past $4 per gallon, a poll conducted earlier in 2008 by California State University, Sacramento, found that 12% of respondents had changed jobs or moved to denser communities in the past year to shorten their commute to work (Wall Street Journal, 2008). This study tries to answer [1] whether the travel pattern varies across neighborhoods (e.g. census tracts), [2] whether their travel behaviors are different from each other, and [3] what are the contributing variables to the neighborhood variations. The paper aims to apply multilevel method to investigate the effects of variables on the trip mode, trip count and trip distance of daily trips.

This article is organized as follows: the following section explores issues relevant to the multilevel analysis and travel behaviors shown in previous research; the methodology section provides a brief explanation of a multilevel model; and the application of the proposed model is demonstrated with empirical analyses of trip survey data in Hamilton County, Ohio. Concluding remarks are given in the final section.

Previous Studies

An activity-based travel model incorporating household decision mechanisms has gradually been studied by transportation researchers. Previous studies provide a useful toolkit for exploring comprehensively multilevel trip behaviors and interaction between individual and neighborhood demonstrating the advantages of analyzing multilevel modeling of trip behaviors. Arentze and Timmermans (2008) described the household behavior based on the concept of need in the context of multi-day, and multi-person activity participation. The need of household or its member is the source of motivations to perform various activities and the change of need consequently generates the utility. The authors introduce the concept of potential to illustrate how and how much an activity could satisfy certain need of a household and/or its member(s). Bricka et al. (2012) has examined the propensities and magnitude of trip making as reported through the survey data and as recorded using GPS units for both work and non-work purposes suggesting that any study considering GPS-collection only should strongly consider the details used to develop the algorithms to assign trip purpose. GPS should be considered as the data collection method when dealing with the younger, more technology savvy individuals as well as those that have high travel propensities or characteristics associated with trip chaining, in order to ensure that all trip details are recorded. However, for the elderly and more leisurely travelers, the traditional survey method is recommended. Trip distance, time, count (frequency) and mode choice are commonly used to define the travel behaviors. For units of measurement, vehicle miles traveled (VMT), vehicle hours traveled (VHT) and vehicle kilometers traveled (VKT) are used as outcomes for the land use-travel models. While both travel distance and time are continuous value, mode choice is usually categorized with dummy variables (Cervero and Kockelman, 1997).

Ewing and Cervero (2010) conducted a meta-analysis of the multitude of built environment-travel literature existing at the end of 2009 in order to draw generalizable conclusions about the relationship between travel and the built environment. Over 150 built-environment/travel studies were summarized in their paper. A similar meta-analysis composed of 17 different studies about the impact of urban form on travel behavior was conducted by Leck (2006). Many papers provide various methods to model the relationship between land use and household travel, encompassing the simultaneous observation and analysis of more than one outcome variable (Boarnet and Crane, 2001; Kockelman, 1997; Naess, 2009; Schimek, 1996; Tracy et al., 2011). Many previous studies masked individual behaviors and concerned about the aggregated data at the household level or even some larger geographic unit such as the census tract, traffic analysis zone (TAZ), or the metropolitan. However, results derived from those studies conducted at aggregated level could not be used to predict individual travel behavior since it is inappropriate to make causal and associative inferences about individuals based on results obtained from aggregate data. Shay and Khattak (2012) modeled the relationship between land use and travel behavior at the personal level. As with travel behaviors, aspects of land use have been quantified in many ways. The commonly used variables in the built environment are three Ds: Density, Diversity and Design. Many studies found density to be negatively associated with car ownership, car use and travel distances. For example, based on the travel data in Belgium, Van Acker and Witlox (2011) found that densely built neighborhoods are associated with lower car use and shorter commuting distances. A similar similar result has been found by Tracy et al. (2011) in Buffalo, New York suggesting that high density development appears to encourage non-motorized travel. Another important aspect of land use is diversity, which measures the number of different land uses in a given area and the degree to which they are represent in land area. Higher diversities are believed to result in lower car ownership levels, lower car use, shorter travel distances and shorter travel times. For instance, Tracy et al. (2011) found that mixed land use development appears to be a valid way to encourage non-vehicle travel. Based on the travel data of Seattle and the San Francisco Bay Area, land use mixing was found to be significantly related to less car use and more walking and transit usage (Cervero et al., 1997; Frank et al., 2000). For the landuse mixture measurement, entropy measures of diversity, wherein low values indicate single-use environments and higher values more varied land uses, are widely used in travel studies (Cervero, 2002; Cervero and Kockelman, 1997; Ewing and Cervero, 2010; Kockelman, 1997).

