An Integrated Model of Intensity of Activity Opportunities on Supply Side and Tour Destination & Departure Time Choices on Demand Side

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Abstract

Land use and transportation interactions exist at all time scales – long, medium, and short. In the long term, business location (and relocation) decisions, aggregate travel patterns and transportation infrastructure development are inter-dependent. In the medium-short term, in any neighborhood, the temporal profile of activity opportunities within a day, and destination and departure time (DDT) preferences of travelers are simultaneously determined. This paper explored these short-term interdependencies between the land-use supply and travel demand systems by developing a simultaneous model of time-of-day specific zonal employment intensity and non-mandatory tour DDT choices. The resulting model takes the form a panel linear regression model with employment intensity, as the dependent variable on the supply side and a mixed logit model with combinations of Traffic Analysis Zones (TAZs) and time periods as alternatives on the demand side. The modeling methodology accounts for possible endogeneity between the two systems and also considers importance sampling methods to reduce the computational burden due to explosion of choice alternatives in the discrete choice model component. The model was used to explore supply demand interactions in the Southern California region. The results not only underscore the importance of the proposed integrated modeling framework but also provide several useful insights into the factors that influence the temporal profile of zonal employment and its interaction with daily travel choices.

Keywords: mixed logit models; joint discrete-continuous modeling; sampling; endogeneity; supply and demand interactions

Introduction

Integrated land use and travel demand modeling is considered to be the appropriate modeling paradigm for analyzing the bi-directional interactions between the supply (built environment) and demand (travel patterns) factors (Pendyala *et al.* 2012). In these integrated models, conditional land use and travel demand models are applied iteratively to replicate the joint distribution of land use and travel patterns in the study region. These integrated models are typically used for modeling long term feedback effects between the two systems. For instance, how does employment relocate in response to new transportation infrastructure in the region or how do travel patterns change in response to new development (e.g., big shopping mall) in the future. However, strong interactions between land use and transportation exist even at short-medium time scales. For instance, the opening and closing hours of businesses (on the supply side) and destination and departure time choice preferences of travelers (on the demand side) are more likely to be determined simultaneously. However, such interactions are not captured in the current modeling approaches.

Typically, zonal land use and employment data serve as inputs for travel demand models (TDMs) to predict the activity-travel patterns of the residential population in the study region. These models implicitly assume that zonal land use and employment serve as indicators of opportunities that attract travelers to pursue different types of activities. While the characterization of these decision processes in activity based models can vary substantially, in general these frameworks have two main components. The first component is the *activity generation* in which the model predicts the activities that each individual plans to undertake during the day. The second component is *activity scheduling* in which the spatial and temporal choices of the planned activities in the *activity generation* step are determined. Within these two components, land use and employment information is predominantly used as follows 1) for zonal accessibility measures that affect daily planning choices in the *activity generation* step, 2) for zonal accessibility measures that affect scheduling choices that are modeled prior to destination choices in the *activity scheduling* step, and 3) as zonal attraction size variables (which are usually linear combinations of different zonal employment variables) in destination choice models in the *activity scheduling* step (Pinjari and Bhat 2011).

Given the importance of considering appropriate land use and employment information in ABMs, there is growing recognition in the field to develop user and context specific measures. Towards this end, space-time accessibility measures that consider variation of activity opportunities both in space and time have been proposed. There are primarily two components to these accessibility measures - (1) size of opportunities, and (2) ease of reachability measured as generalized travel costs and/or mode and time-of-day choice logsums. While gravity-based measures characterize accessibility through a generalized cost function, opportunity-based measures represent size of opportunities within a pre-selected boundary defined based on a generalized cost function (Chen *et al.* 2011, Paleti *et al.* 2014). Irrespective of the type of measures, most of the earlier studies account for temporal variation in accessibility measures using the second component (*i.e.* travel cost) due to changes in the transportation network conditions. For example, increased congestion levels can reduce accessibility during peak time periods. While this is very useful, it is also necessary to recognize that accessibility varies temporally due to variation in size of opportunities arising from opening and closing hours of businesses. For example, neighborhood with restaurants and night life are likely to experience increase traffic in the evening periods while affecting the neighborhood negligibly in the morning peak hours. To be sure, to address this issue, some of the recent studies have started to explicitly model the impact of varying business hours on space-time accessibility measures (Weber and Kwan 2002, Kim and Kwan 2003, Paleti *et al.* 2014).

While these new methods are a significant step forward in capturing linkages between supply and demand side factors, there are avenues for considerable improvements. First, there is no literature on modeling temporal variation of activity opportunities due to varying business hours. The traditional space-time accessibility measures that quantify the impact of this temporal variation use business hours information as an external input. Second, typical modeling frameworks employed to capture the land-use and travel interactions in the short to medium term time scales are sequential in nature and thus do not recognize that these are bi-directional in nature. For instance, daily departure time and destination choices are modeled conditional on employment information. However, there is no feedback from demand components to the supply side components. The primary objective of the current study is to address these two shortcomings of existing methods by developing an integrated modeling framework for analyzing both supply demand side outcomes jointly.

As alluded to earlier, one common assumption across most ABMs is that the supply side opportunities (*i.e.*, zonal employment) do not vary across different hours of the day, *i.e.*, a constant zonal employment profile is assumed. In reality, a more reasonable hypothesis would be a bell-shaped temporal profile of zonal employment consistent with the expected opening and closing hours of most businesses (Paleti *et al.* 2014). This bell shaped temporal profile of opportunities on the supply side has significant implications to the way Destination and Departure Time (DDT) choices are modeled. *First*, DDT choices must be bundled together and viewed as simultaneous choices because zonal attractiveness (typically measured using size variables in destination choice models) changes significantly depending on the departure time. People are likely to compare and evaluate combinations of departure times and destinations instead of making these decisions in any pre-determined sequence. *Second*, the temporal profile of opportunities on supply side is not necessarily a collective decision of business establishments in the zone independent of the travel preferences of people in that region. For instance, businesses are open late night in Manhattan because they see people interested in pursuing activities during late hours. Similarly, people go shopping late night in Manhattan because they know shops are open for longer hours. The observed temporal profile of activity opportunities and the observed DDT choices are most likely the outcomes of equilibrium between the supply and demand factors. So, these two systems (*i.e.*, supply and demand) cannot be analyzed as two separate independent outcomes. A simultaneous model that captures the dynamic interactions between activity opportunities on supply side and DDT choices on demand side is better suited for this choice context. The choices of interest in this study, zonal employment by time-of-day (which is an aggregated outcome of opening and closing hours of business establishments on a day-to-day basis) on the supply side and daily DDT choices on the demand side are typically made in the medium-to-short time horizons. So, in the current study, we aim to uncover these supply and demand side interactions that operate over relatively shorter time periods compared to the long-term land-use and transportation interactions. *Third*, simultaneous modeling of DDT choices will lead to explosion in the number of alternatives because all combinations of time periods and zones in the study region constitute the choice set. So, it is essential to use appropriate sampling mechanisms that can provide consistent parameter estimates for the integrated model.

From a *policy perspective*, models that treat destination and departure time choices as sequential decisions can provide wrong policy implications. For instance, if a new business development that is open late hours comes up in the region, such models do not predict any changes in the departure time patterns but they predict many more people choosing the destination with the new business development during all hours of the day. So, the predicted origin destination flows by time-of-day and the implied vehicle-miles-travelled (VMT) estimates would be wrong. Also, models that do not account for simultaneity between the supply and demand side decisions can lead to inflated estimates of the zonal employment variables on the DDT choices of travelers.

