How reasonable is the typical week modeling time frame approach in activity-based travel demand modeling?

Case study on shopping activity, trip using multi-week trip diary survey data

Report

Author(s):
Nurul Habib, Khander M.; Miller, Eric J.; Axhausen, Kay W.

Publication date:
2007-07

Permanent link:
https://doi.org/10.3929/ethz-a-005562768

Originally published in:
Arbeitsberichte Verkehrs- und Raumplanung 443

How Reasonable is the Typical Week Modeling Time Frame Approach in Activity-Based Travel Demand Modeling? Case Study on Shopping Activity/Trip Using Multi-Week Trip Diary Survey Data

Khandker M. Nurul Habib, PhD
Post Doctoral Fellow
Department of Civil Engineering
University of Toronto
35 St George Street
Toronto, Ontario M4S 1A4, Canada
Phone: 416 978 5049
Fax: 416 978 5054
khandker.nurulhabib@utoronto.ca

Eric J. Miller, PhD
Bahen-Tanenbaum Professor, Department of Civil Engineering
Director of University of Toronto Transportation Centre
University of Toronto
35 St George Street
Toronto, Ontario M4S 1A4, Canada
Phone: 416 978 4076
Fax: 416 978 5054
miller@ecf.utoronto.ca

Kay W. Axhausen, PhD
Professor, Institute for Transport Planning and Systems
Swiss Federal Institute of Technology
CH-8093 Zurich, Switzerland
Phone: +41-44-633 3943 / +41-44-658 2792
Fax: +41-44-633 1057
axhausen@ivt.baug.ethz.ch

Word Count: 5511 + 2500 (3 Figures + 7 Tables = 10 x 250) = 8011

Draft Submission Date: July 27, 2007

Submitted at the 87th Annual Meeting of Transportation Research Board, January 13-17, 2008, Washington D. C. on the topic *Understanding Activity-Travel Pattern in Time and Space* Sponsored by the Committee: ADB10, **Travel Behaviour and Values**

ABSTRACT

This paper investigates the potential of using a 'typical week' time frame in activity-based travel demand modeling. This paper concentrates on a specific activity/trip: shopping, using a 6-week travel diary survey, MobiDrive. Each week of the MobiDrive survey is considered as a random week and models are compared. Weekly shopping trips are modeled using a multivariate ordered probability modeling approach. Each model has two major components: a deterministic and a stochastic component. The deterministic component accommodates various variables and the stochastic component captures the inter-day correlations within the random week. The estimated parameters of the deterministic component reveal different behavioural patterns and the independent nature of the individual days within a week. On the other hand the inter-day correlation patterns of the random weeks reveal that a typical week does represent a minimum cycle of shopping activity behaviour.

INTRODUCTION

Rhythms of activity-travel behaviour have received considerable attention in the literature. [*1, 2, 3, 4, 5, 6, 7*] All of these investigations based on multi-day survey data reveal that a typical day modeling time frame simply cannot capture the dynamics of activity-travel behaviour. All operational activity-based travel demand models, however, consider a typical day for modeling time frame. [*8, 9, 10, 11*] Schönfelder and Axhausen argue that human psychology; dynamics of transportation system performance and the existence of social networks cause the rhythm or the cycle of participation rates of different activities over different prolonged periods of time. [*13*] Within different rhythms (spatial and temporal), temporal rhythms of different activity-travel behaviour are investigated by different authors. [*12, 13, 14, 15, 16*] Strong weekly rhythms, [*3*], strong within-week dependency, [*15, 16*] and similarities of the weekly patterns, [*3, 17*], are demonstrated in the literature. These findings argue strongly for a multi-day time frame for activity-based travel demand modeling. However, moving towards a multi-day modeling time frame poses both data as well as computational challenges.

Multiday modeling obviously requires multiday survey data. Given that multiday survey data are available; the question is what should be the appropriate modeling time frame? Previous studies report that different activities may have different temporal rhythms for different urban settings. However, investigation is required to identify the appropriate time frame for modeling activity-based travel demand. In terms of operational activity-based travel demand models, it is important to identify whether a specific multiday time frame is sufficient to capture the rhythm of activity-travel behaviour or not. Taking previous studies on temporal rhythms of activity-travel behaviour as its starting point, this paper examines the same issue from a different angle. It concentrates on a specific activity/trip: shopping; and it contributes to this issue by identifying an appropriate time frame for practical activity-based travel demand forecasting models. This is the first of two papers by the authors using the same data source. Following the findings of this paper the companion paper concentrates on the activity-agenda level within the same specific time frame.

The paper is organized as follows: the next section discusses modeling shopping activity/trip in general, followed by the sections discussing general methodological framework, mathematical formulations and computational issues, description of data and interpretations of the estimated models. The paper concludes with a summary of the key findings.

MODELING SHOPPING ACTIVITY/TRAVEL

Shopping activity/travel is different from other activity/trip types. [*18*] Bhat *et al* investigate the rhythm of shopping activity over a multiweek time period by modeling the duration between successive shopping events of individuals. [*12*] They identify two distinct types of shopping behavior: erratic shopping behavior and regular shopping behavior. Their findings indicate that the rhythm of shopping behaviour for all types of shoppers is clearly a multiday phenomenon. Schönfelder and Axhausen also investigate the cyclic temporal structure of shopping behavior. [*13*] They investigate whether the increase in demand for shopping over time always follow the same rhythm or not. Their conclusion also indicates that the temporal rhythm of shopping activity/trip varies over a multiple-day time scale.

In all of these studies the main objective is to identify the temporal rhythm of shopping behavior. Application of hazard-based inter-activity duration modeling in these studies makes it clear that a typical week has the potential to be the modeling time frame for activity-based travel demand model. To further investigate this issue, this paper uses a different and an indirect modeling approach to identify the potential of a typical week as representative modeling time frame. The idea is to consider each week as a random week and model the whole weekly shopping pattern jointly. Comparison of the models of a number of random weeks will demonstrate the potential of a typical week modeling approach for activity-based travel demand modeling. The next section describes the methodological framework of this investigation in greater detail.

GENERAL METHODOLOGICAL FRAMEWORK

In order to be a reasonable unit of model time frame in an operational activity-based travel demand model, a typical week should prove that

- Individual days have distinctive features within the week (i.e., a 'typical' is not sufficient to capture shopping behavior).
- The days within the week are highly correlated.
- Individual weeks can be considered as random weeks.

In order to investigate the above-mentioned criteria, we need a modeling framework that can model shopping trip-making decisions jointly for the entire week. We consider the complete week as the model time frame, but individual days within the week are a separate component in the model. Shopping activity/trip-making behavior can be modeled as the number of times the person goes shopping on particular days of the week. Successive participation in shopping activity within a day can be modelled as count, [*19*, *20*], or as ordinal variable, [*18*], model. However, shopping frequency within a specific time (day) is cumulative in nature rather than an isolated count variable. Hence, an ordinal variable approach is more attractive in this application because it accommodates the concept of a latent threshold in the participation in successive shopping activities. Also the ordered assumption implicitly recognizes the sequential correlation of successive participations within a day. Consider the shopping frequency within a day as an ordinal variable; the next challenge is how to correlate individual days within the weekly model time frame.

Figure 1 describes the modeling framework of this investigation. The week is composed of the days Monday to Saturday (elimination of Sunday from the framework is dictated by the dataset used and is discussed further in the data section). Within any specific day, the shopping activity/trip behaviour is explained by a set of probabilities: probability of no shopping trip, probability of 1 shopping trip, probability of 2 shopping trips and so on. Individual days are again correlated with each other within the weekly time frame. The whole week is modeled jointly, where each individual day's probabilities are modeled as well as inter-day correlations. This modeling framework considers each week under investigation as a random week. If the typical random week represents the cycle of shopping activity/trips behaviour, the days within the week must be highly correlated. As the correlations are induced across the days, to be representative of a cycle time, the days within the week should be positively correlated (Markovian process) with gradually reducing correlation value for the first day to the last day of the week. Also, as the individual days within the week are modeled explicitly, the modeling framework will also reveal the individual characteristics of the days within the week. The next section presents the mathematical structure of the modeling framework and also the estimation process.

