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Weekly Rhythm in Joint Time Expenditure for All At-Home and Out-of-Home Activities

Application of Kuhn–Tucker Demand System Model Using Multiweek Travel Diary Data

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This paper uses the Kuhn–Tucker demand system modeling technique to investigate the capacity of a typical week in capturing rhythms in activity-travel behavior. It considers all possible activity types within a weeklong modeling time frame. Complex interactions in time expenditure between at-home and out-of-home activities and among different out-of-home activities are captured by introducing behavioral elements in the model in terms of baseline preference, time translation, and satiation effects. The Kuhn–Tucker demand system model used in this paper is a random utility maximization model with the inherent assumption that every individual maximizes total utility in allocating time to the activities under consideration within the modeling time frame. Models are developed for each individual week of a 6-week travel diary drawn from the MobiDrive data set for Karlsruhe and Halle, Germany. Each model contains 83 variables and reveals behavioral details of complex activity-travel behavior. Based on the performances of the models in terms of fitting observed data and parameter values of specific variables, it is clear that a modeling time frame for a typical week is capable of capturing the rhythms of activity-travel behavior sufficiently. The paper concludes with the recommendation that the availability of activity diary data for a multiweek time period would further enhance understanding on this issue.

Availability of multiweek travel diary survey data makes it possible to investigate temporal rhythms of activity-travel behavior over a prolonged period of time (*1–3*). Identifying temporal rhythms of different activity-travel behavior is crucial to conceptualize a modeling framework for activity-based travel demand. Activity-travel behavior is a complex phenomenon, especially in the case of defining an appropriate modeling time frame for activity-based travel demand modeling (*4*). Researchers often concentrate on specific activity types separately to identify temporal rhythms that have specific policy implications and to help understand specific behavioral processes (*5–7*). Although individual activity types may have individual temporal rhythms, the overall activity generation and scheduling processes that create travel demand are not just collections of isolated univariate activities. From an activity-based travel demand modeling point of view, investigation of all possible activity participation behavior combined within a specific time frame is of importance. Ongoing debate on the appropriate time frame for activity-based travel demand modeling warrants detailed investigation of joint time expenditure or activity participation behavior. Investigation into joint activity-travel decisions within a specific time frame would reveal the overall rhythm of activity-travel behavior that results from different types of trade-offs, including both at-home and out-of-home activities and trade-offs among different out-of-home activities.

This paper concentrates on joint activity-travel decisions within a specific time frame: a typical week. The objective is to investigate the weekly rhythm of joint activity-travel decisions using a multiweek travel diary survey, MobiDrive. A utility-based econometric modeling framework is used to model a whole-week activity-travel pattern that clearly identifies two distinct behavioral trade-off processes: the trade-off between at-home and out-of-home activity time expenditures, and trade-offs among different out-of-home activity time expenditures. Models are developed for each of the 6 weeks of the MobiDrive survey data, and results are compared to identify how successfully a typical week modeling time frame can capture rhythms of all activity-travel behavior.

The paper is organized as follows: the following section discusses modeling time expenditure within a specific time period (time budget constraints) in general. It is followed by a discussion of the utility-based modeling framework, a description of mathematical formulations, descriptions of data and variables considered in the models, and interpretations of the estimated models. The paper concludes with a summary of the key findings.

JOINT TIME EXPENDITURE MODELING WITHIN A SPECIFIC TIME PERIOD

Causal processes as well as dynamics of travel demand are deeply rooted in our trade-offs between earnings and consumption of resources and commodities. Other than material- or service-type resources or commodities, time plays the most critical role in earning and consumption processes (*8–12*). For short-term travel demand modeling, time is the continuous quantity with which researchers mainly deal, considering income and consumption of goods and services as other influential factors. Although for medium- to long-term mobility decisions the budget (representing income and expen-

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diture) is also critical, for short-term travel demand researchers mainly deal with time as the key constraint on behavior (*8*). In addition, scarcity of information concerning detailed day-to-day financial expenditure restricts researchers to focusing on time constraints in the modeling of activity-travel behavior.

It is important to recognize that time expenditures on different activities are interrelated. The interrelationships among time expenditures and different alternative activities are tied to the limitation of time resources and the competition among different activities that need to be performed within a short period of time (*13*). Time limitations in daily life create rhythms in daily activity behavior that consequently drive the dynamics of our travel demand (*14*).