In our study, from a *methodological perspective*, the proposed model takes the form of a simultaneous choice model with two components – 1) a continuous component that models the intensity of activity opportunities (*i.e.*, percentage of zonal employment that is active) during each time period, and 2) a discrete component that analyzes the DDT choices as a combination alternative. The simultaneity between these two model components was accommodated using time-period and zone specific random error terms that enter both the continuous and discrete choice components. For the temporal dimension, five time periods were considered: morning peak (6:00 am to 9:00 am), midday (9:00 am to 3:00 pm), evening peak (3:00 pm to 7:00 pm), evening (7:00 pm to 9:00 pm), and night (9:00 pm to 6:00 am). For the location dimension, the analysis was undertaken at a spatial resolution of Traffic Analysis Zone (TAZ). Given that considering all TAZs can lead to explosion in the number of alternatives in the choice set (because of the combination of temporal and location dimensions), zonal sampling mechanisms that ensure consistent parameter estimates in mixed logit models were used (Guevara and Ben-Akiva 2013). The resulting model was estimated using Maximum Simulated Likelihood inference approach using quasi-Monte Carlo Halton sequences. The proposed model was used to analyze destination choice behavior of residents in the Southern California region. The next section provides details of the methodological framework adopted in the current study.

Data

The primary data source for demand model component was obtained from the Southern California Association of Government (SCAG)'s 2010 Household Travel Survey (HTS) data. In addition to travel diary information, the survey collected detailed socio-demographic information of about 20,000 households. Among these 20,000 households, travel diary information was collected for a weekend (*i.e.*, Saturday or Sunday) for 32% households. So, these household records were excluded from our analysis to focus on weekday travel patterns bringing down the number of valid household samples to about 13,000. The travel diary information for these 13,000 households were processed to construct tours- chain of trips that start and end at home. Together these households reported about 40,000 tours. For each of these 40,000 tours, a primary tour destination was determined based on combination of rules including distance from home, activity purpose, and activity duration at the destination. After this analysis, we observed that out of the total 40,000 tours half were mandatory tours (to work, school, or university) and the remaining half were non-mandatory tours. These non-mandatory tours include both tours made by workers (in addition to mandatory tours) and non-workers. In this study, we focus exclusively on non-mandatory tours made by non-workers (people who are not workers or students) because they are not constrained spatially and temporally by mandatory activities. The travel diary recorded activity purpose at a very disaggregate level. These disaggregate activity purposes were grouped into five broad categories – escorting, shopping, social, maintenance, eating out, and discretionary. The activity purpose at the primary destination of a tour was identified as the primary purpose of that tour. The destination coordinates in the travel diary were geo-coded to one of the 11,267 TAZs covering the six-county region (spanning Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura). We excluded cases with missing tour purpose, destination, and departure time information from our analysis. So, the subset of valid non-mandatory tours made by non-workers with complete information included 16,634 tours. Out of these 16,634 tours, 3,000 tours were randomly sampled to be included in our estimation analysis to keep the dataset size manageable. Table 1 shows the frequency distribution of tour purpose and departure time period along with the type of person undertaking the tour in the estimation sample. Also, Figure 2 depicts the distribution of distance to primary destination of the tour in the final sample.

On the supply side, the business hour information to construct the temporal profile of business activity in each TAZ was obtained using Google Place. The Google Place data for the Southern California included key information of businesses including name of business, phone number, opening and closing hours of business. Based on the phone numbers, the two digit North American Industry Classification System (NACIS) code was obtained from the InfoUSA data. A spatial smoothing method was used to account for missing data. Also, the factors that indicate the percentage of businesses open during different hours of the day were weighted by total zonal employment to capture differences between the temporal profiles of businesses and employment. The reader is referred to (Paleti *et al.* 2014) for further details on the smoothing method. Figure 1 shows the bell-shaped temporal profile of employment intensity for different industrial sectors. These smoothened time-of-day specific factors were used to construct (1) the dependent variable of the supply side model component- employment intensity in the five time periods, and (2) zonal employment during the five time periods that is used as an explanatory variable in the size variable specification of the demand side DDT choice model component.

In addition to these two main data sources, the research team had access to the transportation network skims for the study region. These skims were used to compute time-period specific mode choice logsums. Also, zonal land use information including population composition, quality of transit, bike and pedestrian infrastructure, intersection density, median income of households was also obtained from SCAG. In addition to disaggregate socio-demographic and tour information in the HTS, all these zonal variables and logsums constitute the set of explanatory variables considered in the supply and demand model specifications during model estimation.

Methodological Framework

Supply Side Employment Intensity Model Component

Let *i* be the index for the destination alternative (in our case, TAZ) and *t* be the index for time period (1 = 'Morning Peak', 2 = 'Midday', 3 = 'Evening Peak', 4 = 'Evening', and 5 = 'Night'). The employment intensity defined as the percentage of employment that is active in zone *i* during time period *t*, $EI_{i,t}$ is modeled using a log-linear regression framework as follows:

$$LN\left(\frac{EI_{i,t}}{1-EI_{i,t}}\right) = \boldsymbol{X}'_{i,t}\boldsymbol{\beta}_i + \upsilon_{D_i} + \varepsilon_{i,t} \qquad \text{Equation (1)}$$

The functional form of the dependent variable in EQ(1) ensures that $EI_{i,t}$ is bounded between 0 and 1. In EQ (1) above, $\boldsymbol{X}_{i,t}$ is a $K_1 \times 1$ vector of zonal characteristics during time period *t* and $\boldsymbol{\beta}_i$ is the corresponding zone-specific $K_1 \times 1$ vector of coefficients that capture the impact of $\boldsymbol{X}_{i,t}$ on $EI_{i,t}$ and is assumed to be multivariate normal distributed with mean vector $\boldsymbol{b}$ and covariance $\boldsymbol{\Omega}_1$. So, $\boldsymbol{\beta}_i$ can be written as $\boldsymbol{b} + \widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}}$, where $\tilde{\beta}_i$ is multivariate normal distributed with mean vector of K_1 zeros $\boldsymbol{0}_{K_1}$ and covariance $\boldsymbol{\Omega}_1$, *i.e.*, $\tilde{\beta}_i \sim N\left(\boldsymbol{0}_{K_1}, \boldsymbol{\Omega}_1\right)$. The υ_{D_i} term captures all district (in which zone *i* lies) specific unobserved factors that impact both $EI_{i,t}$ on the supply side and DDT preferences of travelers on the demand side. The study used a district level common error term (as opposed to zonal level) because it is difficult to uncover the presence of common zonal level unobserved factors that affect both supply and demand outcomes from a small subset of sampled zonal alternatives. Lastly, $\varepsilon_{i,t}$ captures all other zonal and time-period specific unobserved factors that affect $EI_{i,t}$. With regard to the distributional assumptions of the error terms, υ_{D_i} and $\varepsilon_{i,t}$ are assumed to be *i.i.d.* realizations across zones and time periods from univariate normal distributions - $\upsilon_{D_i} \sim N(0, \pi^2)$ and $\varepsilon_{i,t} \sim N(0, \sigma_t^2)$, *r*espectively. Using these definitions, EQ (1) may be written as:

$$LN\left(\frac{EI_{i,t}}{1-EI_{i,t}}\right) = \boldsymbol{X}'_{i,t}\boldsymbol{b} + \boldsymbol{X}'_{i,t}\widetilde{\boldsymbol{\beta}}_i + \upsilon_{D_i} + \varepsilon_{i,t} \qquad \text{Equation (2)}$$