MATHEMATICAL FORMULATION AND COMPUTATIONAL ISSUES

The modeling framework as described in the previous section uses the ordered response modeling technique as proposed by McKelvey and Zavonia (1975) and further extended by Bhat and Srinivasan (2005). [*21*, *22*] The mathematical structure of the modeling framework presented in this section is applicable for each individual of the sample data set for investigation. Hence, in the formulation the person specific indications (i) are omitted. In the ordered response model the propensity of shopping activity/trip is specified by a latent variable U for each day. This latent variable is further specified as a function of a set of observed variables (X) with their corresponding parameters (β) and an unobserved random element ε. Observation of a specific propensity (0 or 1 or 2 or more) of shopping activity/trip by the individual in a specific day of the week depends on crossing the corresponding latent threshold bounds of U. The latent threshold bounds as described in the following equation system explain the ordinal behavioural process of shopping activity/trip-making probability. Each equation of this system of equation represents the specific days of the week.

$$
\begin{aligned}
&U^{¿}_{Day\,1}=(\beta X)_{Day\,1}+\varepsilon_{Day\,1}, \quad U^{¿}_{Day\,1}=L_{Day\,1} \quad if \quad \delta U^{1}_{DayL_{1}-1}<U^{¿}_{Day\,1}<\delta U^{1}_{DayL_{1}} \\
&U^{¿}_{Day\,2}=(\beta X)_{Day\,2}+\varepsilon_{Day\,2}, \quad U^{¿}_{Day\,2}=L_{Day\,2} \quad if \quad \delta U^{2}_{DayL_{2}-1}<U^{¿}_{Day\,2}<\delta U^{2}_{DayL_{2}} \\
&U^{¿}_{Day\,3}=(\beta X)_{Day\,3}+\varepsilon_{Day\,3}, \quad U^{¿}_{Day\,3}=L_{Day\,3} \quad if \quad \delta U^{3}_{DayL_{3}-1}<U^{¿}_{Day\,3}<\delta U^{3}_{DayL_{3}} \\
&U^{¿}_{Day\,4}=(\beta X)_{Day\,4}+\varepsilon_{Day\,4}, \quad U^{¿}_{Day\,4}=L_{Day\,4} \quad if \quad \delta U^{4}_{DayL_{4}-1}<U^{¿}_{Day\,4}<\delta U^{4}_{DayL_{4}} \\
&U^{¿}_{Day\,5}=(\beta X)_{Day\,5}+\varepsilon_{Day\,5}, \quad U^{¿}_{Day\,5}=L_{Day\,5} \quad if \quad \delta U^{5}_{DayL_{5}-1}<U^{¿}_{Day\,5}<\delta U^{5}_{DayL_{5}} \\
&U^{¿}_{Day\,6}=(\beta X)_{Day\,6}+\varepsilon_{Day\,6}, \quad U^{¿}_{Day\,6}=L_{Day\,6} \quad if \quad \delta U^{6}_{DayL_{6}-1}<U^{¿}_{Day\,6}<\delta U^{6}_{DayL_{6}}
\end{aligned}
$$

(1)

In this equation system, individual days are independent of each other. To comply with the conceptual modeling framework as explained in Figure 1, the individual day-specific ordinal response models are to be modified to accommodate inter-day correlations. One way to address the correlations is to further split the day specific error terms (ε) into two parts: ε' and ξ. The ε'*s* (ε_{day1}', ε_{day2}', ε_{day3}', ε_{day4}', ε_{day5}', ε_{day6}') are assumed to be standard logistic distribution independent of one another days as well as identically and independently distributed across individuals. Whereas the ξ s (ξ_{day1} , ξ_{day2} , ξ_{day3}, ξ_{day4}, ξ_{day5}, ξ_{day6}) are assumed to be jointly multivariate normal distributed with a mean vector of 0 and covariance matrix Σ. This is the general approach of error correlation. [*23*, *24*] The covariance structure of the error correlation is symmetric and can be written as:

$$
\sum ¿ \begin{bmatrix}
D_{11} & & & & & \\
D_{21} & D_{22} & & & & \\
D_{31} & D_{32} & D_{33} & & & \\
D_{41} & D_{42} & D_{43} & D_{44} & & \\
D_{51} & D_{52} & D_{53} & D_{54} & D_{55} & \\
D_{61} & D_{62} & D_{63} & D_{64} & D_{65} & D_{66}
\end{bmatrix}
$$

(2)

The signs and values of the off-diagonal elements of this matrix represent the nature and extent of inter-day correlations within the modeled week. In case of the diagonal elements of this matrix: as individual days are not mutually exclusive within the week, individual elements of the diagonal are not identifiable. In order to overcome this identification problem the diagonal elements must be fixed and in this case we fix them to unity.

$$\sum \text{¿} \begin{bmatrix} 1 & & & & & \\ D_{21} & 1 & & & & \\ D_{31} & D_{32} & 1 & & & \\ D_{41} & D_{42} & D_{43} & 1 & & \\ D_{51} & D_{52} & D_{53} & D_{54} & 1 & \\ D_{61} & D_{62} & D_{63} & D_{64} & D_{65} & 1 \end{bmatrix} \quad (3)$$

The added advantage in this case is that the estimated covariance matrix will represent the covariance matrix of the days within the week. [*22*] However, such enforcement is not straight-forward. In order to better explain this issue let us write down the general probability equation of the ordinal logit formulation for a specific day:

$$\Pr(\text{Frequency} = \text{N}) = F\left(L - (\beta X + \xi)\right) - F\left((L-1) - (\beta X + \xi)\right) \quad (4)$$

Here L represents the latent threshold and $F(\,.\,)$ represents the cumulative probability of Logistic distribution. It is clear that the likelihood function of this joint model no longer remains in closed form because of the multivariate error term (ξ) and hence Maximum Simulated Likelihood (MSL) or Bayesian Estimation are the options for parameter estimation. Considering MSL method of estimating the model parameters, we have to ensure the positive-definiteness of the correlation matrix. To ensure the positive-definiteness, we have to parameterize the multivariate error component (ξ) in terms of the elements of the Cholesky decomposed matrix of Σ ($\Sigma = TT'$ Here T is the lower triangular matrix, the Cholesky Factor). [Please see *23*]

$$T=\begin{pmatrix} S_{11} & 0 & 0 & 0 & 0 & 0 \\ S_{21} & S_{22} & 0 & 0 & 0 & 0 \\ S_{31} & S_{32} & S_{33} & 0 & 0 & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} & 0 & 0 \\ S_{51} & S_{52} & S_{53} & S_{54} & S_{55} & 0 \\ S_{61} & S_{62} & S_{63} & S_{64} & S_{65} & S_{66} \end{pmatrix}$$

Where

$$D_{11}=\sqrt{S_{11}^2}$$
$$D_{22}=\sqrt{S_{21}^2+S_{22}^2}$$
$$D_{33}=\sqrt{S_{31}^2+S_{32}^2+S_{33}^2}$$
$$D_{44}=\sqrt{S_{41}^2+S_{42}^2+S_{43}^2+S_{44}^2}$$
$$D_{55}=\sqrt{S_{51}^2+S_{52}^2+S_{53}^2+S_{54}^2+S_{55}^2}$$
$$D_{66}=\sqrt{S_{61}^2+S_{62}^2+S_{63}^2+S_{64}^2+S_{65}^2+S_{66}^2}$$

(5)

So in order to impose the restriction on the diagonal element of Σ we have to restrict the Cholesky factors of the Σ. In the estimation process we actually estimate the elements of the Cholesky factor (T) and then can calculate Σ. Bhat and Srinivasan (2005) propose a method of restricting the elements of the Cholesky factor and use unconstrained pseudo likelihood estimation technique. [Please see *22*]

Imposing restrictions on the Cholesky factors as proposed by Bhat and Srinivasan (2005) makes the likelihood function highly non-linear. In such cases researchers have to set a number of elements of the covariance matrix to fixed values arbitrarily to facilitate the estimation process (see Table 3 of Bhat and Srinivasan, 2005). [*22*] In this study we are interested in estimating the full variance-covariance matrix and not interested in fixing any off-diagonal element to zero arbitrarily. Estimating the full variance covariance matrix using the unconstrained likelihood estimation technique is almost impossible in this case. Hence, this study uses the Constrained Maximum Likelihood (CML) estimation technique to restrict the diagonals of Σ (corresponding Cholesky factor) to unity. The likelihood function of the joint weekly model thus becomes as:

$$Max(L) = \int_{\xi_{D1}} \int_{\xi_{D2}} \int_{\xi_{D3}} \int_{\xi_{D4}} \int_{\xi_{D5}} \int_{\xi_{D6}} \left(\prod_{i=1}^{No\ of\ Individual} \left(\prod_{D=Monday}^{Saturday} \left((\Pr_0)^{d0} ¿ (\Pr_1)^{d1} ¿ (\Pr_{2+})^{d2} \right) \right) \right) d\xi_{D1}\ d\xi_{D2}\ d\xi_{D3}\ d\xi_{D4}\ d$$

$$d0 = 1\ ,\ if\ \ 0\ Shopping\ Trip;\quad 0\ Otherwise$$
$$d1 = 1\ ,\ if\ \ 1\ Shopping\ Trip;\quad 0\ Otherwise$$
$$d2 = 1\ ,\ if\ \ 2+\ Shopping\ Trips;\ 0\ Otherwise$$

$$Subject\ To:$$
$$(S_{11})^2 = 1$$
$$(S_{21})^2 + (S_{22})^2 = 1$$
$$(S_{31})^2 + (S_{32})^2 + (S_{33})^2 = 1$$
$$(S_{41})^2 + (S_{42})^2 + (S_{43})^2 + (S_{44})^2 = 1$$
$$(S_{51})^2 + (S_{52})^2 + (S_{53})^2 + (S_{54})^2 + (S_{55})^2 = 1$$
$$(S_{61})^2 + (S_{62})^2 + (S_{63})^2 + (S_{64})^2 + (S_{65})^2 + (S_{66})^2 = 1$$