Accessibility, a frequently used concept referring to the ability to reach activities or locations by means of a combination of travel modes (Geurs and van Wee, 2004), is an important land use characteristic. Kitamura et al. (1997) found that better accessibility by public transport result in more trips by public transport. A popular functional form for quantifying accessibility was provided by Kockelman (1997), which was built with the attractiveness of destination and the travel time from origins to destinations. In fact, accessibility is highly correlated with other land use characteristics, especially density. Higher density usually indicates a higher likelihood of having destinations within reach, hence high accessibility. Kockelman (1997) even found that the impact of density was negligible after accessibility was controlled. However, even though some authors have noticed the autocorrelation between accessibility and density, they did not really discuss about this problem in their studies. Therefore, a suggestion for future research would be to consider the autocorrelation between accessibility and built density, and then assign different weight to their effects on travel behavior when build the land use-travel model.

Recently, there is a growing interest in the issue of residential self-selection (e.g., Naess, 2009; Xinyu et al., 2009), which refers to a tendency of people to choose places of residence based on their travel abilities, needs and preferences. About the existence of residential self-selection issue, numerous studies indicated that socio-demographics have played an important role in shaping travel behavior (Cervero and Kockelman, 1997; Naess, 2009; Shay and Khattak, 2012; Van Acker and Witlox, 2011). Tracy et al. (2011) found that including median household income, household vehicles, household students, household workers, and household size helped address the residential self-selection problem to some extent. On the other hand, Naess (2009) pointed out that inclusion of those household variables may result in an under-estimation of the effects of the built environment. Therefore, it would be better to examine the effects of land use on travel behavior with and without controlling for the socio-demographics for person and household. Nevertheless, the inclusion of socio-demographics may depend on the geographic scale of the study unit. If a study is conducted at the metropolitan level like Cervero and Murakami’s study (2010), it is meaningless to take individual socio-demographics into account.

Despite the importance of neighborhood context discussed, most previous empirical studies devoted to individual travel behaviors have not considered interaction between individual and neighborhood. The impact of using different level of spatial unit (i.e., individual vs. neighborhood) on empirical findings concerning travel patterns remains unexplored.

Study Area

The study area is Hamilton County in Ohio, located in the southwest corner of the state of Ohio, as shown in Figure 1. The census of 2010 reported that the population of this county is 802,374, making it the third most populous county in Ohio. This study explores the trip behavior from two hierarchical levels: individual and neighborhood (census tract). The tract boundary used in this paper was released in 2010, which has overall 222 census tracts.

Data Sources and Variable Specification

The primary data source is the household trip survey data collected between the year of 2009 and 2010 for Hamilton County. This survey recorded the trip information for each individual of every sampled household during weekdays, including trip purpose, origin locations, destination locations, transportation means, trip count, travel time, travel distance, and so on. In addition, this dataset also provides the socioeconomic and demographic information of each individual participating in the survey as well as the household information, such as gender, age, job type, income, household type and so on. In Hamilton County, there were overall 2009 individuals of 1171 households who participated in this survey. The spatial distribution of the sampled households (one household may include several individuals) is illustrated by Figure 1. Some samples were ruled out in order to ensure that every selected tract has at least 5 sampled individuals. The final samples used in this study include 1863 individuals distributed in 153 census tracts.