Demand Side Destination and Departure Time (DDT) Choice Model Component

Let *q* be the index for the decision maker (*i.e.*, the traveler) and $U_{i,t}^q$ denote the utility associated with zonal destination *i* during time period *t* for individual *q*. The utility $U_{i,t}^q$ can be written as:

$$U_{i,t}^q = V_i^q + V_t^q + V_{i,t}^q + \upsilon_{D_i} + \xi_{i,t}^q \qquad \text{Equation (3)}$$

where, V_i^q and V_t^q are dimension-specific utility components of zonal alternative *i* and time period *t*, respectively; $V_{i,t}^q$ is the utility component that captures cross-dimension effects for combinations of zonal and time period alternatives; $\xi_{i,t}^q$ captures all other zonal and time period specific unobserved factors that influence DDT choice preferences. The $\xi_{i,t}^q$ error components are assumed to be *i.i.d.* realizations across both zones and time-periods from a standard Gumbel distribution. Please note that υ_{D_i} is the common term in EQ (2) and EQ (3) that captures unobserved factors that influence both supply and demand side outcomes.

V_i^q composes of several distance decay terms (linear and non-linear) and their interaction with traveler. This component captures the spatial proximity effects on destination choice dimension where as V_t^q captures average departure time preferences of different socio-demographic segments. $V_{i,t}^q$ includes time-period specific zonal attraction size terms and impedance measures (e.g., travel times, travel costs, and mode choice logsums). The specification details of these three components are explained below.

$V_i^q = (\boldsymbol{Z}_i^q)'\boldsymbol{\gamma}^q = (\boldsymbol{Z}_i^q)'\bar{\boldsymbol{\gamma}} + (\boldsymbol{Z}_i^q)'\tilde{\boldsymbol{\gamma}}^q$, where $\boldsymbol{Z}_i^q$ is $K_2 \times 1$ vector of zonal and traveler characteristics that do not vary over time (e.g., inter-zonal distances, age, gender, *etc.*), $\bar{\boldsymbol{\gamma}}$ is the corresponding mean vector of coefficients and $\tilde{\boldsymbol{\gamma}}^q \sim N(\boldsymbol{0}_{K_2}, \boldsymbol{\Omega}_2)$ is the random component of parameter effects that is normally distributed across travelers with covariance $\boldsymbol{\Omega}_2$.

$V_t^q = (\boldsymbol{W}_t^q)'\boldsymbol{\delta}_{\boldsymbol{t}}^{\boldsymbol{q}} = (\boldsymbol{W}_t^q)'\bar{\boldsymbol{\delta}}_t + (\boldsymbol{W}_t^q)'\tilde{\boldsymbol{\delta}}_t^q$, where $\boldsymbol{W}_t^q$ is $K_3 \times 1$ vector of time-period attributes and their interaction with traveler characteristics, $\bar{\boldsymbol{\delta}}_t$ is the corresponding mean vector of coefficients and $\tilde{\boldsymbol{\delta}}_t^q \sim N(\boldsymbol{0}_{K_3}, \boldsymbol{\Omega}_3)$ is the random component of parameter effects that is normally distributed across travelers with covariance $\boldsymbol{\Omega}_3$.

$V_{i,t}^q = LN(S_{i,t}) + \boldsymbol{LOS}_{i,t}'\bar{\boldsymbol{\lambda}} + \boldsymbol{LOS}_{i,t}'\tilde{\boldsymbol{\lambda}}^q$, where $S_{i,t}$ is the zonal and time period specific attraction size term; $\boldsymbol{LOS}_{i,t}'$ is $K_4 \times 1$ vector of level-of-service variables characterizing travel to destination *i* during time period *t*, $\bar{\boldsymbol{\lambda}}$ is the corresponding mean vector of coefficients and $\tilde{\boldsymbol{\lambda}}^q \sim N(\boldsymbol{0}_{K_4}, \boldsymbol{\Omega}_4)$ is the random component of parameter effects that is normally distributed across travelers with covariance $\boldsymbol{\Omega}_4$. Lastly, the size term $S_{i,t}$ comprises of several zonal population and employment variables and may be written as follows:

$$S_{i,t} = \sum_p I_p^q \times \boldsymbol{\alpha}_p'\boldsymbol{A}_{i,t} \qquad \text{Equation (4)}$$

where *p* is the index for tour purpose, I_p^q is the indicator variable for whether the tour purpose is *p* (1= 'Escorting', 2 = 'Shopping', 3 = 'Maintenance', 4 = 'Eating out', 5 = 'Social', and 6 = 'Discretionary'), $\boldsymbol{A}_{i,t}$ is $K_5 \times 1$ vector of zonal attraction variables, and $\boldsymbol{\alpha}_p$ is the corresponding vector of coefficients on attraction variables specific to tour purpose *p*. $\boldsymbol{A}_{i,t}$ may include variables describing zonal population composition and zonal employment $E_{i,t}^s$ in industry sector *s*. The zonal employment variable $E_{i,t}^s$ is related to employment intensity $EI_{i,t}$ in EQ (1) as:

$$E_{i,t}^s = EI_{i,t} \times E_i^s \qquad \text{Equation (5)}$$

where E_i^s is the total employment in zone *i* in industry sector *s*.

For each tour purpose *p*, one of the $\boldsymbol{\alpha}_p$ parameters must be normalized to one and the effect of other attraction variables are estimated relative to this normalized parameter. So, the overall utility expression may be re-written as follows:

$$U_{i,t}^q = (\boldsymbol{Z}_i^q)'\bar{\boldsymbol{\gamma}} + (\boldsymbol{W}_t^q)'\bar{\boldsymbol{\delta}}_t + LN(S_{i,t}) + \boldsymbol{LOS}_{i,t}'\bar{\boldsymbol{\lambda}} \qquad \text{Equation (6)}$$

$$+(\boldsymbol{Z}_i^q)'\tilde{\boldsymbol{\gamma}}^q + (\boldsymbol{W}_t^q)'\tilde{\boldsymbol{\delta}}_t^q + \boldsymbol{LOS}_{i,t}'\tilde{\boldsymbol{\lambda}}^q + \upsilon_{D_i} + \xi_{i,t}^q$$

Maximum Simulated Likelihood Estimation

The likelihood contribution of zone *i* during time period *t* from the supply side model component conditional on the random components would be:

$$L_{i,t}^{Supply}\left(\boldsymbol{b}, \boldsymbol{\Omega}_1, \pi, \sigma_t | \widetilde{\boldsymbol{\beta}}_i, \upsilon_{D_i}\right) = \frac{1}{\sigma_t} \phi \left[\frac{LN\left(ED_{i,t}\right) - \left(\boldsymbol{X}'_{i,t}\boldsymbol{b} + \boldsymbol{X}'_{i,t}\widetilde{\boldsymbol{\beta}}_i + \upsilon_{D_i}\right)}{\sigma_t}\right] \qquad \text{Equation (7)}$$

where $\phi(.)$ is the standard univariate normal probability density function.