The MSL technique can be applied within CML estimation. The Quasi-Monte Carlo (QMC) method using Halton sequences is used in this analysis. Details of the Halton sequence and its generation procedure are available in Bhat (2001). [*25*]

CML uses the Sequential Quadratic Programming (SQP) Method where the parameters are updated in a series of iterations beginning with a provided starting value. [*26*, *27*] CML is becoming increasingly unavoidable in econometric modeling. [*28*] The advantage of CML in our case that it not only can impose restrictions in the parameters but also the SQP is highly efficient in handling nonlinear likelihood functions. [*28*]

DATA

The data source for the analyses of this paper is MobiDrive, which is a six-week travel dairy survey archived at the Institute of Transport Planning and Transport Systems (IVT), ETH Zürich. [*1*, *2*, *3*, *29*, *30*] The MobiDrive data set was collected in Karlsruhe and Halle, Germany in the spring and fall of 1999 with the aim of understanding the rhythms of daily life. This is one of the most recent data sources that have a span of 6 weeks. A total of 160 households participated in the survey. 360 individuals who were over 6 years old in the sampled households filled the weekly survey form to write down all trip information of the weeks. The survey began with a 40 to 60 minute face-to-face interview to explain the weekly diary form to the participants. The survey form was designed following the well-known 'KONTIV' format to provide sufficient space to the respondents to report weekly travel information. [*29*] Respondents returned the forms every week by post-paid envelop. The filled forms were checked thoroughly and phoned back to the respondents in case of any query or question about the completed forms.

The participation rate in the survey was very high with only 1 or 2 households dropping out. The paper-based travel diary survey instrument was supplemented by further survey elements to cover the socio-demographic characteristics of the households, household's auto ownership, household members' transit usage as well as many other attributes.

Investigation of shopping activity/trip behaviour within a weekly modeling time frame of this paper is based on the data sample generated from MobiDrive. After cleaning the sample data set for some missing values a total of 333 individuals were selected for the investigation. In 1999, Sunday shopping was still very restricted in Germany except in a few locations, (mainly the occasional bakery in the morning, gas station or train station) in the cities. As a result, the survey data does not report any significant shopping activity on Sunday. This is the reason Sunday is excluded from the weekly shopping model in this paper.

Complying with the objective of this investigation each week of the MobiDrive survey is considered as a random week. Investigation is done on each week individually and all 6 weeks pooled together. To ensure the treatment of the weeks as random week, any legal holidays during the survey weeks that caused the stores to be closed are not considered explicitly in the models. The idea is that such random incidents in the week will be reflected in the stochastic part of the weekly shopping models, as is discussed in the following sections.

INTERPRETATIONS OF THE EMPIRICAL MODELS

Seven models are reported in this paper. Tables 1 to 6 report the six models corresponding to the six random weeks and Table 7 reports the model for 6 weeks pooled together (total 333 times 6 observations). Each table reports the parameter values and corresponding standard error of the covariates of the joint model as well as the Cholesky factors of inter-day covariance. The Variance-Covariance (which is same as the correlation matrix) is calculated from the Cholesky factor. In the case of CML estimation, it is customary to report the standard error rather than the usual t-statistics. In such case, simply dividing the parameter estimates by their standard errors to calculate t-statistics is incorrect because they do not account for boundaries placed on the distributions of the parameters by the constraints. [*27*] A Rho-square value for each model that indicates its goodness-of-fit is also reported in the tables. Rho-square values are calculated with respect to the null model.

Performances of the Models in Fitting Observed Data: We can judge performances of the models in fitting observed by the goodness-of-fit values. Rho-square values of the models are very high, ranging from 0.44 to 0.48 with the highest value being for the 5th week of the survey. The pooled data model has a goodness-of-fit that is the average of all 6 weeks. High values of goodness-of-fit of the models support the appropriateness of the modeling technique used in this paper. At the same time, the low variation of the goodness-of-fit measured across the 6 random weeks supports the notion of a typical week model time frame. As mentioned in the data section, the models do not consider any specific events or incidents, which occurred during the survey period that influenced the shopping activities of the respondents; rather each week is considered as a random week. The models presented in this paper are capable of capturing the randomness in the week; again supporting the notion that a typical week model time frame can adequately capture the temporal rhythm of shopping activity/trip, if appropriate modeling techniques are used.

Threshold Parameters: Threshold parameter of such multidirectional mixed ordered logit model represents the demarcation points on the continuous latent propensity scale that identifies observed discrete values of shopping trip making (0, 1, 2, and 2+). [*22*] Although it is difficult to interpret the individual threshold parameters behaviourally, they express the baseline distribution of shopping trip making behaviour nonparametrically. Figure 2 plots the probability distributions of different shopping trip making propensities for each individual random week based on the threshold values only (all covariates are considered to be zero). It is clear that the models catch the trend of shopping behaviour in the survey area: Friday is the shopping day that has the highest probability of making 1 or more shopping trips and the middle of the week has lowest probability of having any shopping trips. The baseline trend of shopping trip making probability is the same for all random weeks except for some minor variations. This is another indication in favor of the typical week modeling time frame.

Activity-Specific Variables: Different activity-specific variables are considered in this investigation, e.g. duration of the activity, travel time to reach the shopping location, number of people involved in the activities etc. However only duration and travel time variables are retained in the model based on lower values of the standard errors for other variables. The duration and travel time variables used in the model are the observed day-specific average values of that individual. As the purpose of this investigation is to understand the behavioral process, the activity specific variables represent the observed average values of the corresponding day. The reason for using average value is the formulation process of ordered probability model. In ordered probability models the covariates remain the same across the latent propensities (no shopping trip, 1 shopping trip, 2 or more shopping trips). So, it is unavoidable to use the average values for the day to use the variable in the day specific component of the model. [*31*] However the marginal effect of the same variable is different for different orders (as per equation 4).

In all estimated models both duration and travel time variables have a positive sign (except for the Friday of Week 6) and as per the model formulation, a positive parameter sign means a negative effect on the propensity and vise versa. The positive parameter sign complies with the intuition that if shopping activity takes longer duration the probability of lower daily frequency is higher compared to the probability of higher daily frequency. At the same time if the shopping trips take longer travel time to reach the shopping location, it also reduces the probability of higher number of shopping trips. The exception of a negative parameter sign of the duration variable for Fridays of Week

6 is probably due to the unreliable information for that week or due to any special events occurring during the survey time period for that week. The last week of a 6-week long survey may cause some fatigue effects among the respondents that can induce unreliable information.

In terms of the values of the parameters of the duration variable, it is clear that different days have different values. Also not all days have a duration variable. This complies with the argument that individual days are different within a weekly cycle time. [*32*] On the other hand, the coefficients of travel time variable show less variability across the days within the week. Considering total trip time as the summation of travel time to get the location and the activity episode duration, it seems that the day-to-day dynamics of shopping trip time is reflected mainly in the episode duration component. This has implications for the activity-travel generation and scheduling models.

Household-Specific Variables: Three main household-specific variables entered into the models, these are: number of household members (household size), number of household vehicles and annual household income in '000 Euros. It is interesting to note that it was found to be difficult to include household-specific variables in the models. The variables household size and household income did not show consistent effects for shopping trip-making behaviour across the random weeks. However, according to the pooled data model, higher income people are less likely to go for shopping on Thursday; given that Friday is the main shopping day in the survey area. On the other hand, household automobile ownership always have a negative sign that means they have positive effect on shopping trip frequency, which is intuitive.

Person-Specific Variables: Among the number of person-specific variables, age, gender and employment status entered into each model. Age is categorized into a number of categories (below 30, 30-40, 41-50, 51-55, 56-60, 61-65, 65+) based on the age distribution of the participants and the ease of including specific categories in the model. However, only three categories of age entered into the models (below 30, 30-40 and above 55). It is interesting to note that age, although a categorical variable, always has a negative sign, and thereby a positive effect on shopping frequency, with a decreasing rate with increasing age.

That is, younger people are more likely to make a higher number of shopping trips than older people, which is intuitive. The gender specific dummy variable shows that males are more likely to make higher shopping trips on Monday, Wednesday and Friday compared to females. A dummy variable representing full time employment status enters into the model for Fridays only, with a positive sign. This means that people with full time employment are less likely to make a higher number of shopping trips on Friday compared to people with other types of employment status.