The investigation of time expenditure behavior under specific time-budget constraints requires an appropriate econometric modeling framework. Simple statistical data analysis does not always reveal the behavioral processes. It is necessary to model the behavioral processes to investigate the critical interrelationships in time expenditure between different alternative activities. The first step in the investigation is to recognize two broad categories of activities: at-home and out-of-home. Although in travel demand modeling investigators are mainly interested in out-of-home activities, it is very important to recognize that the dynamics of out-of-home time expenditure are mainly influenced by the total time left to spend at home. Trade-offs in time allocation between at-home and out-of-home activities are crucial in modeling rhythms of activity-travel behavior (*15*). Given the overall trade-offs between at-home and out-of-home activities, an appropriate modeling technique is also necessary to address the competitions among different out-of-home activities. A utility-based modeling framework for modeling time expenditure on different activities under time budget constraints is an attractive approach in this regard. With the increasing complexities of our daily life and the changing dynamics of transportation system behavior, application of a utility-based modeling approach in travel demand modeling seems to be almost unavoidable (*13*). The next section concentrates on the utility-based demand system modeling approach for time expenditure.

UTILITY-BASED MODELING FRAMEWORK

The definition of activity utility depends on the role of time in activity planning and scheduling. Following the explanations of Winston (*16*), Habib and Miller argue that specifications of activity utility should be different based on the stage-of-time allocation (*8*). In the case of planning for different activities within a limited time period, people actually allocate limited time among different activities, which is similar to the way they allocate resources (*8, 16*). When people start participating in or executing different activities, they basically spend time, which is similar to they way they consume any commodity. Thus, it can be assumed that in activity planning (i.e., activity generation) time plays the role of a resource, but in activity execution (i.e., activity scheduling) time plays the role of a commodity. In either stage, when allocating or expending time to alternative activities is dealt with, it becomes an optimization problem with the assumed time limitation (time budget). For such a mathematical optimization problem, several properties should be enforced:

- Time expenditure to specific activity cannot be negative.
- Individuals do not always participate in all types of activities within a given time period (i.e., the time expenditure allocated to any specific activity can be zero).
- Total time expenditures must sum up to the total time budget for the time period being modeled.

The Kuhn–Tucker demand system model is a mathematical optimization approach that can satisfy all three of these conditions. This model uses the optimality conditions proposed by Kuhn and Tucker to derive likelihood function to estimate model parameters (*17*). In mathematical optimization, the allocation of zero time to a given activity is called a corner solution. First proposed by Wales and Woodland in 1982, the Kuhn–Tucker model has been widely used in resource expenditure problems in economics (*18, 19*). In transportation, Bhat (*20, 21*) and also Habib and Miller (*8, 14*) have been the first to apply this technique with different distributional assumptions for activity-based travel demand analysis.

In activity-based travel demand modeling, the Kuhn–Tucker demand system framework allows us to investigate complex inter-activity trade-offs in time expenditure in a very tractable way. This framework ensures the time budget constraint by introducing the composite activity concept (*8*). Composite activity refers to the broad set of activities that, although not important to the researcher individually, must have the total time expended on them modeled so as to ensure that the total time budget constraint holds. This requirement is derived from the Hicksian composite-good concept (*22*). This investigation is not interested in at-home activities separately; nonetheless, the total time allocated to all at-home activities is important to ensuring that the multidimensional trade-offs in activity behavior among at-home and out-of-home activities and among different out-of-home activities is properly accounted for.

As mentioned before, the utility function definition should depend upon the stages-of-time allocation. At the activity planning stage, time is basically allocated to alternative activities, but at the scheduling stage, time is actually consumed or spent. Thus, the utility function defined for the activity scheduling stage should consider more about taste and satiation effects than that defined for the activity planning (generation) stage (*8*). Habib and Miller proposed a utility function specification for the activity planning (generation) stage in which the marginal utility in time allocation to specific activities is specified as logarithmic functions multiplied with a baseline utility component (*7*). This study uses a travel diary survey that collected only the revealed time expenditure information. Data from the travel diary survey reflect the final scheduled information of the individual participants. Thus, time expenditure study using this data requires utility function specification that reflects the satiation effects of time expenditure on different types of activities more precisely. Bhat proposed a specification based on a generalized version of translated continuous expenditure system utility function to accommodate details of marginal utility variations across the activity types (*20*). Thus, for the travel diary data used in this study, the Bhat specification is used in this paper. The specification is described in the next section in detail (*20*).