The likelihood function of zone *i* across all time periods is obtaining by taking the product of time period specific likelihood functions in EQ (7) as:

$$L_{i}^{Supply}\left(\boldsymbol{b}, \boldsymbol{\Omega}_1, \pi, \boldsymbol{\sigma} | \widetilde{\boldsymbol{\beta}}_i, \upsilon_{D_i}\right) = \prod_{t=1}^{5} L_{i,t}^{Supply}\left(\boldsymbol{b}, \boldsymbol{\Omega}_1, \pi, \sigma_t | \widetilde{\boldsymbol{\beta}}_i, \upsilon_{D_i}\right) \qquad \text{Equation (8)}$$

The unconditional likelihood function for zone *i* can be obtained by integrating out the random components as:

$$L_{i}^{Supply}\left(\boldsymbol{b}, \boldsymbol{\Omega}_1, \pi, \boldsymbol{\sigma}\right) = \int_{\widetilde{\boldsymbol{\beta}}_i, \upsilon_{D_i}=-\infty}^{\widetilde{\boldsymbol{\beta}}_i, \upsilon_{D_i}=\infty} L_{i}^{Supply}\left(\boldsymbol{b}, \boldsymbol{\Omega}_1, \pi, \boldsymbol{\sigma} | \widetilde{\boldsymbol{\beta}}_i, \upsilon_{D_i}\right) \qquad \text{Equation (9)}$$

where $\boldsymbol{\sigma}$ is the vertically stacked vector of σ_t $(t = 1,2, \ldots T)$

So, the overall likelihood conditional contribution from the supply side model component is:

$$L^{Supply}\left(\boldsymbol{b}, \boldsymbol{\Omega}_1, \pi, \boldsymbol{\sigma}\right) = \prod_{i} L_{i}^{Supply}\left(\boldsymbol{b}, \boldsymbol{\Omega}_1, \pi, \boldsymbol{\sigma}\right) \qquad \text{Equation (10)}$$

For the purpose of notational convenience, define two additional vectors $\boldsymbol{\alpha} = (\boldsymbol{\alpha}'_1, \boldsymbol{\alpha}'_2, \ldots, \boldsymbol{\alpha}'_5)'$ and $\overline{\boldsymbol{\delta}} = \left(\overline{\boldsymbol{\delta}}'_1, \overline{\boldsymbol{\delta}}'_2, \ldots, \overline{\boldsymbol{\delta}}'_5\right)'$. On the demand side, because of the logit kernel, the probability that traveler *q* chooses destination *i* during time period *t* conditional on all the random components is given by:

$$L_{i,t}^{q,Demand}\left(\overline{\boldsymbol{\gamma}}, \overline{\boldsymbol{\delta}}_t, \boldsymbol{\alpha}, \overline{\boldsymbol{\lambda}}, \boldsymbol{\Omega}_2, \boldsymbol{\Omega}_3, \boldsymbol{\Omega}_4, \pi | \widetilde{\boldsymbol{\gamma}}^q, \widetilde{\boldsymbol{\delta}}_t^q, \widetilde{\boldsymbol{\lambda}}^q, \upsilon_{D_i}\right) = \qquad \text{Equation (11)}$$

$$\frac{e^{\left(\boldsymbol{z}_i^q\right)'\overline{\boldsymbol{\gamma}} + \left(\boldsymbol{w}_t^q\right)'\overline{\boldsymbol{\delta}}_t + LN\left(S_{i,t}\right) + \boldsymbol{LOS}'_{i,t}\overline{\boldsymbol{\lambda}} + \left(\boldsymbol{z}_i^q\right)'\widetilde{\boldsymbol{\gamma}}^q + \left(\boldsymbol{w}_t^q\right)'\widetilde{\boldsymbol{\delta}}_t^q + \boldsymbol{LOS}'_{i,t}\widetilde{\boldsymbol{\lambda}}^q + \upsilon_{D_i}}}{\sum_{j,\tilde{t}} e^{\left(\boldsymbol{z}_j^q\right)'\overline{\boldsymbol{\gamma}} + \left(\boldsymbol{w}_{\tilde{t}}^q\right)'\overline{\boldsymbol{\delta}}_{\tilde{t}} + LN\left(S_{j,\tilde{t}}\right) + \boldsymbol{LOS}'_{j,\tilde{t}}\overline{\boldsymbol{\lambda}} + \left(\boldsymbol{z}_j^q\right)'\widetilde{\boldsymbol{\gamma}}^q + \left(\boldsymbol{w}_{\tilde{t}}^q\right)'\widetilde{\boldsymbol{\delta}}_{\tilde{t}}^q + \boldsymbol{LOS}'_{j,\tilde{t}}\widetilde{\boldsymbol{\lambda}}^q + \upsilon_{D_j}}}$$

Sampling Strategy

The denominator in EQ (11) is a summation across all TAZs in the region (*i.e.*, the universal set of TAZs) and all time periods. The study region considered in this paper has about 11,267 TAZs. Given that it is computationally infeasible to consider all these TAZs in our modeling, we sampled a subset of TAZs using an importance sampling mechanism. Specifically, up to 50 TAZs were sampled with replacement for each record in our estimation data using a simple multinomial logit (MNL) model with TAZ specific size term and a coefficient of -0.1 for "Distance from Home TAZ" variable. The conditional likelihood function in Equation (10) was modified to account for the sampling mechanism by adding a correction term $LN\left(\frac{n_i}{N\times q(i)}\right)$ to the utility of the i^{th} sampled alternative. In this correction term, n_i is the number of times alternative i is sampled into the choice set, N is the sample size (in our case, N = 50), and $q(i)$ is the sampling probability of alternative i obtained using the simple MNL model used for sampling. Guevara and Ben-Akiva (Guevara and Ben-Akiva 2013) proved that a naïve estimator with this added correction term will provide consistent estimates for logit mixture models.

So, the modified conditional likelihood function for individual q is given by:

$$\tilde{L}_{i,t}^{q,Demand}\left(\bar{\boldsymbol{\gamma}}, \bar{\boldsymbol{\delta}}_t, \boldsymbol{\alpha}, \bar{\boldsymbol{\lambda}}, \boldsymbol{\Omega}_2, \boldsymbol{\Omega}_3, \boldsymbol{\Omega}_4, \pi | \tilde{\boldsymbol{\gamma}}^q, \tilde{\boldsymbol{\delta}}_t^q, \tilde{\boldsymbol{\lambda}}^q, \upsilon_{D_i}\right) = \quad \text{Equation (12)}$$

$$\frac{e^{(\boldsymbol{Z}_i^q)'\bar{\boldsymbol{\gamma}} + (\boldsymbol{W}_t^q)'\bar{\boldsymbol{\delta}}_t + LN(S_{i,t}) + \boldsymbol{LOS}'_{i,t}\bar{\boldsymbol{\lambda}} + LN\left(\frac{n_i}{N\times q(i)}\right) + (\boldsymbol{Z}_i^q)'\tilde{\boldsymbol{\gamma}}^q + (\boldsymbol{W}_t^q)'\tilde{\boldsymbol{\delta}}_t^q + \boldsymbol{LOS}'_{i,t}\tilde{\boldsymbol{\lambda}}^q + \upsilon_{D_i}}}{\sum_{j\in C_q,\tilde{t}} e^{(\boldsymbol{Z}_j^q)'\bar{\boldsymbol{\gamma}} + (\boldsymbol{W}_{\tilde{t}}^q)'\bar{\boldsymbol{\delta}}_{\tilde{t}} + LN(S_{j,\tilde{t}}) + \boldsymbol{LOS}'_{j,\tilde{t}}\bar{\boldsymbol{\lambda}} + LN\left(\frac{n_j}{N\times q(j)}\right) + (\boldsymbol{Z}_j^q)'\tilde{\boldsymbol{\gamma}}^q + (\boldsymbol{W}_{\tilde{t}}^q)'\tilde{\boldsymbol{\delta}}_{\tilde{t}}^q + \boldsymbol{LOS}'_{j,\tilde{t}}\tilde{\boldsymbol{\lambda}}^q + \upsilon_{D_j}}}$$

where C_q is the set of TAZ alternatives sampled for individual q.