[Insert Figure 1. Study area here]

There are four dependent variables: 1) mode choice which is binary logit variable (1 as using automobile, 0 as using other transportation means); 2) trip count which is average daily trip number of an individual during weekdays; 3) trip distance which is average daily overall travel distance of an individual during weekdays; and 4) trip time which is average daily overall travel time of an individual during weekdays. It is assumed that the trip behavior is influenced by both individual and neighborhood (census tract) factors. The explanatory variables are nested into two levels: individual and neighborhood level, and the detailed descriptions of the variables are shown in Table 1. Spatial distribution of neighborhood level variables are shown in Figure 2.

The population density, white percentage and bachelor above percentage of each tract were obtained from U.S. Census Bureau 2010 data. The land use mixture index was calculated using landcover/landuse which includes 12 categories. An entropy measure representing the evenness of distribution of several landuse types was used to calculate this land use mixture indicator by using following equation:

$$Landuse_{Mix} = -100 * \sum_{i=1}^{n} p_i \ln p_i \quad (1)$$

where n is the number of different landuse types in the area, and p_i is the proportion of landuse type i in each area. The calculated entropy varies from 0 representing homogeneous landuse to 100 representing most mixed landuse. The transportation accessibility was measured by calculating the average shortest network distance to all the tracts in Hamilton County, as shown in following equation:

$Dis\_Avg_i = \frac{1}{n}\sum_{j=1}^{n} d_{ij}$ (2)

where d_{ij} is the shortest network distance between tract i and j. Inter-zonal ($i \neq j$) distances between centroids of tracts are calculated as street network distance, while the intra-zonal ($i = j$) distance is calculated by following equation:

$d_{ii} = \sqrt{R_i/\pi}$ (3)

where R_i is the area of tract i. To ensure the intra-zone distance is smaller than inter-zone distance, equation (3) needs to be checked by following equation:

$d_{ii}^{*} = \frac{D_i^{min}}{d_{ii}} * D_i^{min}\ (if\ d_{ii} > D_i^{min})$ (4)

where d_{ii}^{*} is the new intra-zonal distance for tract i, and D_i^{min} is the minimum distance from tract i to all other tracts. As the transportation accessibility increases with the decrease of average network distance, this index is calculated by first standardizing Dis_Avg to the range of 0-1 as Dis_Avg_{std} and then subtracting Dis_Avg_{std} from 1.

The jobs-housing balance often shows spatial patterns of commuting by neighborhoods. The jobs to housing (workers) ratio represents many spatial aspects, such as the degree of land use mixture, job accessibility, thus reflects the imbalance between jobs and housing in an area (Cervero,1989; Cervero, 1996). A ratio of jobs to housing greater than 1 in a neighborhood normally suggests that jobs outnumber resident workers. Geographically, it is often close to downtown areas with rich job opportunities. In this study, based on this ratio we divide neighborhoods into 3 categories: balanced (0.8~1.2), housing (less than 0.8), jobs (more than 1.2).

[Insert Table 1 here]

[Insert Figure 2. Spatial distributions of level-2 variables here]

Multilevel Regression Model

Multilevel regression models are used to analyze trip behaviors. The data are nested in two levels: individual and neighborhood (tract) level. The multilevel model consists of fixed effects and random effects for both intercept and variable slope. By using different combination of these two effects, variability of trip behaviors on different levels can be explained. The equations (5) and (6) show simple null models while equations (7) and (8) are used for modeling random intercept and random slope models.

Level-1: $Y_{ij} = \beta_{0j} + r_{ij}$ (5)

Level-2: $\beta_{0j} = \gamma_{00} + \mu_{0j}$ (6)

Level-1: $Y_{ij} = \beta_{0j} + \beta_{1j} * X1_{ij} + \cdots + \beta_{nj} * Xn_{ij} + r_{ij}$ (7)

Level-2: $\beta_{nj} = \gamma_{n0} + \gamma_{n1} * W_j + \cdots \gamma_{nm} * W_{mj} + \mu_{nj}$ (8)

Where Y_{ij} is the dependent variable value for individual i in neighborhood j; Xn_{ij} represents level-1 variables, and W_j represents level-2 variables; β_{0j}, β_{1j},… β_{nj} are the slope of variables; μ_{1j},…, μ_{nj} represent level-2 variation (variation across neighborhood region) and r_{ij} represents level-1 variation (variation within neighborhood region).