MATHEMATICAL FORMULATION

Equation 1 defines the total utility function for the weeklong time expenditure of an individual. The utility function is composed of a number of additively separable subutility functions for the out-of-home activities (specific activities) under consideration and the subutility function for the at-home time expenditure: the composite activity. Each specific activity subutility function is composed of a baseline utility component and an additional utility component. The baseline utility component models the baseline preference in involving a specific out-of-home activity with respect to the composite activity. The additional utility component of a specific out-of-home activity is specified so as to ensure the possibility of a corner solution in the mathematical optimization and the capturing of satiation effects in time expenditure behavior. Two specific parameters are used in the specific utility component. On the one hand, the φ parameter is mainly the translating parameter that ensures the potential for a corner solution, but it also reflects the satiation effect in time expenditure to the specific out-of-home activities with respect to the composite activity. On the other hand, the ρ parameter purely reflects the satiation effects in time expenditure. Considering the total modeling time frame (T) as a typical week, the total utility function stands as

$$U_{\text{total}} = \sum_{j=1}^{\substack{\text{no. of}\\ \text{specific}\\ \text{activities}}} \left(\frac{\varphi_j}{\rho}\right)\exp\left(\left(\beta_p X_p\right)_j + \epsilon_j\right)\left(\left(\frac{Y_j}{\psi_j}+1\right)^{\rho} - 1\right) + \frac{1}{\rho}\exp\left(\epsilon_z\right)\left(z\right)^{\rho}$$

subject to

$$\sum_j Y_j + z = T \qquad Y_j \geq 0 \tag{1}$$

where

ϵ = error term;
Y_j = total time spent on activity $j = d_j x_j$, where d_j is average duration and x_j is frequency;
z = composite activity time;
T = total time budget;
$\exp(\beta_p X_p + \epsilon)_j$ = baseline marginal utility of activity j;
$\varphi_j = \exp(\beta_a X_a)$ = translating satiation parameter for activity j, and it must be positive;
$\rho = 1 - \exp(-\beta_z X_z)$ = satiation parameter for composite activity z, and it must be less than 1;
X = variables; and
β = corresponding parameters.

To derive the likelihood function for estimating the structural parameters of the model, Kuhn–Tucker optimality conditions can be applied (*17*):

Kuhn–Tucker Optimality Conditions (Lemma 1)

$$\frac{\partial U}{\partial Y_j} - d_j\lambda \leq 0 \quad \text{and} \quad \frac{\partial U}{\partial z} - \lambda \geq 0 \tag{2}$$

where λ is the Lagrange multiplier.

With the above-mentioned condition, the utility function can be transformed to specify the deterministic utility component of specific and composite activities as follows:

Deterministic part (transformed) of the specific activity subutility:

$$V_j = \left(\beta_p X_p\right)_j + (\rho - 1)\ln\left(\varphi^{-1} Y_j + 1\right) - \ln\left(d_j\right)$$

Deterministic part (transformed) of the composite activity subutility:

$$V_z = (\rho - 1)\ln(z) \tag{3}$$

Now, with the "transformation of variable theorem" and the error term (ϵ) distributional assumption as the Type I extreme value distribution, the probability of spending positive amounts of time (Y) on a set of out-of-home activities can be derived as follows. [Readers can refer to Habib and Miller (*8*) and to Bhat (*20*) for details on the mathematical formulation of the derivations.]

$$p\left(Y_1, Y_2, Y_3, Y_4, \ldots, 0, 0, 0, Y_j\right) = \frac{1}{\sigma^{A-1}}\left(\prod_{j=1}^{A}\frac{1-\rho}{Y_j+\varphi_j}\right)\left(\sum_{j=1}^{A}\frac{d_j\left(Y_j+\varphi_j\right)}{1-\rho}\right)\left(\frac{\prod_{j=1}^{A}\exp\left(\frac{V_j}{\sigma}\right)}{\sum_{k=1}^{K}\exp\left(\frac{V_k}{\sigma}\right)}\right) \tag{4}$$

where

σ = scale parameter of Type I extreme value distribution, ϵ;
A = number of activities with nonzero frequency; and
K = number including all specific as well as composite activities.