Location-Specific Variables: Location-specific effects are captured by simple city-specific dummy variables. The MobiDrive survey was conducted in two German Cities: Karlsruhe and Halle. Dummy variable representing Karlsruhe entered into the models. However, except for Tuesday, no city-specific variations are captured by the models. Moreover, the values of the standard error relative to the parameter value increase from the first week to the last week. This indicates that the deterministic city-specific effect on the citizens' shopping behaviour is not very strong in the survey sample used in this study.

Inter-Day Correlations: The previous subsections described the deterministic parts of the models. The stochastic part of the model is mainly designed to capture the inter-day correlation of each random week. The variance-covariance matrices presented in each table from Table 1 to Table 6 represent the inter-day correlations of the random weeks. Moreover to compare the nature of the assumed random weeks the correlations tables are plotted as color contours and presented in Figure 3. It is very clear that the days are highly and positively correlated, with the correlation values ranging from 0.85 to 0.99. This finding indicates that a week does represent a cycle or rhythm of shopping trip-making behaviour. Figure 3 also makes it clear that the general patterns of inter-day correlations across the random week are the same. This supports the notion of a random week as the time frame for activity-based travel demand modeling. However, the color patterns of the random weeks show some variations as well. Such variations are due to the randomness of the individual weeks. As mentioned in the data section, there were some special events during some survey weeks, but those were not explicitly addressed in the model to keep the randomness of the individual weeks. The inter-day correlations capture the randomness. However, the general pattern of inter-day correlation is reflected by the pattern of the 6 week pooled data model. It is clear that within a random week the days are correlated with a decreasing rate from the starting day of the week to the last day of the week.

CONCLUSIONS

This paper concentrates on a specific activity/trip type: shopping. Investigation is conducted considering each MobiDrive week as a random week and no specific special events or occurrences during any specific survey week are considered explicitly. The idea is to model each random week jointly with explicit day-specific component within the week. The random week assumption is assured by formulating a multivariate ordered response model for each week. Each model has two major components: a deterministic component and a random component. The deterministic component accommodates different covariates and the random component captures the randomness of the survey week and induces inter-day correlations.

A total of seven models are estimated: one for each random week and one for all six weeks pooled together. The estimated models are compared both quantitatively and through graphical representation of different elements. In terms of fitting the observed data the models demonstrate that the modeling approach used in this paper sufficiently captures the observed behaviour (high Rho-square value). Also the low variation of the goodness-of-fit value across the random weeks supports the notion that a typical week modeling time frame captures the rhythm of shopping activity/trip behaviour to a considerable extent. This is further supported by the low variations in baseline probability distribution for different shopping frequencies across the survey weeks.

The covariates parameters of the estimated models refer to the individual days within a random week and have separate features. The stochastic parts of the models capture the inter-day correlations within the random weeks. The estimated inter-day correlation patterns of the random weeks suggest that days within the random week are highly and positively correlated. The positive correlation has a decreasing rate from the first day to the last day of the week. This finding implies that a typical week represents a cycle of shopping trip-making behavior. The implication of this finding for practical modeling of activity-based travel demand is that in case of a weeklong travel demand model, a dynamic modeling approach should be considered. Under a dynamic framework of activity-travel demand the modeling time frame should be at least a week. For such a weeklong modeling time frame the history dependence should be considered for more than one previous day, rather the whole week length should be under consideration.

However, this paper uses a single activity type to understand the rhythm of activity-travel behavior. As discussed before it is found difficult to accommodate many household and person specific variables in the model. Although the models presented in this paper are robust enough to capture the randomness of activity-travel behavior to a great extent, this investigation focused on a specific activity type. So, based on the findings of this paper, a companion paper investigates all out-of-home activities together under a weeklong time budget constraint to further investigate the issue of modeling time frame. [*33*]

ACKNOWLEDGEMENTS

This research was supported by a Transport Canada TPMI grant, as well as financial contributions by the Neptis Foundation, EJLB Foundation, McLean Foundation, Salamander Foundation, and the Greater Toronto Airports Authority.

REFERENCES

1. Axhausen, K.W., A. Zimmermann, S. Schönfelder, G. Rindsfüser, and T. Haupt. Observing the rhythms of daily life. *Transportation*: 29, pp. 95-124, 2002.

2. Schlich, R., and K.W. Axhausen. Habitual travel behaviour. *Transportation* 30, pp. 13-36, 2003

3. Schönfelder, S. *Urban Rhythms: Modelling the Rhythms of Individual Travel behaviour*. PhD thesis, Institute of Transport Planning and Systems, Swiss Federal Institute of Technology, Zurich, 2006

4. Hanson, S., and J.O. Huff. Assessing day-to-day variability in complex travel patterns. *Transportation Research Record:* Journal of the Transportation Research Board , TRB, National Research Council, Washington D.C. 1982, Vol. 891, pp. 18-24

5. Pass, E.I. Interpersonal variability and model goodness-of-fit. *Transportation Research Part A* 21(6), pp. 431-438, 1987

6. Pass, E.I., and S. Sundar. Intra-personal variability in daily urban travel behaviour: some additional evidence. *Transportation* 22, pp. 135-150, 1995

7. Pass, E.I. Weekly activity travel behaviour. *Transportation* 15, pp. 89-109, 1998

8. Arentze, T., and H. Timmermans. *ALBATROSS Version 2.0 A Learning Based Transportation Oriented Simulated System*, EIRSS, 2005

9. Bhat, C.R., J.Y. Guo., S. Srinivasan, and A. Sivakumar. A Comprehensive Econometric Micro-simulator for Daily Activity Travel Pattern (CEMDAP). Paper presented at the *83rd Annual Meeting of Transportation Research Board*, Washington, D.C., 2004

10. Pendyala, R., R. Kitamura, A. Kikuchi, T. Yamamato, and S. Fujii. FAMOS: The Florida Activity Mobility Simulator. Paper presented at *the 83rd Annual Meeting of Transportation Research Board*, Washington, D.C., 2004

11. Miller, E.J., and M.J. Roorda. Prototype model of household activity/travel scheduling (TASHA). In *Transportation Research Record*: Journal of the Transportation Research Board, TRB, National Research Council, Washington D.C., 2003, Vol. 1831, pp. 114-121

12. Bhat, C.R., T. Frusti, H. Zhao, S. Schönfelder, and K.W. Axhausen. Intershopping duration: an analysis using multiweek data. *Transportation Research Part B* 38, pp. 39-60, 2004

13. Schönfelder, S. and K.W. Axhausen. Analysing the rhythms of travel using survival analysis. Paper presented at the *80th Annual Meeting of Transportation Research Board*, Washington, D.C., January 2001

14. Cirillo, C., and K.W. Axhausen. Dynamic model of activity type choice and scheduling. Paper presented at the *European Transport Conference*, October 2006

15. Cirillo, C. and K.W. Axhausen. Comparing urban activity travel behaviour. Paper presented at *the 81st Annual Meeting of Transportation Research Board*, Washington, D.C., January 2002

16. Simma, A., and K.W. Axhausen. Successive days, related travel behaviour. *Arbeitsberichte Verkehrs- und Raumplanung, 62, Institut für Verkehrsplanung, Transporttechnik, Strassen- und Eisenbahnbau*, ETH Zürich, Zürich, 2001.

17. Schlich, R. Measurement issues in identifying in variability in travel behaviour. Paper presented at *1st Swiss Transport Research Conference*, Monte Verità. March 2001

18. Habib, K.M.N., and E.J. Miller. Modelling individuals' frequency and time allocation behaviour for shopping activities considering household level random effects. In *Transportation Research Record*: Journal of the Transportation Research Board, TRB, National Research Council, Washington D.C., 2006, Vol. 1985 pp. 78-87

19. Kasturirangan, K., R.M. Pendyala, and F.S. Koppelman. History dependence in daily activity participation and time allocation for commuters. *Transportation Research Record*: Journal of the Transportation Research Board, TRB, National Research Council, Washington D.C., 2003, Vol. 1807, Paper no. 02-3591

20. Ma, J., and K.G. Goulias. Application of Poisson regression models to activity frequency analysis and prediction. *Transportation Research Record*: Journal of the Transportation Research Board, TRB, National Research Council, Washington D.C., 1999, Vol. 1676, pp. 86-94

21. McKelvey, R.D., and W. Zavonia. A statistical model for analysis of ordinal-level dependent variables. *Journal of Mathematical Sociology* 4, pp. 103-120, 1975

22. Bhat, C.R., and S. Srinivasan. A multidimensional mixed ordered response model for analyzing weekend activity participation. *Transportation Research Part B* 39(3), pp. 255-278, 2005

23. Train, K.E. *Discrete Choice Analysis with Simulation*. Cambridge University Press, Cambridge, 2002

24. Walker, J. *Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables*. PhD Thesis, Department of Civil Engineering, MIT, 2001