Results and Analysis

Multilevel models are estimated using MLwiN 2.7 to investigate what individual and neighborhood (census tract level) factors influence the trip behavior of the residents in Hamilton County from four dimensions: mode choice, trip count, trip distance and trip time. Tables 2, 3, 4, and 5 present the estimated results of the three multilevel models for each dependent variable: 1) Null model; 2) Mixed model-1; and 3) Mixed model-2. All of the three models contain random variations of intercept among different neighborhoods (level-2). The first model includes only intercept and corresponding variance term, which can be used to examine whether the dependent variable varies significantly at the neighborhood level. In the second model, all of the level-1 (individual level) variables are taken into account to examine which individual factors have significant effects on the dependent variable. According to the estimates of the second model, the third model would exclude the statistically insignificant level-1 variables, and incorporate all the level-2 (neighborhood level) variables into the model, to explore the contextual effects of geographical units on individual trip behaviors. Table 6 summarizes the results of the final models which contain only a range of significant level-1 and level-2 explanatory variables.

To compare the contribution of a multilevel approach, we tested the regression models that included only individual-level independent variables. Various sets of socio-economic-demographic independent variables were entered into the models (See Tables 2-5). Mixed model-1 only contains individual-level variables, and mixed model-2 has the variables at two levels. Mixed model-1 in each table examined the effect of individual-level. Mixed model-2 included land use mixture, accessibility, and jobs-housing balance along with neighborhood-level socio-demographic attributes. Each model was estimated by Markov Chain Monte Carlo (MCMC) methods which allow Bayesian models to be fitted. For goodness of fit, the Deviance Information Criterion (DIC), which is a generalization of the Akaike Information Criterion (AIC) is used to measure the fit of each model.

Mode choice

Binomial logit multilevel modeling was used to analyze the binary mode choice between using automobile (1) and using other means (0). According to the results shown in Table 2, the estimated intercept of the null model is 2.891, indicating that the average probability of choosing automobile as mode choice is about 94.7% which is equal to $1/(1+e^{-2.891})$. The intraclass correlation coefficient (ICC) represents the contribution of the neighborhood level on the overall variance in automobile use, which is fairly large. From the estimates of the second model, it is noted that the probability of using automobile is significantly related to gender, age, income, and job type, while the factor of household type has insignificant effect on mode choice. Controlling for other variables, female has 68.5% $[1/(1+e^{-0.776})]$ higher probability than their male counterparts to drive an automobile. Besides, the possibility of choosing automobile increases with the rise of age and income. Job types also play quite important roles in affecting people's mode choice. The full-time paid workers are more likely to use automobile than the part-time paid workers and the individuals with other job types (mainly unemployed). Comparing to unemployed residents, full-time paid and part-time paid residents have 79.3% and 69.9% higher possibility of using automobile respectively, after controlling for other level-1 variables.

In the mixed model-2, the level-2 contextual variables are introduced to further explain the variation of the intercepts among different neighborhoods. The estimates of the coefficients show that the variables of population density, white percentage, landuse mixture and jobs-housing balance are insignificant statistically, suggesting that residents' mode choice is not influenced by these characteristics of the neighborhoods they live in. After excluding these variables, the results illustrated by Table 6 indicate that the transportation accessibility has significant negative effects on mode choice, suggesting that people who live in the areas with highly-developed transportation networks are more likely to use other means rather than automobiles. Generally, most of the areas with high transportation accessibility are very close to CBD, consequently, the residents in these areas have higher access to jobs, groceries, schools and other facilities, thus weakening the necessity of using automobiles. In contrast, the bachelor above percentage is positively correlated with the probability of choosing automobile as mode choice. The education level of one area is usually highly correlated with its income level. In general, better educated and higher income population tend to dwell in suburban area rather than highly-developed CBD area, thus they need to travel longer distance to work or shopping, increasing automobile use.