The unconditional likelihood function for traveler q can be obtained by integrating out the random components as follows:

$$L_{i,t}^{q,Demand}\left(\bar{\boldsymbol{\gamma}}, \bar{\boldsymbol{\delta}}, \boldsymbol{\alpha}, \bar{\boldsymbol{\lambda}}, \boldsymbol{\Omega}_2, \boldsymbol{\Omega}_3, \boldsymbol{\Omega}_4, \pi\right) = \quad \text{Equation (13)}$$

$$\int_{\tilde{\boldsymbol{\gamma}}^q, \tilde{\boldsymbol{\delta}}_t^q, \tilde{\boldsymbol{\lambda}}^q, \upsilon_{D_i}=-\infty}^{\tilde{\boldsymbol{\gamma}}^q, \tilde{\boldsymbol{\delta}}_t^q, \tilde{\boldsymbol{\lambda}}^q, \upsilon_{D_i}=\infty} \tilde{L}_{i,t}^{q,Demand}\left(\bar{\boldsymbol{\gamma}}, \bar{\boldsymbol{\delta}}_t, \boldsymbol{\alpha}, \bar{\boldsymbol{\lambda}}, \boldsymbol{\Omega}_2, \boldsymbol{\Omega}_3, \boldsymbol{\Omega}_4, \pi | \tilde{\boldsymbol{\gamma}}^q, \tilde{\boldsymbol{\delta}}_t^q, \tilde{\boldsymbol{\lambda}}^q, \upsilon_{D_i}\right)$$

However, one important point to note here is that, during the integration, the same draws of $\upsilon_{i,t}$ that are used in EQ (9) of the supply side model component will be used in EQ (13) of the demand side model component.

The overall unconditional likelihood contribution from the demand side model component is:

$$L^{Demand}\left(\bar{\boldsymbol{\gamma}}, \bar{\boldsymbol{\delta}}, \boldsymbol{\alpha}, \bar{\boldsymbol{\lambda}}, \boldsymbol{\Omega}_2, \boldsymbol{\Omega}_3, \boldsymbol{\Omega}_4, \pi\right) = \prod_q L_{i,t}^{q,Demand}\left(\bar{\boldsymbol{\gamma}}, \bar{\boldsymbol{\delta}}, \boldsymbol{\alpha}, \bar{\boldsymbol{\lambda}}, \boldsymbol{\Omega}_2, \boldsymbol{\Omega}_3, \boldsymbol{\Omega}_4, \pi\right) \quad \text{Equation (14)}$$

The total likelihood function for the joint demand-supply model can be written using EQ (9) and EQ (14) as follows:

$$L\left(\boldsymbol{b}, \bar{\boldsymbol{\gamma}}, \bar{\boldsymbol{\delta}}, \boldsymbol{\alpha}, \bar{\boldsymbol{\lambda}}, \boldsymbol{\Omega}_1, \boldsymbol{\Omega}_2, \boldsymbol{\Omega}_3, \boldsymbol{\Omega}_4, \pi, \boldsymbol{\sigma}\right) = \quad \text{Equation (15)}$$

$$L^{Supply}(\boldsymbol{b}, \boldsymbol{\Omega}_1, \pi, \boldsymbol{\sigma}) \times L^{Demand}\left(\bar{\boldsymbol{\gamma}}, \bar{\boldsymbol{\delta}}, \boldsymbol{\alpha}, \bar{\boldsymbol{\lambda}}, \boldsymbol{\Omega}_2, \boldsymbol{\Omega}_3, \boldsymbol{\Omega}_4, \pi\right)$$

The MSL estimation was undertaken using 150 randomized Halton sequences (Bhat 2003) and the standard errors of parameters estimates were obtained using the inverse of the Godambe sandwich information matrix (Godambe 1960).

Empirical Results

Table 2 presents the estimation results of the supply side employment intensity model estimation results for the five time periods and Tables 3 and 4 present the final model parameters of the DDT choice component. Only parameters that were significant at 95% confidence level were retained in the final model specification.

<u>Supply Side Employment Intensity Model</u>

The constants in the model do not have any substantive interpretive meaning because there are several other continuous variables in the model. Notwithstanding this, it can be observed based on the relative magnitude of constants that employment intensity is highest during the 'Midday' and 'Evening Peak' time periods whereas 'Night' time period has the least employment intensity. Zones with higher household population have higher employment activity during all time periods. Also, higher population in older age category (65 years and above) were found to be associated with higher employment activity during all time periods. However, higher college enrollment was found to decrease the employment intensity during all time periods. Zones with high proportion of high income households (>$100,000) were found to have higher employment activity during all time period. This result is probably indicative of more perceived demand by business owners in zones with more high income households.

Zones with high intersection density have higher employment intensity during all time periods compared to zones with lower intersection density. This result is intuitive given that intersections in urban and suburban areas usually serve as activity centers with shopping malls, restaurants, and other businesses. It is also likely that this variable is serving as a proxy for degree of local transportation network connectivity within the zone. So, higher intersection density is probably indicative of better transportation infrastructure in the region. Zones that have bike lane access, high bus stop density, and higher percentage of zone in High Quality Transit Area (HQTA) have higher employment activity during all time periods. Overall, these variables suggest that better transit and non-motorized infrastructure is conducive to more economic activity. Lastly, zones that fall in the CBD region have high employment intensity during all the five time periods compared to non-CBD zones. The study also found strong evidence for the presence of time invariant zone specific random effects that impact employment intensity.

<u>Demand Side DDT Model Component</u>

Destination Dimension Utility Component: Spatial Proximity Effects

Among different non-linear distance effects that we tested, the logarithmic specification of distance gave the best data fit. Figure 3 shows the impact of distance on the utility of zonal alternatives for different demographic segments and tours of different purposes. The baseline effect is always below the x-axis suggesting that, all else being same, zones father away from the home zone are less preferred compared to other zonal alternatives with the relation being non-linear (due to the logarithmic function). Female travelers were found to be more sensitive to distance compared to their equivalent male counterparts and tend to travel to closer destinations. Also, people tend to travel shorter distances for shopping and escorting tours whereas they were found to be willing to travel longer distances for social and maintenance tours. These results are consistent with average durations of activity participation associated with these different activities. People are willing to travel farther to undertake longer activities, however, if the duration of activity is very short, it probably does not make sense to travel farther. Distance interactions with indicator variable for joint tour were also tested during model estimation but did not turn out to be statistically significant. This is different from the findings of earlier studies that found that joint tours have higher mileage compared to individual tours (Paleti *et al.* 2011).

Destination Dimension Utility Component: Other Zonal Factors

The mean parameter estimate on the CBD indicator variable was negative suggesting that zones in CBD region were, on average, less attractive compared to non-CBD zones for undertaking non-mandatory tours. This result is not necessarily unintuitive because we are focusing on non-mandatory tours of non-workers and the model already controls for higher employment effects in the CBD region through the size variable. So, the CBD indicator variable is serving as a token variable for inconvenience and additional costs associated with traveling to CBD regions such as high congestion levels and parking costs. However, the standard deviation parameter on CBD indicator variable was 1.9859 indicating that nearly 24% of CBD zones are preferred over non-CBD zones (everything else being the same). Lastly, zones with high intersection density and zones that bike lane access were found to be preferred over other zones. This result is probably capturing the ease of reaching other nearby areas after reaching the destination. For instance, people can park their vehicle and move within the zone to explore different opportunities in close proximity.