25. Bhat, C.R. Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transportation Research Part B* 35, pp. 677-693, 2001

26. GAUSS 7.0. Aptech Systems Inc, 2007

27. CML2.0 Manual. Aptech Systems Inc, 2007

28. Wen, C-H., and F.S. Koppelman. The generalized nested logit model. *Transportation Research Part B* 35 (2001) 627-641

29. PTV AG, B. Fell, S. Schönfelder und K.W. Axhausen. Mobi*drive* questionaires, *Arbeitsberichte Verkehrs- und Raumplanung*, **52**, Institut für Verkehrsplanung, Transporttechnik, Strassen- und Eisenbahnbau, ETH Zürich, Zürich, 2000

30. Chalasani, V.S., S. Schönfelder, K.W. Axhausen. Archiving travel data: The MobiDrive example. *Arbeitsbericht Verkehrs- und Raumplanung*, **129**, Institut für Verkehrsplanung und Transportsysteme (IVT), ETH Zürich, Zürich. 2002

31. Ronning, G., and M. Kukuk. Efficient estimation of ordered probit model. *Journal of American Statistical Association* 91(435), pp. 1120-1129

32. Habib, K.M.N., and E.J. Miller. 2006. Modelling daily activity program generation considering within-day and day-to-day dynamics. Paper presented at the *86th Annual Meeting of Transportation Research Board*, Washington, D.C., January 2006

33. Habib, K.M.N, E.J. Miller, and K.W. Axhausen. Weekly rhythm in joint time expenditure to all at-home and out-of-home activities: Application of Kuhn-Tucker demand system model using a multi-week travel diary data. Paper submitted for presentation at the *87th Annual Meeting of Transportation Research Board*, Washington D.C., January 2008