This equation gives a closed form likelihood function and can be estimated using any conventional estimation technique. This paper used the Broyden–Fletcher–Goldfarb–Shanno gradient search algorithm to estimate the model parameters (*23*).

DATA

The data source for the analyses of this paper is the MobiDrive data, representing 6 weeks of travel diary data archived at the Institute of Transport Planning and Transportsysteme (IVT), ETH Zürich (*1–3, 24, 25*). This 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 the most recent data source with a span of 6 weeks. A total of 160 households participated in the survey. A total of 360 individuals over 6 years of age in the households completed the weekly survey form, which captured information concerning all trips made during the 6-week survey period. The survey began with a 40- to 60-min face-to-face interview to explain the weekly diary form to the participants. The survey form was designed in the well-known KONTIV (Continuous Survey on Travel Behavior) form to provide sufficient space to the respondents to report weekly travel information (*24*). Respondents returned the forms every week by post-paid envelop. The filled forms were checked thoroughly and the respondents were called if there were any queries or questions about the completed forms.

The participation rate in the survey was very high, with only one or two households dropping out. The paper-based travel diary survey instrument was supplemented by further survey elements to cover the sociodemographic characteristics of the households, the households' auto ownership, the household members' transit usage, and many other attributes.

After cleaning the sample data set for some missing values, a total of 333 individuals were selected for the investigation. All at-home activities were considered in general as a composite activity, and all out-of-home activities are broadly classified into eight types. The specific out-of-home activity types are as follows:

1. Basic need: walk or stroll, household obligation–type activities:
2. Work and school activities;
3. Pick up or drop off person;
4. Shopping (including window shopping);
5. Services: car care, refueling, gardening, house or cottage, private business;
6. Recreation and entertainment: active sports, excursion (nature);
7. Social: disco, pub, restaurant, cinema, excursion (culture), group or club meeting, meeting friends, meeting relatives or family; and
8. Others: all other out-of-home activities that do not fall into the above types.

For each individual in the sample data set, the total time ($24 \times 7 = 168$ h) was considered as the time budget for weekly time expenditure. The average duration of any activity type of any individual was considered to be the observed weekly average duration of that particular person.

The different components of the utility function were specified as functions of different variables. The following variables were considered, in general: person-specific variables, household-specific variables, location-specific variables, and activity-specific variables. For person-specific variables, age, gender, driving license possession, job status, student status, and so forth were considered. For household-specific variables, household size, household annual income, number of household automobiles, number of household children, and so forth were considered. For location-specific variables, location of households in the city [central business district (CBD), suburban location, etc.], distance of bus stop from home, city-specific dummy variables, and so forth were considered. For activity-specific variables, activity-specific dummies (constants), the number of people involved in the activity, and the travel ratio were considered.

The travel ratio variable was defined as the ratio of the summation of the activity episode duration and travel time to the activity episode location (*26*). It refers to the price of activity time expenditure in terms of travel time expenditure and, by definition, is greater than one. The longer the travel time required getting to an activity location, the higher the value of the travel ratio. The ratio thus also acts as an indicator of accessibility of the individuals to different activity locations. This variable brings information on transportation system performance inside the total utility function in a normalized way, making the models sensitive to transportation system performances.

In line with the objective of this paper, each week of the MobiDrive survey was considered as a random week. Investigation was done on each week individually and on all 6 weeks pooled together. Parameters were estimated and results compared. The next section discusses the estimated models in details.

INTERPRETATIONS OF THE EMPIRICAL MODELS

For eight types of out-of-home activities and a weeklong modeling time frame, the models became complex, with a large number of parameters. However, the large number of parameters also revealed considerable behavioral detail. A total of seven models were estimated: one for each week and one for all weeks pooled together. Recognizing the fact that there is a relatively small data set compared with the large number of parameters to be estimated, the standard for statistical significance of the parameters was considered to be a 90% confidence limit, for which the *t* statistics should be greater than or equal to 1.64 for a two-tailed test. However, variables with statistically insignificant parameters were also retained in the model when they provided insight into the behavioral process, under the assumption that if a larger data set were available, these parameters might show statistical significance. An adjusted likelihood ratio index (adjusted rho square) was computed to measure the goodness-of-fit values as follows:

$$\text{adjusted rho square} = 1 - \frac{\text{log likelihood of full model} - k}{\text{log likelihood of constant-only model}}$$

where k is the number of parameters in the full model over the constant-only model.