Time Period Dimension Utility Component

The constants in the time period specific utility component do not have substantive behavioral meaning because of several other continuous variables in the model. Female travelers were found to have higher preference for 'Morning Peak', 'Midday', and 'Evening Peak' time periods compared to male travelers. Shopping tours are less likely to be made during 'Morning Peak' hours whereas they are most likely to be made undertaken during the 'Midday' time period. This finding is consistent with the typical shopping travel patterns of non-working adults. Maintenance tours, on the other hand, are mostly made during 'Midday' period. This is intuitive given that activities such as visiting a bank or a doctor that constitute the "maintenance" category are typically undertaken during afternoon hours. Social tours are most likely to be undertaken during the 'Evening Peak' time period. This is intuitive because social activities are typically undertaken with friends/families during later hours of the day because some of them might be working during daytime. Eating out tours are mostly undertaken during the 'Evening Peak' time period consistent with typical dinner hours. Lastly, joint tours with other household members are more likely to be scheduled in the 'Evening Peak' time period.

Destination & Time Period Cross Dimensions Utility Component

Table 4 presents the parameters in the size variable specification of the final model. The employment levels for the same zone can be different for different time periods because of business opening and closing hours. So, although we sample only 50 zones, the employment for each of these 50 zones varies across the five time periods. Also, one of the coefficients in the size variable specification is normalized to one for each tour purpose and the effect of other employment variables is estimated relative to the attraction variable with fixed coefficient. For instance, for shopping tours, the coefficient on "Retail & Other Services" employment was fixed to one and the effect of employment in the "Art & Entertainment" industry was estimated to be 0.1841. It can be seen that the attraction size variable is a function of different sets of employment variables depending on the activity purpose of the tour. This is intuitive because opportunities for activity participation vary depending on the purpose of the activity. So, it is not correct to have one single size variable specification for tours of all purposes. For instance, the most relevant attraction variables for escorting tours are "Total Number of Households" and employment in the "Educational" industrial sector. Employment in other industry sectors was found to not have any significant effect on the attraction size variable for escorting tours. Other coefficients in the Table 4 may be interpreted similarly for other tour purposes. Lastly, in the final model, the parameter estimate on time period specific mode choice logsum was fixed to 1 indicating that there is no simultaneity in mode and DDT choices. However, this logsum variable makes the overall model sensitive to evaluating the impact of a host of policy scenarios including changes in level-of-service (LOS) characteristics of auto, transit, and non-motorized modes.

Endogeneity & Model Fit

Our models for employment intensity and DDT choices do not include all possible variables that can influence these two response variables. For example, zones located in districts that contain major tourist attractions (which is not controlled in our models) might be intrinsically attractive to customers on the demand side (that is people who pursue out-of-home non-mandatory activities) as well as business establishments on the supply side. Such common unobserved variables can lead to correlation between the employment intensity and utility equations in the supply and demand model components, respectively. Ignoring this correlation between the two model components and estimating them independently will lead to bias and inconsistency of model parameters (Louviere *et al.* 2005). To see this, note that employment intensity enters the utility equations in the DDT choice as the size variable which will be correlated with the error term in the utility equation. This is because employment intensity is influenced by unobserved variables that are also common to the error terms in the utility equation. So, this leads to the endogeneity problem whereby the explanatory variables in the observed portion of the utility equation are correlated with the error term in the utility equation. To account for this endogeneity problem, a common error term υ_{D_i} that is assumed to an independent realization (across districts) from univariate normal distribution (with zero mean) is added to the employment intensity and utility equations that is integrated out during model estimation. If the standard error π of this common error term turns out to be zero, it would imply that there is no endogeneity problem. So, the parameter estimates from the independent model would be correct. However, in the empirical application, the standard error of this common unobserved term was found to be 2.608. This finding underscores the importance of the joint modeling framework developed in this study for analyzing DDT choices that are traditionally modeled conditional on total zonal employment obtained from supply side models.

Also, the log-likelihood (LL) of the final model that accounts for endogeneity and parameter heterogeneity both in the supply and demand side model components was -68,923.65 (M1: 94 parameters). The LL of the model that ignores endogeneity but accounts for random parameter heterogeneity in the two model components was -69,818.74 (M2: 93 parameters) and the LL of model that ignores endogeneity as well as random parameter heterogeneity was -90,257.9 (M3: 91 parameters). It can be seen that the log-likelihood ratio (LR) test statistics of comparison of the final model M1 against models M2 and M3 are much higher than the critical chi-square values for 1 and 3 degrees of freedom at any level of significance respectively; thus clearly indicating statistically superior data fit in the final model (M1).

Post Estimation Analysis

This section presents the results of post model estimation analysis that was undertaken to demonstrate the applicability of the joint model developed in this study. As part of this exercise, four policy scenarios were considered – (1) increase bus stop density by 100%, (2) increase intersection density by 100%, (3) double the percentage of zone in HQTA by 100%, and (4) provide bike lane access to a zone.[1] These changes were applied only to zones in District 34 that corresponds to the Los Angeles downtown area. For each of these four scenarios, the employment intensity during the five time periods was predicted using the regression model component parameters before and after the change in the variable of interest. Next, the probabilities of all DDT alternatives were computed for each time period both before and after the change for each scenario. To maintain computational tractability, 50 zonal alternatives were sampled for each tour as was done during model estimation. Lastly, the percentage change in the average probability of all the DDT alternatives in District 34 was computed due to the policy change. This change in average probability can be either because the variable of interest appears directly in the utility equation of the DDT choice component (e.g., intersection density) or because of change in employment intensity on supply side that translated into changes in zonal employment affecting size variables in the utility of DDT choice alternatives. It is important to note that there is some time-lag between the changes on the supply side (employment intensity) and the associate changes on the demand side (*i.e.*, DDT choices) because of the above changes to transportation infrastructure. However, for the purposes of demonstration, these changes are assumed to be instantaneous. Also, it is possible that improved transportation infrastructure can induce new trips over a longer time-horizon compared to the changes in DDT choices we considered in the policy simulation exercise. While accounting for this induced demand is beyond the scope of the current study, it can be captured using spatio-temporal accessibility measures in the activity generation model components of ABMs.

Table 5 presents the results of the post-estimation analysis. It can be seen from the table that the percentage change in the average probability is different across different time periods. Traditional DDT choice models that assume total employment to be available during the entire day cannot capture this time varying effect of different policy scenarios because of time varying employment intensity on the supply side. The percentage changes are relatively higher during ‘Night’ compared to other time periods because the average probabilities in the base case (before the policy change)

[1] If the percentage of zone in HQTA exceeded 100% in the policy scenario, it was set to 100%.

are lower for this time period mainly due to fewer opportunities on the supply side (*i.e.,* low employment intensity) during night hours. Also, the results suggest that providing bike lane access and increasing intersection density within a zone (*i.e.,* better local accessibility) are more conducive to increasing travel demand to a zone (from the perspective of business owners in that zone) than improving the quality of public transit in that zone.

Conclusion

In most travel demand models, the interactions between land use and transportation are captured either by (1) using an integrated land use and travel demand model to capture long term inter-dependencies between the two systems, or (2) using land use information as an external input to the travel choice models. However, these existing methods cannot account for short term inter-dependencies between the two systems. For instance, daily travel choices such as destination and departure time (DDT) choices depend on spatial and temporal distribution of activity opportunities on the supply side. However, it is also true that spatial and temporal profile of activity opportunities in a region depend on the estimated level of demand for these opportunities by businesses located in that region. So, within each day, we observe an equilibrium between the temporal profile intensity of activity opportunities (as determined by the opening and closing hours of businesses) on the supply side and DDT choices of travelers on the demand side.