From the null model to the mixed model-2, the neighborhood-level variance is decreased from 0.462 to 0.027, indicating that the level-1 variables of gender, age, income and job type, and the level-2 variables of bachelor above percentage and transportation accessibility can explain 94% variation on the neighborhood level. The decline of ICC and DIC can also enhance the effectiveness of the introduction of these variables.

[Insert Table 2 here]

Trip count

The trip count dependent variable for each sampled individual is obtained by averaging the number of trips of each sampled weekday. It is assumed that the number of trips during weekdays is characterized by the social roles of the individuals. For example, the full-time worker families with children may go to school or nursery before going to work, and after work, they may go to the groceries and pick up their children before going back home. Therefore, the trips made during weekdays are not just home-work trips or other single purpose trips, but may be composed by multiple-purpose trips. According to the estimates illustrated by Table 3, the null model shows that the average number of trips made by residents in Hamilton County during weekdays is about 5, with the variance between individuals of 8.4, and the variance between neighborhoods of 0.02. The ICC is about 0.26%, which indicates that the variation of trip count is determined mostly by individual differences, and does not vary significantly across neighborhoods. In other words, the count of trips during weekdays is not much influenced by the contextual factors of the neighborhoods.

The mixed model-1 considered all the level-1 variables, and the estimates of the coefficients suggest that the indicators of age and household type are significantly associated with trip count. The trip count increases with the increase of age, that is, the older people make more trips during weekdays than younger people. This finding is different from results by Hanson (1982) reporting no difference between trip frequency and age, whilst age explains some of the variation in trip frequency by Prevedouros and Schofer (1991).

The household type plays also quite important role in affecting the trip count. Comparing to retired household, adult household, household with children and adult student household are more likely to take multiple-purpose trips. In addition, individuals in adult student households make more trips than those in households with children, while households with children have more trips than adult household with no children. However, the gender and job types do not have significant effect on trip count, that is, the number of trips does not vary between males and females, neither between full-time paid workers and unemployed individuals.

The mixed model-2 excludes the variables of "female" and "job type" and does not contain neighborhood level variables. As shown in Table 3, the estimates of the coefficients of age and household type are similar with the second model, except that the variable of income becomes significantly correlated to the trip count with a 95 percent confidence interval. And this relation is negative, indicating that low income population tends to make more trips than high income population. Interestingly and surprisingly the relationship between trip count (frequency) and household income is negative unlike the previous research where a consistent positive association is found. Thus, this negative tie might be only true in this particular study area with this dataset, thus cannot be universally applied to other areas. See Hanson (1982) for a positive link between trip frequency and household income, Cervero (1996) for a positive linkage between commuting distance and income, and Næss and Sandberg (1996) for a positive association between household income and the trip distance per person. According to the estimates of variance, the selected level-1 variables can explain additional 2% [(8.373-8.217)/8.373] variation between different individuals in trip count. This suggests that other individual factors need to be considered to further explain the variation.

[Insert Table 3 here]

Trip distance

As illustrated in Table 4, the null model reveals that the average trip distance for residents in Hamilton County during weekdays is about 29.7 miles. The estimated variance terms show that the variation of trip distance between individuals is about 545.6 and that between neighborhoods is about 52.2, with ICC of 8.74%. This fairly high ICC and the statistically significant variance indicate that the variation of trip distance needs to be explained on both individual level and neighborhood level.

According to the results of mixed model-1, the indicators of gender, age, job type and household type have significant influence on trip distance, while income is not as significant as other factors. Females would like to travel less distance than males during weekdays, and the average difference between males and females in trip distance is about 2.8 miles. The possible reason is that females prefer to work near home or choose part-time jobs. Full-time paid workers would travel much longer distance than other workers and unemployed residents. Compared to unemployed residents, part-time paid workers do not have significant difference, but full-time workers would travel more than about 6.7 miles longer on average after controlling other variables. The households with adult students travel longer distance than the households with children, and the households with children travel longer than households without children. From the estimates of variance, the level-1 variables can reduce the variation between individuals by 5%.