This value ranges from 0 to 1. A summary of all estimated models is presented in Figure 1. It is clear that the log likelihood values are almost the same for all random weeks. The goodness-of-fit measures are plotted, indicating that the variations across the weeks are very low. Although the models have not considered any special events that might have occurred during the survey time period, the overall performances of the individual weekly models are almost the same. This indicates that considering all possible activity types within a specific time period captures interactivity interactions. The utility-based modeling framework for all possible activity types presented in this paper captures more behavioral details than models for individual activities individually. Table 1 presents the estimated parameters of the models. The following subsections discuss the parameters in details.

Baseline Utility Component

The baseline utility component refers to the marginal utility at the point of no time expenditure. To ensure the positivity of utility, it is expressed as an exponential function. Baseline utility has two components: deterministic and random. The deterministic part is expressed as a linear-in-parameter function of different variables. The random component is assumed to have a Type I extreme value distribution that facilitates having a closed form likelihood function. As shown in Equation 4, it is possible to estimate the scale parameter of the random error component. However, in this case it was found that normalization of the scale parameter to 1 gives better specification in terms of a higher number of statistically significant parameters and higher goodness-of-fit values. The baseline utility functions of specific activities are estimated with respect to the composite activity. For the composite activity, all parameters of the deterministic part of baseline utility functions are assumed to be zero; hence, the baseline reference utility for all specific activities is $\exp(0) = 1$.

The deterministic component of baseline utility function for each out-of-home activity types is composed of a constant term and a number of socioeconomic variables. The final specifications of the models include a generic constant term for all specific activities. Constant terms of the random week vary from −12.8 to −18.8 with an average value of −14.8 (for the pooled data model). The exponential of these constants of the weekly models indicates that the baseline marginal utility for out-of-home activities with respect to at-home activities is very low and that the variation across the week is also very low (the exponential of the constant terms of the individual random weeks does not vary significantly).

	Full Model No. of Parameters	Null Model No. of Parameters	Full Model LogLikelihood	Null Model LogLikelihood	**Rho-Square**	**Adjusted Rho-Square**
Week 1	84	3	-5913.8802	-7860.1653	0.2476	0.2373
Week 2	84	3	-5920.827	-7859.511	0.2467	0.2364
Week 3	84	3	-6130.8576	-7950.096	0.2288	0.2186
Week 4	84	3	-5795.3306	-7531.6171	0.2305	0.2198
Week 5	84	3	-5781.8072	-7660.3902	0.2452	0.2347
Week 6	84	3	-5769.1137	-7650.1054	0.2459	0.2353
6 Weeks Pooled	84	3	-35668.465	-46531.7745	0.2335	0.2317

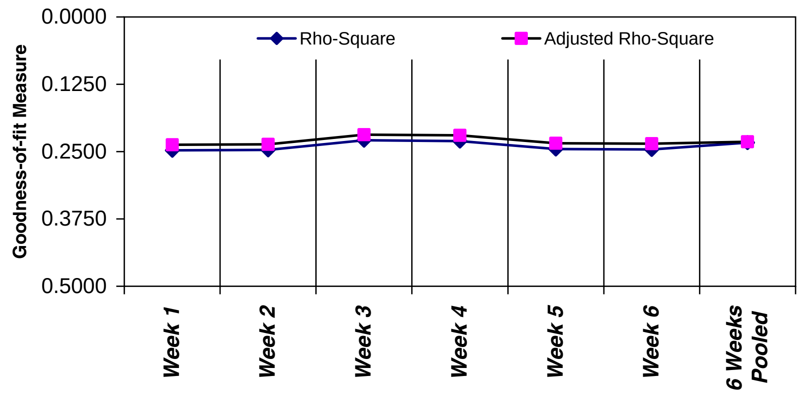

FIGURE 1 Summary of models.

Among other variables in the baseline utility function component, the city-specific dummy variable refers to the city of Karlsruhe with respect to the city of Halle. Individual out-of-home activity-specific components of the city-specific dummy variable reveal that people in Karlsruhe spend more time in out-of-home basic need–type activities compared with the people of Halle. For work and school activity, it was difficult to get statistically significant parameters except for the 5th week. According to the 5th week model, it seems that people in Halle spend more time on work and school activities than do the people of Karlsruhe. This finding is consistent with the findings of Jara-Díaz et al., who compared value-of-time variations across a number of cities for work activities (*27*). However, considerable variations in values and parameter signs are visible across the weeks. This is probably related to the fact that the study did not consider whether any specific event (e.g., a holiday) occurred during the survey time period that affected the work and school activities of the survey areas.