To explore such inter-dependencies, an integrated modeling framework was developed that (a) accounts for potential endogeneity between the outcomes in the two systems because of common unobserved factors that influence both employment intensity on supply side and utility of travelers on the demand side; (b) treats DDT choices as a single bundle where in travelers evaluate combinations of destinations and departure time periods as opposed to any pre-determined sequence of these two choices; and (c) can accommodate importance sampling mechanisms to reduce the computational burden associated with explosion in size of choice sets because of combinations of destination and departure time alternatives. This integrated model was used to analyze temporal variation of zonal employment intensity and non-mandatory DDT choices in the Southern California region. The results offer new insights into the relationship between temporal profile of zonal employment intensity within a day and zonal demographics and transportation infrastructure. The DDT choice model component also uncovered several nonlinear spatial proximity effects, sensitivity to transportation network conditions of different modes, differences in departure time preferences across different tours and demographic segments, and tour purpose specific attraction size effects. The study also found evidence for the presence of time invariant random effects in the supply side employment intensity model component, random parameter heterogeneity in the DDT choice model component, and endogeneity between the supply and demand model components. Lastly, the post estimation analysis results demonstrated the ability of the joint model developed in the study to capture the time varying effect of different policy scenarios on travelers' DDT choice preferences arising due to differences in employment intensity patterns.

There are several possible avenues for improving this study in the future. First, one of the assumptions in this study was that employment intensity profile is the same across all industrial sectors in a zone. So, the same employment intensity proportions were applied to all employment variables in the size terms of DDT choice model component. However, this is a restrictive assumption that is not necessarily true because the employment intensity profile can be different across different industrial sectors. This would imply that the regression model component in the supply side must be completely segmented by industrial sector increasing the computational burden in the joint model estimation. Second, the departure time choice dimension on the demand side was analyzed by defining aggregated time periods as choice alternatives instead of using of using a finer temporal resolution (e.g., 15 minutes time bins). This also has implications to the supply side model because as the temporal resolution increases, the number of time periods in the panel regression model for employment intensity also increase. Third, this study only models the destination preferences of the primary destination of a tour. In this study, primary tour destination in the survey data was defined based on a combination of rules considering distance from home, activity purpose, and activity duration at the destination. In some cases, (particularly among non-mandatory tours) the definition of primary tour destination is fuzzy because there might be tours with multiple stops that are equally important. So, extending the modeling framework to deal with simultaneous destination choices of multiple stops in a tour presents unique challenges both in terms of computational complexity as well as identifying smart mechanisms for sampling chains of stop locations as opposed to individual locations. Lastly, in some cases, a sequential approach where departure time choices are modeled conditional on destination choices is better suited than the joint DDT choice model adopted in this study. For instance, a sequential approach is better suited for modeling DDT choices of eating out activities with reservations and special events such as sporting events or concerts. In the past, researchers have used latent class modeling methods with all possible dependency pathways as alternatives to address this problem (Waddell *et al.* 2007). For example, there are three dependency pathways in DDT choices: (1) destination choice followed by departure time, (2) departure time followed by destination choice, and (3) joint DDT choice model. Future studies must explore these alternate dependency pathways in DDT choices of non-mandatory activities.

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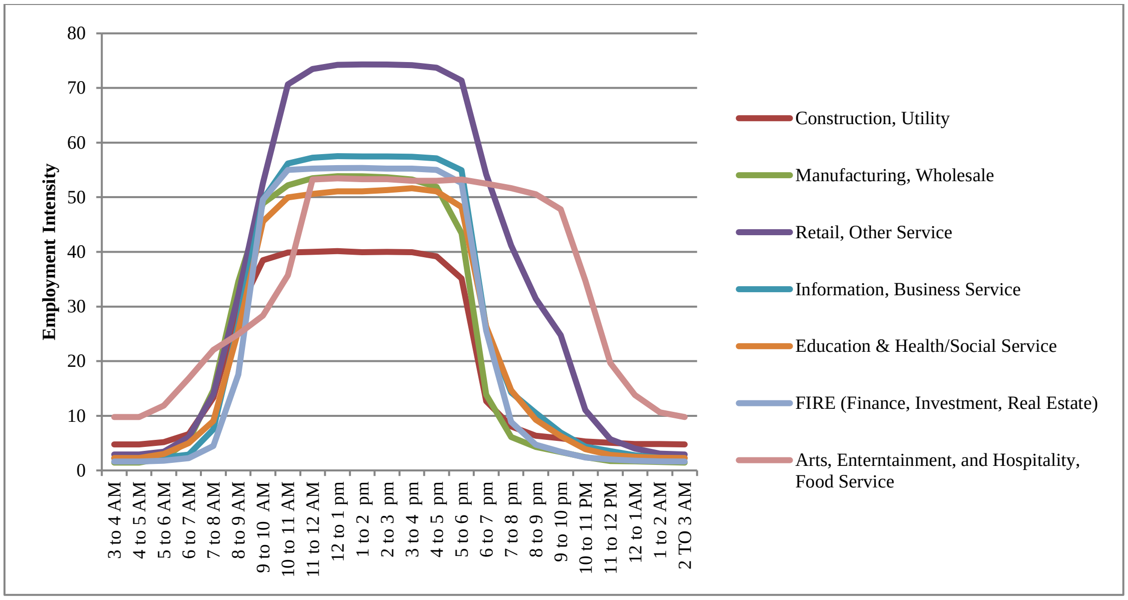

Figure 1: Employment Intensity by Industry Sector and Hour of Day

Table 1: Key Descriptive Statistics in the Estimation Sample

	Frequency	Percent
Tour Purpose		
Escort	558	18.6
Shopping	667	22.2
Maintenance	546	18.2
Social	129	4.3
Entertainment	98	3.3
Visiting Friends/Family	233	7.8
Active Recreation	346	11.5
Eating Out	156	5.2
Other	267	8.9
Tour Departure Time Period		
AM	706	23.5
Midday	1430	47.7
PM	668	22.3
Evening	121	4.0
Night	75	2.5
Person Type		
Full-time Worker	551	18.4
Part-time Worker	469	15.6
Student	93	3.1
Non-worker	1162	38.7
Retiree	659	22.0
Driving Age Child	66	2.2