The mixed model-2 contains a range of significant level-1 variables and all level-2 variables. From the estimated coefficients and T-ratio, it is noted that residents' trip distance is significantly affected by the population density, transportation accessibility and jobs-housing balance of the neighborhoods they reside in. The contextual factors of white percentage, bachelor above percentage and landuse mixture are not significantly related to travel distance. After excluding those insignificant variables, the final estimates are shown in Table 6. It is shown that population density and transportation accessibility are both negatively associated with trip distance. That is, the residents would travel less distance during weekdays if they dwell in the neighborhoods where the population density is high and transportation network is developed. Generally, such neighborhoods are located in urban area or close to CBD, which are highly developed with multiple functions and job opportunities, thus attracting the residents to the local job markets and facilities. The relationship between jobs-housing balance and trip distance is negative, suggesting that people who live in jobs-housing balanced neighborhoods tend to travel longer distance than people who live in jobs-housing unbalanced neighborhoods. This conclusion is contrary to the general assumption that people in jobs-housing balanced areas could save trip cost. This contradiction can be explained by the following reasons. The neighborhoods which have more jobs than housing units are usually the highly-developed areas, thus the residents have high accessibility to local job markets and facilities, resulting in less trip distance than other areas. Although the neighborhoods which have more housing than jobs could not satisfy the local needs, the reason why the residents travel less distance is that they choose to work or shop in nearby neighborhoods. However, for the balanced neighborhoods, although the job opportunities are equivalent with the local demand, the residents choose to work in remote neighborhoods rather than the neighborhoods they dwell in (See also Cervero (1989) and Loo & Chow (2011) for other metropolitan area cases). This imbalance may reflect the gaps between occupations and workers, and can be further explained by job types (See Kim et al. 2012 and Sang et al. 2011 for more details).

In the mixed model-2, the level-2 variance is decreased to 18.2, with reduction of 65% compared with the null model. ICC is also decreased from 8.74% to 3.38%, illustrating the explanatory ability of the selected neighborhood-level variables. In addition, the decline of DIC highlights the improvement of the models.

[Insert Table 4 here]

Trip time

According to the results shown in Table 5, the average daily travel time for the residents in Hamilton County is about 67 minutes. The variance between individuals is 1643.7, while the variance between neighborhoods is 60.1, with ICC of 3.53%. Although the between-neighborhood variation is significant, the largest part of variation in trip time is contributed by the individual level, which is quite different with the situation of trip distance.

The mixed model-1 contains all the individual-level variables, and the results reveal that the indicators of age, job type and household type are statistically significantly related to daily trip time, while gender and income do not have significant effects. Unlike trip distance, trip time is not differentiated by gender roles. The age is positively related to trip time, suggesting that older people tend to spend more traveling time than younger people. This is consistent with results by Stead (2001) suggesting people between 30 and 39 travel more than most other age groups.

Compared to unemployed residents, full-time paid workers travel longer time, and this difference is significant. In contrast, although part-time paid workers spend longer trip time than unemployed residents, this difference is not significant. Full-time paid workers would travel longer. The possible reason is that the major activities for full-paid workers are to commute during weekdays. With respect to the factor of household type, adult student households have longer trip time than other households, which is similar with travel distance. According to the change of variance components, the level-1 variables can reduce the level-1 variance by 5%.

From the estimates of the mixed model-2, the white percentage, bachelor above percentage, landuse mixture and job-housing balance cannot explain the neighborhood-level variation significantly. According to the estimates of the mixed model-2, among all the contextual factors, only transportation accessibility significantly affects trip behavior in travel time. This relation is negative, suggesting that people dwelling in the neighborhoods of high transportation accessibility would spend less traveling time. In the mixed model-2, the variance between neighborhoods is 31.7, decreased by 47% compared to the null model.