Gender-specific dummy variables capture the difference of males in spending time on out-of-home activity relative to females. For work and school activities, considerable variations are visible across the weeks; the only statistically significant value is for the 3rd week, in which it is indicated that males spend more time on work/school activities than do females. For shopping activities, statistically significant parameters are found in the 5th week and in the pooled data model only. It is clear that males are less wiling to spend time on shopping activities than are females. For services activities, statistically significant parameters are found in the 3rd week and in the pooled data model only, in which males were found to be more wiling to spend time on services or private business activities than were females. In case of social activity, males prefer spending more time than did females (statistical significance limit was achieved for the 3rd week, the 5th week, and the pooled data model). In the case of the other activities, females preferred spending more time on these activities than did males (statistical significance limit was achieved for the 1st week, the 2nd week, and the pooled data model).

Having a driving license was consistently found to result in spending more time on out-of-home activities across all weeks, with high t statistics. Having more than one automobile in the household did not seem to have a significant influence on household members' activity-travel behavior, except for the 1st week, in which higher numbers of household automobiles resulted in more time spent out of home. Employed household members spent more time in out-of-home activities than in at-home activities consistently across the weeks. However, being a parent resulted in spending less time on out-of-home activities relative to at-home activities, which is intuitive. Having transit service in the neighborhood also affected the activity-travel behavior; it is clear that longer the distance from home to the nearest transit stop, the lower the possibility of spending more time in out-of-home activities. People who live in the CBD have lower utility gain in spending time in out-of-home activities compared with people living outside the CBD, and this effect was consistent across the random weeks.

An individual's employment status influenced his or her time expenditure on out-of-home activities. It is clear that people with full-time employment had higher baseline utility for basic need and for work and school and shopping activities and had lower baseline utility for drop-off and pick-up, services, and recreation-type activities compared with people with other types of employment status. This behavior was consistent across the random weeks. In the case of social and other types of activities, considerable variations exist in baseline preference compared with at-home activities.

The number of household children had a very strong influence on household members' activity-travel behavior. The number of household children had a negative effect on time expenditure for all out-of-home activities except work and school. This is intuitive because work and school activity is a fundamentally different type of activity than all other out-of-home activities. In particular, by working, people earn money, whereas in other out-of-home activities people generally spend money. It makes sense that having a higher number