LIST OF FIGURES AND TABLES

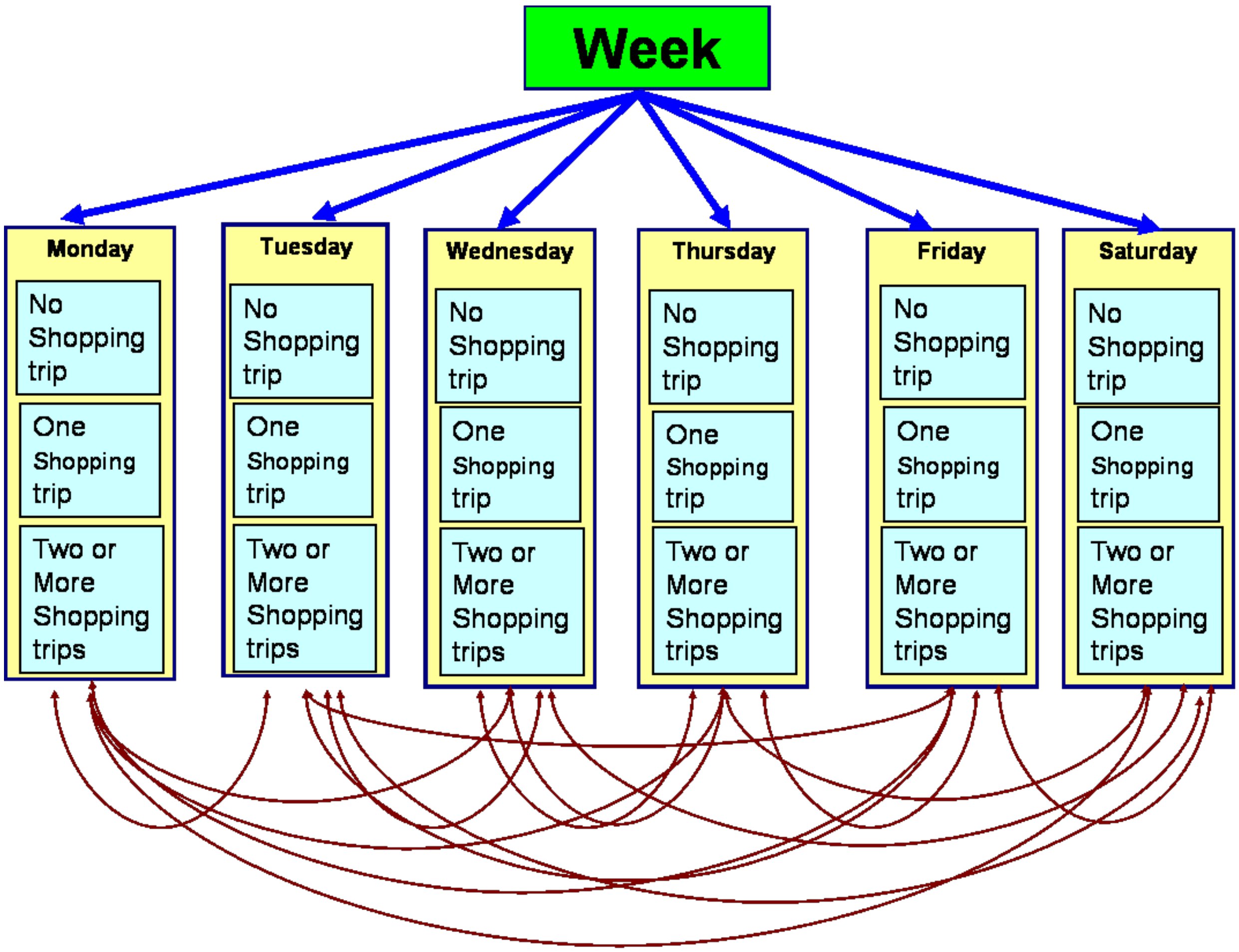

Figure 1: Modeling Framework for Weekly Shopping Activity/Trip

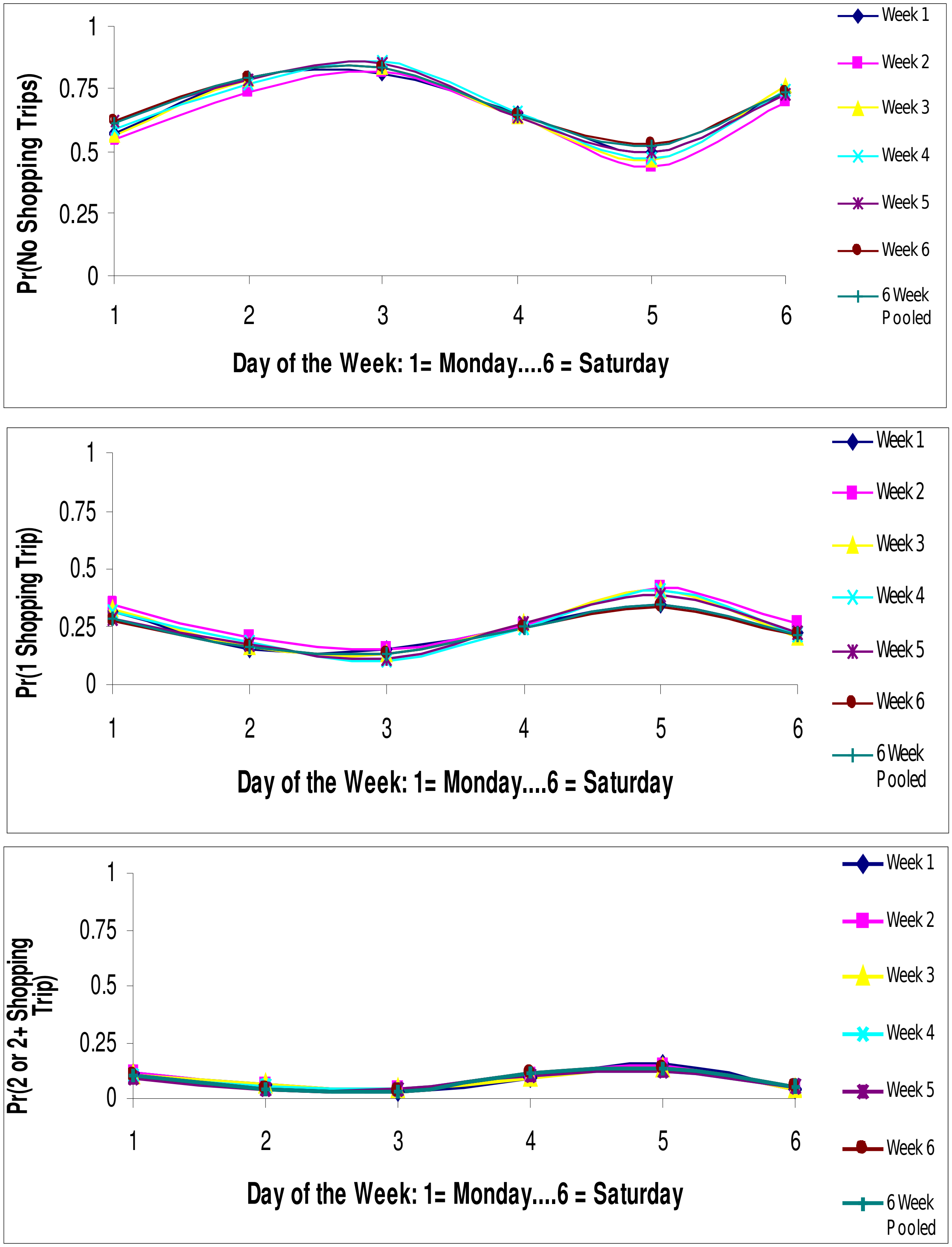

Figure 2: Baseline Probability Distributions

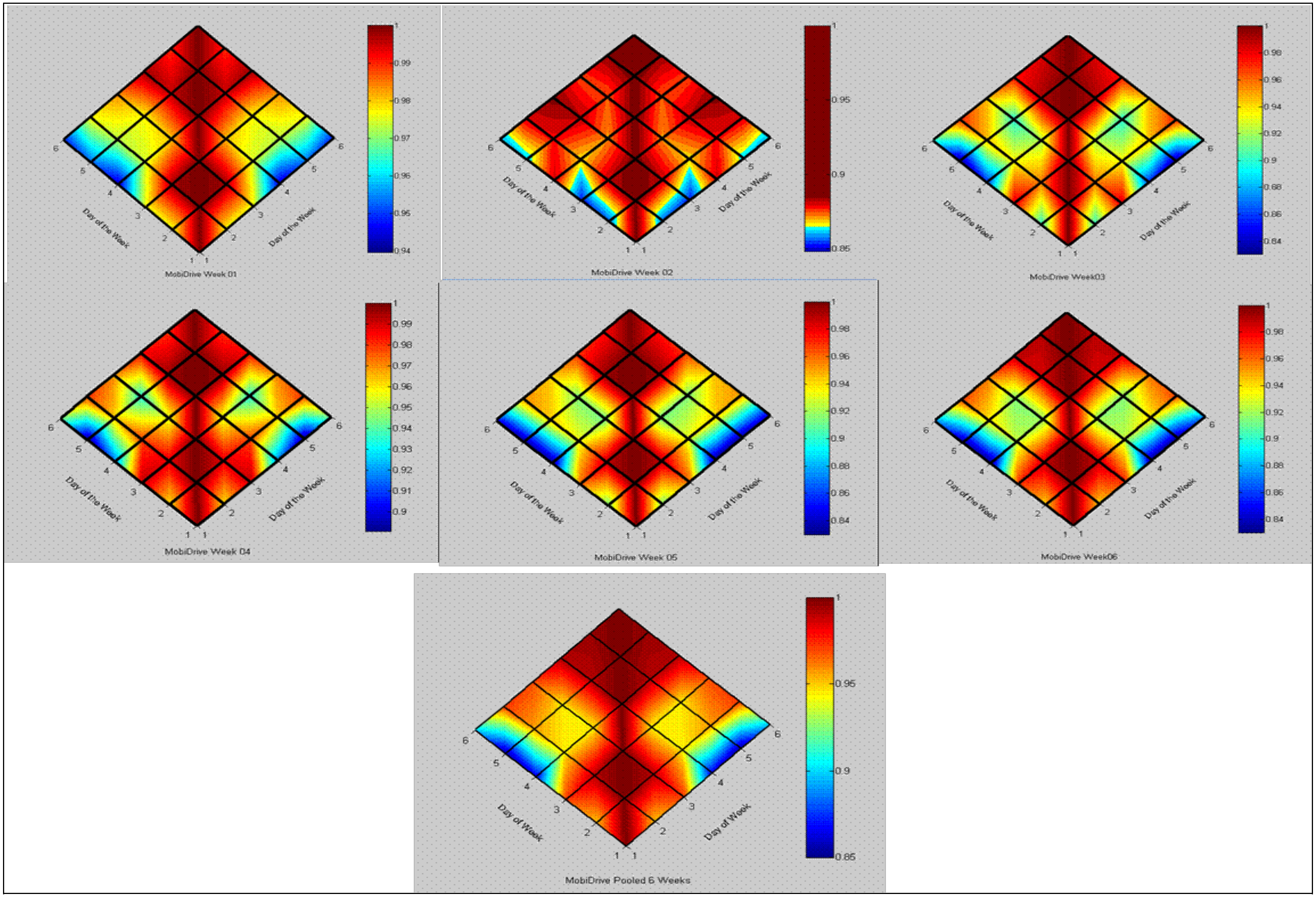
Day of the Week
MobiDrive Week 01
MobiDrive Week 02
MobiDrive Week03
MobiDrive Week 04
MobiDrive Week 05
MobiDrive Week06
Day of Week
MobiDrive Pooled 6 Weeks

Figure 3: Graphical Representation of Inter-Day Correlations within the Weeks

Table 1: Model for Week 1 of MobiDrive

WEEK 01:	**Monday**		**Tuesday**		**Wednesday**		**Thursday**		**Friday**		**Satureday**	
	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err
Threshold_1	0.2668	0.4335	1.3366	0.4157	1.4628	0.2591	0.6231	0.5219	-0.022	0.5027	1.0149	0.2244
Threshold_2	2.0672	0.4512	2.7693	0.4442	3.3077	0.3203	2.3069	0.5489	1.6801	0.5148	3.0691	0.3073
Average Duration_hr	0.0116	0.0374	0.0563	0.0579	0.1553	0.0705	---	---	0.0754	0.0438	---	---
Average TravelTime_Min	0.1592	0.0166	0.1958	0.0233	0.173	0.0182	0.2216	0.0235	0.1201	0.0171	0.2504	0.0243
No. of HH Members	---	---	---	---	---	---	-0.0778	0.1685	---	---	---	---
No. of HH Vehicles	---	---	-0.0897	0.0858	---	---	-0.0593	0.0993	---	---	---	---
HH Income_000	-0.1092	0.075	---	---	---	---	-0.042	0.09	-0.121	0.08	---	---
Age: < 30	-0.9076	0.348	-1.0134	0.384	---	---	-0.632	0.367	-1.026	0.357	-0.72	0.3406
Age: 30-40	---	---	---	---	---	---	---	---	---	---	-0.317	0.411
Age: >55	-0.5032	0.363	-0.4582	0.409	---	---	-0.867	0.417	-0.506	0.372	---	---
Gender: Male_Dummy	-0.582	0.286	---	---	-0.39	0.3	---	---	-0.308	0.299	---	---
Full Time Employee	---	---	---	---	---	---	---	---	0.185	0.45	---	---
City: KarlShurehe	---	---	0.6036	0.331	---	---	---	---	---	---	---	---
LogLikehood at Convergence:						**-1290**						
LogLikehood of Null Model:						**-2195**						
Rho-Square:						**0.412**						

	Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err
S11	1	--	---			---			---			---			---		
S21	0.9751	0.0427	**S22**	-0.2217	0.188	---			---			---			---		
S31	0.9742	0.0616	**S32**	-0.2143	0.267	**S33**	-0.071	0.265	---			---			---		
S41	0.9396	0.109	**S42**	-0.2542	0.227	**S43**	-0.131	0.264	**S44**	-0.188	0.251	---			---		
S51	0.9496	0.1531	**S52**	-0.2024	0.189	**S53**	-0.093	0.325	**S54**	-0.21	0	**S55**	0.0661	0.378	---		
S61	0.9436	0.1165	**S62**	-0.2466	0.126	**S63**	-0.139	0.381	**S64**	-0.162	0	**S65**	-0.058	0	**S66**	-0.003	0.3441

Variance-Covariance Matrix = LL'

1.00	0.98	0.97	0.94	0.95	0.94
0.98	1.00	1.00	0.97	0.97	0.97
0.97	1.00	1.00	0.98	0.98	0.98
0.94	0.97	0.98	1.00	1.00	1.00
0.95	0.97	0.98	1.00	1.00	0.99
0.94	0.97	0.98	1.00	0.99	1.00

Table 2: Model for Week 2 of MobiDrive

WEEK 02:	Monday		Tuesday		Wednesday		Thursday		Friday		Satureday	
	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err
Threshold_1	0.1745	0.449	1.0338	0.4166	1.4787	0.2712	0.5623	0.551	-0.259	0.45	0.8178	0.259
Threshold_2	2.0526	0.471	2.8351	0.4722	3.294	0.3404	2.1374	0.57	1.8025	0.473	3.0773	0.327
Average Duration_hr	0.1772	0.089	0.0877	0.0486	0.037	0.092	---	---	0.0649	0.062	---	---
Average TravelTime_Min	0.1915	0.02	0.2785	0.0289	0.1854	0.0222	0.1903	0.023	0.1699	0.019	0.2096	0.022
No. of HH Members	---	---	---	---	---	---	0.2995	0.173	---	---	---	---
No. of HH Vehicles	---	---	-0.2167	0.0921	---	---	-0.15	0.101	---	---	---	---
HH Income_000	-0.22	0.079	---	---	---	---	-0.223	0.099	-0.183	0.073	---	---
Age: < 30	-0.523	0.354	-1.1233	0.4009	---	---	-1.056	0.399	-0.826	0.35	-1.0879	0.339
Age: 30-40	---	---	---	---	---	---	---	---	---	---	-0.5616	0.4
Age: >55	-0.6194	0.391	-0.7689	0.4354	---	---	-0.882	0.428	-0.547	0.353	---	---
Gender: Male_Dummy	-0.5456	0.296	---	---	-0.712	0.3204	---	---	-0.511	0.293	---	---
Full Time Employee	---	---	---	---	---	---	---	---	0.6134	0.431	---	---
City: KarlShurehe	---	---	0.5503	0.3529	---	---	---	---	---	---	---	---
LogLikehood at Convergence:						**-1201**						
LogLikehood of Null Model:						**-2195**						
Rho-Square:						**0.4529**						

	Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err
S11	1	--	---			---			---			---			---		
S21	0.865	0.2909	**S22**	-0.5017	0.5016	---			---			---			---		
S31	0.8484	0.1694	**S32**	-0.4881	0.2773	**S33**	-0.205	0.4066	---			---			---		
S41	0.9721	0.1454	**S42**	-0.1508	0.3295	**S43**	-0.171	0.5319	**S44**	0.0547	0.726	---			---		
S51	0.8898	0.1461	**S52**	-0.3873	0.2908	**S53**	-0.1768	0.4059	**S54**	-0.161	0.434	**S55**	0.034	0.3536	---		
S61	0.8787	0	**S62**	-0.4224	0.1643	**S63**	-0.2092	0.3177	**S64**	-0.058	0.675	**S65**	-0.049	0.2259	**S66**	-0.0062	0

Variance-Covariance Matrix = LL'

1.00	0.87	0.85	0.97	0.89	0.88
0.87	1.00	0.98	0.92	0.96	0.97
0.85	0.98	1.00	0.93	0.98	0.99
0.97	0.92	0.93	1.00	0.94	0.95
0.89	0.96	0.98	0.94	1.00	0.99
0.88	0.97	0.99	0.95	0.99	1.00

Table 3: Model for Week 3 of MobiDrive

WEEK 03:	Monday		Tuesday		Wednesday		Thursday		Friday		Satureday	
	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err
Threshold_1	0.2592	0.4338	1.2777	0.4187	1.5947	0.2638	0.5678	0.5029	-0.162	0.5017	1.1478	0.2878
Threshold_2	2.1536	0.451	2.7925	0.4505	3.1669	0.3298	2.271	0.5472	1.8658	0.5268	3.1702	0.3384
Average Duration_hr	0.0739	0.0364	-0.049	0.0588	0.7018	0.4004	---	---	0.843	0.3625	---	---
Average TravelTime_Min	0.2136	0.0213	0.1796	0.0193	0.223	0.0327	0.2129	0.02	0.1426	0.0247	0.2482	0.0239
No. of HH Members	---	---	---	---	---	---	-0.071	0.1769	---	---	---	---
No. of HH Vehicles	---	---	-0.042	0.0856	---	---	-0.165	0.1046	---	---	---	---
HH Income_000	-0.1236	0.0762	---	---	---	---	0.0248	0.09	-0.172	0.0824	---	---
Age: < 30	-1.0413	0.3516	-0.997	0.3688	---	---	-0.588	0.3682	-1.028	0.3524	-0.758	0.3383
Age: 30-40	---	---	---	---	---	---	---	---	---	---	-0.625	0.4263
Age: >55	-0.5345	0.3824	-0.469	0.3862	---	---	-0.862	0.4115	-0.535	0.3727	---	---
Gender: Male_Dummy	-0.6858	0.2953	---	---	-0.485	0.3119	---	---	-0.399	0.2952	---	---
Full Time Employee	---	---	---	---	---	---	---	---	0.2286	0.4629	---	---
City: KarlShurehe	---	---	0.4898	0.3261	---	---	---	---	---	---	---	---
LogLikehood at Convergence:						**-1214**						
LogLikehood of Null Model:						**-2195**						
Rho-Square:						**0.447**						

	Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err
S11	1	--	---			---			---			---			---		
S21	0.9707	0	**S22**	-0.24	0	---			---			---			---		
S31	0.9951	0.0261	**S32**	-0.089	0	**S33**	-0.044	0	---			---			---		
S41	0.9578	0.0886	**S42**	-0.213	0	**S43**	-0.113	0	**S44**	-0.156	0.405	---			---		
S51	0.9488	0.1073	**S52**	-0.263	0.193	**S53**	-0.064	0	**S54**	-0.164	0.3349	**S55**	-0.008	0.3872	---		
S61	0.9702	0.1156	**S62**	-0.209	0.3359	**S63**	0.0001	0	**S64**	-0.12	0.415	**S65**	-0.022	0.334	**S66**	-0.0198	0.394

Variance-Covariance Matrix = LL'

1.00	0.97	1.00	0.96	0.95	0.97
0.97	1.00	0.99	0.98	0.98	0.99
1.00	0.99	1.00	0.98	0.97	0.98
0.96	0.98	0.98	1.00	1.00	0.99
0.95	0.98	0.97	1.00	1.00	1.00
0.97	0.99	0.98	0.99	1.00	1.00

Table 4: Model for Week 4 of MobiDrive

WEEK 04:	Monday		Tuesday		Wednesday		Thursday		Friday		Satureday	
	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err
Threshold_1	0.347	0.4583	1.2171	0.4162	1.787	0.2698	0.6316	0.495	-0.1174	0.4603	1.0616	0
Threshold_2	2.2125	0.4979	2.9925	0.4587	3.2162	0.3323	2.1668	0.524	1.9947	0.5038	2.9978	0.2434
Average Duration_hr	0.0985	0.0738	0.0982	0.0365	0.1571	0.0788	---	---	0.0923	0.048	---	---
Average TravelTime_Min	0.2443	0.0262	0.2403	0.0286	0.2535	0.0284	0.1689	0.022	0.2272	0.0246	0.1654	0.0192
No. of HH Members	---	---	---	---	---	---	0.0286	0.17	---	---	---	---
No. of HH Vehicles	---	---	-0.102	0.0846	---	---	-0.1453	0.096	---	---	---	---
HH Income_000	-0.135	0.0813	---	---	---	---	0.0227	0.083	-0.1955	0.0768	---	---
Age: < 30	-0.98	0.3784	-0.801	0.3833	---	---	-0.7263	0.358	-1.0938	0.3703	-0.7006	0.3406
Age: 30-40	---	---	---	---	---	---	---	---	---	---	-0.4459	0.4191
Age: >55	-0.698	0.3965	-0.496	0.4149	---	---	-0.5993	0.405	-0.4689	0.3822	---	---
Gender: Male_Dummy	-0.736	0.3132	---	---	-0.616	0.3466	---	---	-0.4945	0.3061	---	---
Full Time Employee	---	---	---	---	---	---	---	---	0.1675	0.4701	---	---
City: KarlShurehe	---	---	0.3596	0.3228	---	---	---	---	---	---	---	---
LogLikehood at Convergence:						**-1156**						
LogLikehood of Null Model:						**-2195**						
Rho-Square:						**0.473**						

	Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err
S11	1	--	---			---			---			---			---		
S21	0.961	0.0816	**S22**	-0.277	0.2834	---			---			---			---		
S31	0.9921	0.0288	**S32**	-0.125	0.2312	**S33**	-0.0133	0.2627	---			---			---		
S41	0.9174	0.1078	**S42**	-0.351	0.1793	**S43**	-0.1568	0.2874	**S44**	-0.1048	0.2609	---			---		
S51	0.8903	0.1298	**S52**	-0.391	0.1731	**S53**	-0.1563	0.2827	**S54**	-0.1742	0.1642	**S55**	0.0084	0.2205	---		
S61	0.9433	0.0922	**S62**	-0.268	0	**S63**	-0.0726	0	**S64**	-0.142	0	**S65**	-0.089	0	**S66**	0.0695	0

Variance-Covariance Matrix = LL'

1.00	0.96	0.99	0.92	0.89	0.94
0.96	1.00	0.99	0.98	0.96	0.98
0.99	0.99	1.00	0.96	0.93	0.97
0.92	0.98	0.96	1.00	1.00	0.99
0.89	0.96	0.93	1.00	1.00	0.98
0.94	0.98	0.97	0.99	0.98	1.00