[Insert Table 5 here]

[Insert Table 6 here]

Conclusion and Discussion

This research used a multilevel approach to investigate the trip behaviors from four dimensions: mode choice, trip count, trip distance, and trip time. Trip data are conceptualized into two levels: individual and neighborhood (census tract). The results indicate that trip behaviors differentiated across different neighborhoods. Moreover, the trip patterns are influenced by both individual and neighborhood characteristics. For the mode choice, variables such as gender, income, economic activity and household relationship are strongly correlated to the probability of using an automobile to travel. The neighborhood contextual variables such as transportation accessibility, job accessibility, and income levels explain the variations among different neighborhoods. With respect to the trip count, age, income, and household type are significantly related while gender roles do not have a significant relationship with the variation of trip count between individuals. Trip distance has a large variation between neighborhoods. The individual factors affecting trip distance include average trip count of multiple-purpose trip, gender, household income, employment status, and household role. The neighborhood variables such as density of workers, education level well explain the variance across neighborhoods. Moreover, accessibility factors such as transportation accessibility can decrease the individual variations on trip distance.

From the possible concerns of spatial multicollinearity among accessibility variables, the correlation matrix showed that the coefficients among pairwise distance are low. A collinearity test of a variance inflation factor also indicated a value of less 2 suggesting less problematic. However, a future work could design variables that might capture the true forces of each dependent variable more directly rather than identical sets of variables across different outcomes.

The urban form, in terms of commuting structure whether it is centralized, self-contained, or decentralized, cannot statistically explain the variations of trip patterns among neighborhoods. This might be only true in this particular study area, thus cannot be universally applied to other cities. A possible reason for this is that level-2 units have rather small geographical extend which is insufficient to reflect the urban structure by using the ratio of in and out of commuting trips.

Neighborhood travel behaviors aggregated by individuals influenced by neighborhood characteristics that require policy makers to consider not only individual characteristics but surrounding environment. In other words, one individual's activity participation patterns with respect to mode choice, trip count, trip distance and trip time, under a variety of spatio-temporal constraints, tend to be affected by shared characteristics within the same neighborhood boundaries. The vehicle miles traveled (VMT) is influenced by both individual behaviors (socio-economic-demographic) and neighborhood contexts (accessibility, urban form and land-use patterns) on motorized travel. VMT per capita is one of important indicators of environmental pollution in local, regional and global perspective. In our analysis, we found that the effect of land use mixture on trip behaviors might not be as strong as initially expected. However, transportation accessibility in the neighborhoods is a significant indicator. A detailed empirical findings suggest that transportation planning policy can help a city to be sustainable by successfully reducing car use, trip distances and times. In particular, the land use patterns in the neighborhoods with respect to jobs-housing balance have significant effects on trip distances.

References

Antipova, A., Wang, F. et al. (2011). Urban land uses, socio-demographic attributes and commuting: A multilevel modeling approach. *Applied Geography*, 31(3), 1010-1018.

Arentze, T.A., & Timmermans, H.J.P. (2009). A need-based model of multi-day, multi-person activity generation. *Transportation Research. Part B: Methodological*, 43(2), 251-265

Badland, H., Schofield, G. et al. (2009). Understanding the Relationship between Activity and Neighbourhoods (URBAN) Study: research design and methodology. *BMC Public Health*, 9(1), 224.

Bricka, S. G., Sen, S. et al. (2012). An analysis of the factors influencing differences in survey-reported and GPS-recorded trips. *Transportation Research Part C: Emerging Technologies*, 21(1), 67-88.

Cervero, R. (1989). Jobs-Housing Balancing and Regional Mobility. *Journal of the American Planning Association*, 55(2), 136 - 150.

Cervero, R. (1996). Jobs-housing balancing revisited. *Journal of the American Planning Association*, 62(4), 492-511.

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and Environment*, 2(3), 199-219.

Cervero, R., & Murakami, J. (2010). Effects of built environments on vehicle miles traveled: evidence from 370 US urbanized areas. *Environment and Planning A*, *42*(2), 400-418.