TABLE 1 Estimated Model Parameters

Baseline Utility Component Variable	Week 1		Week 2		Week 3		Week 4		Week 5		Week 6		Pooled	
	Par.	*t*	Par.	*t*	Par.	*t*	Par.	*t*	Par.	*t*	Par.	*t*	Par.	*t*
Constant: Generic														
All specific activity	–14.4	*–17.28*	–18.78	*–16.2*	–12.8	*–15.129*	–13.5	*–16.14*	–18.1	*–17.73*	–17.3	*–16.901*	–14.8	*–57.246*
City: Karlsruhe (dummy)														
Basic need	0.75	*3.38*	0.18	*0.85*	0.77	*3.39*	0.95	*4.16*	0.18	*0.78*	0.42	*1.94*	0.56	*7.34*
Work and school	–0.19	*–0.89*	–0.29	*–1.31*	0.27	*1.22*	0.32	*1.32*	–0.53	*–2.28*	–0.32	*–1.38*	–0.10	*–1.32*
Drop off and pick up	–0.18	*–0.84*	–0.74	*–3.21*	0.02	*0.07*	0.11	*0.48*	–0.65	*–2.83*	–0.28	*–1.24*	–0.29	*–3.70*
Shopping	0.09	*0.39*	–0.11	*–0.56*	0.29	*1.26*	0.23	*1.06*	0.14	*0.62*	–0.02	*–0.07*	0.13	*1.71*
Services and private business	–0.17	*–0.77*	–0.60	*–2.93*	0.12	*0.55*	0.14	*0.64*	–0.29	*–1.31*	–0.63	*–2.90*	–0.22	*–3.03*
Recreation	0.51	*2.23*	0.09	*0.40*	0.51	*2.02*	0.64	*2.51*	0.27	*1.07*	0.58	*2.24*	0.43	*4.99*
Social	0.77	*3.35*	0.30	*1.38*	1.11	*5.16*	0.82	*3.46*	0.28	*1.20*	0.25	*1.18*	0.61	*8.06*
Others	0.29	*0.51*	–0.25	*–0.58*	0.79	*1.75*	0.81	*1.51*	0.29	*0.53*	0.32	*0.50*	0.34	*1.98*
Gender: Male (dummy)														
Basic need	0.41	*1.74*	0.34	*1.52*	0.66	*2.38*	0.23	*0.86*	0.35	*1.64*	0.28	*1.27*	0.39	*4.87*
Work and school	0.00	*–0.02*	0.02	*0.11*	0.41	*1.69*	0.11	*0.40*	0.06	*0.28*	–0.07	*–0.29*	0.12	*1.45*
Drop off and pick up	0.02	*0.08*	–0.29	*–1.22*	0.31	*1.34*	0.01	*0.03*	–0.26	*–1.08*	–0.06	*–0.24*	–0.03	*–0.32*
Shopping	–0.03	*–0.12*	–0.30	*–1.45*	0.11	*0.44*	0.11	*0.42*	–0.43	*–2.18*	–0.35	*–1.60*	–0.14	*–1.75*
Services and private business	0.23	*1.02*	0.22	*1.08*	0.61	*2.60*	0.39	*1.62*	0.10	*0.47*	–0.11	*–0.52*	0.26	*3.45*
Recreation	–0.23	*–0.90*	–0.25	*–1.05*	0.15	*0.60*	–0.06	*–0.21*	–0.30	*–1.26*	–0.28	*–1.14*	–0.13	*–1.45*
Social	0.26	*1.08*	0.10	*0.48*	0.59	*2.38*	0.39	*1.47*	0.53	*2.45*	–0.01	*–0.03*	0.32	*4.00*
Others	–1.14	*–2.00*	–1.13	*–2.10*	–0.24	*–0.52*	–0.08	*–0.19*	–0.89	*–1.60*	–0.99	*–1.51*	–0.71	*–3.95*
Household Income														
Basic need	0.07	*1.34*	0.25	*4.69*	0.11	*2.08*	0.20	*3.39*	0.12	*2.11*	0.23	*4.73*	0.16	*9.45*
Work and school	–0.04	*–0.63*	0.11	*1.97*	–0.06	*–0.95*	0.03	*0.41*	–0.06	*–0.97*	0.05	*0.88*	0.00	*0.15*
Drop off and pick up	–0.30	*–5.09*	–0.14	*–2.33*	–0.29	*–4.92*	–0.19	*–2.81*	–0.23	*–3.66*	–0.16	*–2.82*	–0.21	*–10.59*
Shopping	–0.03	*–0.63*	0.12	*2.15*	0.01	*0.19*	0.09	*1.36*	–0.02	*–0.31*	0.10	*2.15*	0.05	*2.58*
Services and private business	0.00	*–0.04*	0.18	*3.49*	–0.02	*–0.32*	0.09	*1.52*	0.02	*0.32*	0.13	*2.52*	0.07	*3.81*
Recreation	–0.18	*–3.09*	–0.04	*–0.69*	–0.15	*–2.59*	–0.06	*–0.92*	–0.14	*–2.49*	–0.13	*–2.24*	–0.11	*–5.86*
Social	–0.08	*–1.61*	0.02	*0.30*	–0.12	*–2.40*	0.02	*0.38*	–0.08	*–1.45*	0.12	*2.38*	–0.02	*–1.37*
Others	–0.92	*–7.32*	–0.64	*–6.01*	–0.95	*–8.51*	–0.92	*–7.38*	–1.00	*–7.02*	–0.83	*–5.80*	–0.86	*–21.47*
Drivers License Holder (dummy)														
All specific activity	0.35	*1.02*	0.59	*2.23*	0.46	*1.60*	0.40	*1.53*	0.68	*2.55*	0.72	*2.65*	0.47	*4.81*
Household Vehicle: More Than or Equal to 1 (dummy)														
All specific activity	0.51	*1.72*	0.06	*0.21*	0.10	*0.35*	–0.03	*–0.12*	0.21	*0.87*	–0.10	*–0.33*	0.13	*1.46*

(continued on next page)