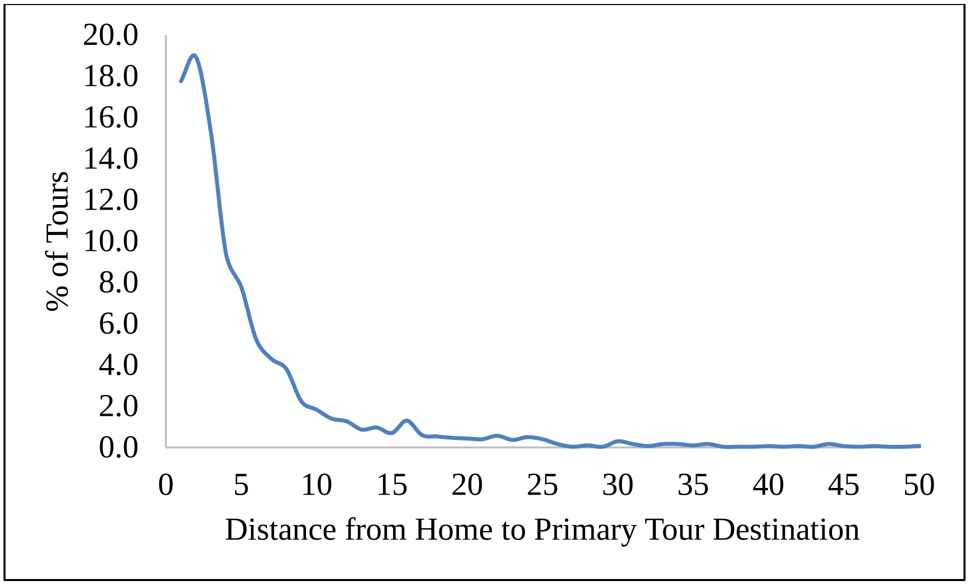

Figure 2: Percentage Distribution of Tours by Distance to Primary Destination

Table 2: Supply Side Employment Intensity Model Estimation Results

Parameter	**Morning Peak**	**Midday**	**Evening Peak**	**Evening**	**Night**
Constant	-2.5898	-0.8187	-1.0836	-2.6896	-3.8682
Number of Households in TAZ (×1000)	0.2671	0.2159	0.2343	0.3248	0.1931
Population Aged 65 and over (×1000)	0.0329	0.1629	0.1659	0.1500	0.1657
College Enrollment (×1000)	-0.0128	-0.0091	-0.0090	-0.0104	-0.0152
Households with income > $100,000 (×1000)	0.1449	0.9309	0.9448	0.5033	0.1262
Intersection density (3- and 4- legs)	0.7887	1.2511	1.3498	1.3753	1.1093
Bike lane access (1= if a TAZ has bike lane)	0.2090	0.3272	0.3189	0.2464	0.1283
Total Bus Stop Density	0.0478	0.0470	0.0454	0.0542	0.0624
% of TAZ in HQTA	0.3038	0.4648	0.4639	0.4640	0.3799
Central Business District	0.0800	0.2958	0.2676	0.1508	0.1175
Time Invariant Random Effects	0.3874				
Standard Error of Residual Error Term (σ_t)	0.4240	0.1937	0.1000	0.5313	0.5798
Number of Observations (TAZs)	11,267				

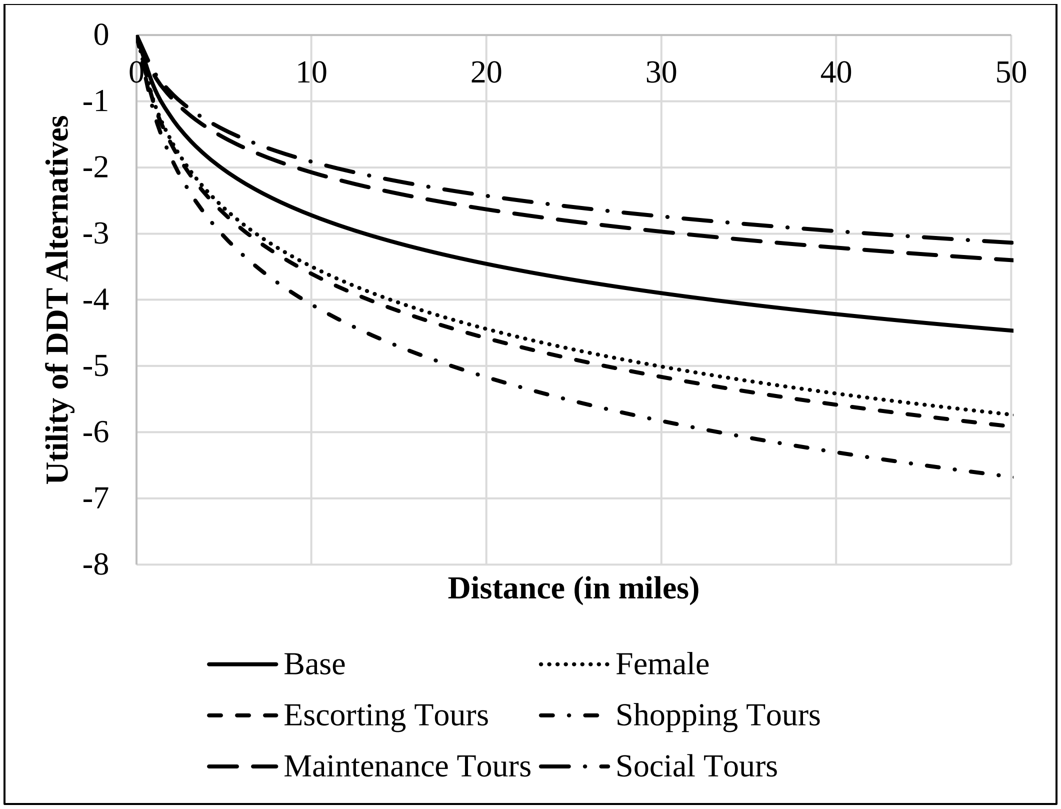

Figure 3: Distance Effects on Utility of DDT Alternatives

Table 3 DDT Model Estimation Results: Dimension Specific Utility Components

Explanatory Variables	**Zonal Dimension Utility Component**		**Time Period Dimension Utility Component (Base: Night)**			
	Spatial Proximity Effects LN[1+Distance]*	**Other Zonal Factors**	**Morning Peak**	**Midday**	**Evening Peak**	**Evening**
Constant	-1.1353		1.3988	0.6019	0.0000	-0.9354
Traveler Socio-demographics						
Female	-0.3230		0.3953	0.5600	0.5665	
Tour Characteristics						
Escorting tour	-0.3686					
Shopping tour	-0.5621		-0.5545	0.7927		
Maintenance tour	0.2705			0.4236		
Social tour	0.3376				0.2717	
Meal tour					0.3881	
Joint Tour Party Composition						
Joint tour (all adults)					0.7151	

Joint tour (adults & children)					0.6145	
Built Environment Effects						
CBD		-1.4120				
Standard Deviation		1.9859				
Intersection Density		0.9814				
Bike Lane Access		0.2140				

Table 4 DDT Model Estimation Results: Cross Dimensions Utility Component

Size Variables	Tour Purpose					
	Escorting	**Shopping**	**Social**	**Maintenance**	**Eat out**	**Discretionary**
Total Number of Households	1.0000			1.1063		0.6203
Employment						
Agriculture						
Construction & Transportation						
Manufacturing & Wholesale						
Retail & Other Service		1.0000	1.0000	1.0000	0.3513	1.0000
Information & Professional						
Educational	0.0163					
Financial Institution & Real Estate						
Art & Entertainment		0.1841	0.3722		1.0000	
Public Administration				0.2891		
Time Period Specific Mode Choice Logsum	1.0000					

Table 5 Post Estimation Analysis Results: % Increase in Average Probability of Visiting a Zone in District 34

Time Period	100% Increase in Bus Stop Density	100% Increase in Intersection Density	100% Increase in % of Zone in HQTA	Provide Bike Lane Access
Morning Peak (6:00 am to 9:00 am)	6.4%	15.4%	6.8%	16.2%
Mid-Day (9:00 am to 3:00 pm)	0.4%	11.9%	2.5%	13.9%
Evening Peak (3:00 pm to 7:00 pm)	0.4%	11.4%	3.3%	13.8%
Evening (7:00 pm to 9:00 pm)	7.3%	24.1%	13.4%	19.9%
Night (9:00 pm to 6:00 am)	16.2%	26.7%	16.0%	18.2%