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment. *Journal of the American Planning Association*, 76(3), 265-294.

Frank, L. D., Sallis, J. F. et al. (2010). The development of a walkability index: application to the Neighborhood Quality of Life Study. *British Journal of Sports Medicine*, 44(13), 924-933.

Frost, M., Linneker, B., Spence. N. (1998), Excess or wasteful commuting in a selection of British cities. *Transportation Research Part A*, 32, 529-538.

Geurs, K. T., & van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography*, 12(2), 127-140.

Hanson, S. (1982). The determinants of daily travel-activity patterns: relative location and sociodemographic factors. *Urban Geography*, 3(3), 179-202.

Kim, C., Sang, S. et al. (2012). Exploring urban commuting imbalance by jobs and gender. *Applied Geography*, 32(3), 532-545.

Kitamura, R., Mokhtarian, P. L. et al. (1997). A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area. *Transportation*, 24(2), 125-158.

Kockelman, K. (1997). Travel Behavior as Function of Accessibility, Land Use Mixing, and Land Use Balance: Evidence from San Francisco Bay Area. *Transportation Research Record: Journal of the Transportation Research Board*, 1607, 116-125.

Leck, E. (2006). The Impact of Urban Form on Travel Behavior: A Meta-Analysis. *Berkeley Planning Journal*, 19(1), 37-58.

Loo, B. P. Y. & Chow, A. S. Y. (2011). Jobs-housing balance in an era of population decentralization: An analytical framework and a case study. *Journal of Transport Geography*, 19(4), 552-562.

Mercado, R., & Paez, A. (2009). Determinants of distance traveled with a focus on the elderly: A multilevel analysis in the Hamilton CMA, Canada. *Journal of Transport Geography*, 17(1), 65-76.

Næss, P. (2009). Residential Self-Selection and Appropriate Control Variables in Land Use: Travel Studies, *Transport Reviews*, 29(3), 293-324.
Næss, P., & Sandberg, S.L. (1996). Workplace location, modal split and energy use for commuting trips. *Urban Studies,* 33(3), 557-580.
Prevedouros, P.D., & Schofer, J. (1991). Trip characteristics and travel patterns of suburban residents. Transportation Research Board, 1328, 49-57.
O'Kelly, M. E. & Lee, W. (2005). Disaggregate journey-to-work data: implications for excess commuting and jobs-housing balance. *Environment and Planning A*, 37(12), 2233-2252.
Sang, S., O'Kelly, M. E. et al. (2011). Examining Commuting Patterns: Results from a Journey-to-work Model Disaggregated by Gender and Occupation. *Urban Studies*, 48(5), 891-909.
Schwanen, T., Dieleman, F. M. et al. (2004). The Impact of Metropolitan Structure on Commute Behavior in the Netherlands: A Multilevel Approach. *Growth and Change*, 35(3), 304-333.
Shay, E. (2012). Household Travel Decision Chains: Residential Environment, Automobile Ownership, Trips and Mode Choice. *International Journal of Sustainable Transportation*, 6(2), 88-110.
Stead, D. (2001). Relationships between land use, socioeconomic factors, and travel patterns in Britain. *Environment and Planning B,* 28(4), 499-528.
The Wall Street Journal. (2008). With Gas Over $4, Cities Explore Whether It's Smart to Be Dense. http://online.wsj.com/news/articles/SB121538754733231043.
Tracy, A., Su, P. et al. (2011). Assessing the impact of the built environment on travel behavior: a case study of Buffalo, New York. *Transportation*, 38(4), 663-678.
Van Acker, V., & Witlox, F. (2011). Commuting trips within tours: how is commuting related to land use? *Transportation*, 38(3), 465-486.
Van Dyck, D., Cardon, G. et al. (2010). Neighborhood SES and walkability are related to physical activity behavior in Belgian adults. *Preventive Medicine*, 50, S74-S79.
Xinyu, C., Mokhtarian, P. L. et al. (2009). Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings. *Transport Reviews*, 29(3), 359-395.