Table 5: Model for Week 5 of MobiDrive

WEEK 05:	Monday		Tuesday		Wednesday		Thursday		Friday		Satureday	
	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err
Threshold_1	0.487	0.508	1.274	0.4314	1.722	0.252	0.5552	0.51	-0.026	0.494	0.963	0.252
Threshold_2	2.254	0.549	3.125	0.4807	3.283	0.326	2.2083	0.54	1.9797	0.533	2.831	0.286
Average Duration_hr	0.118	0.048	0.093	0.0706	0.106	0.066	---	---	0.0258	0.06	---	---
Average TravelTime_Min	0.298	0.03	0.303	0.0296	0.231	0.024	0.1873	0.021	0.2005	0.022	0.178	0.019
No. of HH Members	---	---	---	---	---	---	0.045	0.172	---	---	---	---
No. of HH Vehicles	---	---	-0.161	0.0949	---	---	-0.1321	0.101	---	---	---	---
HH Income_000	-0.222	0.097	---	---	---	---	-0.0885	0.093	-0.135	0.079	---	---
Age: < 30	-1.025	0.416	-0.831	0.4102	---	---	-0.6922	0.374	-1.088	0.358	-0.62	0.323
Age: 30-40	---	---	---	---	---	---	---	---	---	---	-0.46	0.409
Age: >55	-0.655	0.424	-0.554	0.4264	---	---	-0.5964	0.412	-0.399	0.376	---	---
Gender: Male_Dummy	-0.684	0.338	---	---	-0.44	0.327	---	---	-0.528	0.307	---	---
Full Time Employee	---	---	---	---	---	---	---	---	0.2507	0.482	---	---
City: KarlShurehe	---	---	0.218	0.3532	---	---	---	---	---	---	---	---
LogLikehood at Convergence:						**-1142**						
LogLikehood of Null Model:						**-2195**						
Rho-Square:						**0.48**						

	Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err
S11	1	--	---			---			---			---			---		
S21	0.9437	0.065	**S22**	-0.331	0.1839	---			---			---			---		
S31	0.9736	0.046	**S32**	-0.223	0	**S33**	-0.048	0	---			---			---		
S41	0.86	0.216	**S42**	-0.437	0.1378	**S43**	-0.177	0	**S44**	-0.195	0.366	---			---		
S51	0.8547	0.156	**S52**	-0.475	0.1279	**S53**	-0.137	0	**S54**	-0.153	0.301	**S55**	-0.04	0.3312	---		
S61	0.8968	0.164	**S62**	-0.374	0.2564	**S63**	-0.151	0	**S64**	-0.094	0.467	**S65**	-0.12	0.43	**S66**	0.0984	0.4753

Variance-Covariance Matrix = LL'

1.00	0.94	0.97	0.86	0.85	0.90
0.94	1.00	0.99	0.96	0.96	0.97
0.97	0.99	1.00	0.94	0.94	0.96
0.86	0.96	0.94	1.00	1.00	0.98
0.85	0.96	0.94	1.00	1.00	0.98
0.90	0.97	0.96	0.98	0.98	1.00

Table 6: Model for Week 6 of MobiDrive

WEEK 06:	Monday		Tuesday		Wednesday		Thursday		Friday		Satureday	
	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err
Threshold_1	0.494	0.455	1.3411	0.435	1.599	0.249	0.6108	0.478	0.117	0.474	1.0369	0.2443
Threshold_2	2.144	0.48	3.1287	0.47	3.452	0.328	2.0742	0.509	1.88	0.502	3.0231	0.3065
Average Duration_hr	0.092	0.076	0.0915	0.076	0.017	0.048	---	---	-0.149	0.143	---	---
Average TravelTime_Min	0.207	0.025	0.287	0.033	0.246	0.026	0.1047	0.016	0.152	0.021	0.2243	0.0228
No. of HH Members	---	---	---	---	---	---	0.0719	0.166	---	---	---	---
No. of HH Vehicles	---	---	-0.064	0.091	---	---	-0.193	0.108	---	---	---	---
HH Income_000	-0.141	0.079	---	---	---	---	0.0338	0.084	-0.144	0.082	---	---
Age: < 30	-0.981	0.389	-0.843	0.404	---	---	-0.655	0.369	-1.044	0.38	-0.747	0.3457
Age: 30-40	---	---	---	---	---	---	---	---	---	---	-0.443	0.3872
Age: >55	-0.631	0.401	-0.591	0.438	---	---	-0.448	0.395	-0.296	0.371	---	---
Gender: Male_Dummy	-0.626	0.313	---	---	-0.456	0.309	---	---	-0.486	0.313	---	---
Full Time Employee	---	---	---	---	---	---	---	---	0.138	0.476	---	---
City: KarlShurehe	---	---	0.0783	0.336	---	---	---	---	---	---	---	---
LogLikehood at Convergence:						**-1212**						
LogLikehood of Null Model:						**-2195**						
Rho-Square:						**0.45**						

	Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err
S11	1	--	---			---			---			---			---		
S21	0.9531	0.092	**S22**	-0.303	0.289	---			---			---			---		
S31	0.9751	0.057	**S32**	-0.2	0.197	**S33**	-0.096	0.1586	---			---			---		
S41	0.8488	0.172	**S42**	-0.426	0.175	**S43**	-0.201	0.1133	**S44**	-0.24	0.363	---			---		
S51	0.8341	0.202	**S52**	-0.512	0.307	**S53**	-0.141	0.3651	**S54**	-0.134	0.565	**S55**	-0.068	0.4987	---		
S61	0.8951	0.142	**S62**	-0.395	0.223	**S63**	-0.134	0	**S64**	-0.145	0.402	**S65**	-0.058	0.3676	**S66**	0.0252	0.3129

Variance-Covariance Matrix = LL'

1.00	0.95	0.98	0.85	0.83	0.90
0.95	1.00	0.99	0.94	0.95	0.97
0.98	0.99	1.00	0.93	0.93	0.96
0.85	0.94	0.93	1.00	0.99	0.99
0.83	0.95	0.93	0.99	1.00	0.99
0.90	0.97	0.96	0.99	0.99	1.00

Table 7: Model for 6 Weeks of MobiDrive Pooled Together

6 WEEK Pooled:	Monday		Tuesday		Wednesday		Thursday		Friday		Satureday	
	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err	Param	Sd Err
Threshold_1	0.4647	0.184	1.36	0.1734	1.643	0.1114	0.5917	0.2098	0.087	0.1869	1.027	0.1133
Threshold_2	2.169	0.1936	3.12	0.1901	3.435	0.1401	2.104	0.2201	1.919	0.1991	3.029	0.1373
Average Duration_hr	0.0734	0.0207	0.077	0.0218	0.087	0.0285	---	---	0.054	0.0229	---	---
Average TravelTime_Min	0.2071	0.0088	0.246	0.0109	0.223	0.0098	0.1684	0.0083	0.157	0.008	0.211	0.009
No. of HH Members	---	---	---	---	---	---	0.0626	0.0691	---	---	---	---
No. of HH Vehicles	---	---	-0.047	0.036	---	---	-0.154	0.0411	---	---	---	---
HH Income_000	-0.13	0.0323	---	---	---	---	-0.047	0.0362	-0.125	0.0309	---	---
Age: < 30	-0.961	0.1495	-0.842	0.1586	---	---	-0.651	0.1513	-1.022	0.1465	-0.749	0.1385
Age: 30-40	---	---	---	---	---	---	---	---	---	---	-0.417	0.1646
Age: >55	-0.628	0.1584	-0.567	0.1716	---	---	-0.429	0.1629	-0.287	0.1471	---	---
Gender: Male_Dummy	-0.609	0.1237	---	---	-0.458	0.1294	---	---	-0.471	0.1226	---	---
Full Time Employee	---	---	---	---	---	---	---	---	0.117	0.1876	---	---
City: KarlShurehe	---	---	0.099	0.1344	---	---	---	---	---	---	---	---
LogLikehood at Convergence:						**-1225**						
LogLikehood of Null Model:						**-2195**						
Rho-Square:						**0.442**						

	Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err		Param	Sd Err
S11	1	--	---			---			---			---			---		
S21	0.9516	0.0433	**S22**	-0.307	0.1341	---			---			---			---		
S31	0.9708	0.0258	**S32**	-0.219	0.1139	**S33**	-0.098	0.1724	---			---			---		
S41	0.8645	0.0726	**S42**	-0.399	0.1177	**S43**	-0.19	0.1688	**S44**	-0.241	0.1517	---			---		
S51	0.8526	0.0677	**S52**	-0.474	0.108	**S53**	-0.147	0.1789	**S54**	-0.155	0.1515	**S55**	-0.0562	0.1496	---		
S61	0.8973	0.074	**S62**	-0.385	0.1324	**S63**	-0.138	0.2066	**S64**	-0.152	0.1827	**S65**	-0.061	0.1772	**S66**	0.02	0.1798

Variance-Covariance Matrix = LL'

1.00	0.95	0.97	0.86	0.85	0.90
0.95	1.00	0.99	0.95	0.96	0.97
0.97	0.99	1.00	0.95	0.95	0.97
0.86	0.95	0.95	1.00	0.99	0.99
0.85	0.96	0.95	0.99	1.00	0.99
0.90	0.97	0.97	0.99	0.99	1.00