TABLE 1 *(continued)* **Estimated Model Parameters**

Baseline Utility Component Variable	Week 1 Par.	Week 1 *t*	Week 2 Par.	Week 2 *t*	Week 3 Par.	Week 3 *t*	Week 4 Par.	Week 4 *t*	Week 5 Par.	Week 5 *t*	Week 6 Par.	Week 6 *t*	Pooled Par.	Pooled *t*
Employed Household Member (dummy)														
All specific activity	0.60	*2.13*	0.78	*2.50*	0.23	*0.84*	0.37	*1.19*	0.72	*2.68*	0.78	*2.58*	0.51	*5.26*
Ln (distance of bus stop from home)														
All specific activity	0.14	*0.45*	–0.13	*–0.42*	–0.42	*–1.61*	–0.59	*–1.99*	–0.54	*–1.97*	–0.69	*–2.47*	–0.32	*–3.54*
Home Location in CBD (dummy)														
All specific activity	–0.03	*–0.36*	–0.04	*–0.41*	–0.11	*–1.28*	–0.04	*–0.53*	–0.04	*–0.45*	0.00	*0.02*	–0.03	*–1.17*
Student (dummy): Generic Variable														
All specific activity	–1.48	*–3.98*	–0.95	*–2.64*	–1.22	*–3.40*	–1.40	*–3.93*	–1.08	*–3.47*	–1.02	*–3.16*	–1.13	*–9.01*
Parent in Home (dummy)														
All specific activity	–0.79	*–2.26*	–0.07	*–0.17*	0.40	*0.94*	–0.12	*–0.30*	0.21	*0.49*	0.80	*2.00*	0.11	*0.84*
Full-Time Employee (dummy)														
Basic need	0.33	*1.18*	0.20	*0.69*	0.79	*2.30*	0.52	*1.61*	–0.07	*–0.26*	0.15	*0.57*	0.31	*3.25*
Work and school	2.04	*7.65*	1.70	*6.25*	2.30	*7.59*	1.72	*5.35*	1.75	*6.24*	1.97	*7.00*	1.87	*20.04*
Drop off and pick up	–0.44	*–1.66*	–0.03	*–0.11*	0.41	*1.34*	–0.27	*–0.83*	–0.69	*–2.27*	–0.45	*–1.57*	–0.23	*–2.37*
Shopping	0.02	*0.09*	0.19	*0.67*	0.64	*1.93*	0.10	*0.32*	0.20	*0.73*	0.23	*0.88*	0.24	*2.62*
Services and private business	–0.41	*–1.54*	–0.64	*–2.51*	0.05	*0.15*	–0.35	*–1.20*	–0.64	*–2.45*	–0.20	*–0.83*	–0.37	*–4.17*
Recreation	–0.11	*–0.38*	–0.26	*–0.82*	0.28	*0.80*	–0.18	*–0.53*	–0.34	*–1.01*	–0.03	*–0.09*	–0.11	*–1.07*
Social	0.03	*0.11*	0.69	*2.51*	0.91	*2.96*	0.51	*1.63*	–0.16	*–0.52*	0.00	*0.01*	0.34	*3.57*
Others	–1.49	*–1.00*	0.17	*0.29*	0.57	*0.97*	0.20	*0.32*	–0.35	*–0.54*	–0.74	*–0.83*	–0.14	*–0.67*
No. of Children in Household (more than or equal to 1 dummy)														
Basic need	–0.90	*–1.81*	–0.42	*–0.80*	–0.42	*–0.87*	–0.87	*–1.82*	–0.74	*–1.67*	–0.85	*–1.46*	–0.42	*–2.79*
Work and school	0.32	*0.63*	0.60	*1.04*	0.68	*1.63*	–0.14	*–0.28*	0.32	*0.67*	0.36	*0.60*	0.60	*3.80*
Drop off and pick up	–1.74	*–3.47*	–1.21	*–2.10*	–1.40	*–2.99*	–1.72	*–3.38*	–1.40	*–2.94*	–2.10	*–3.62*	–1.31	*–8.16*
Shopping	–1.88	*–3.54*	–1.49	*–2.67*	–1.39	*–3.03*	–2.24	*–4.72*	–1.41	*–3.03*	–2.11	*–3.79*	–1.48	*–9.69*
Services and private business	–2.55	*–5.35*	–2.10	*–4.18*	–1.96	*–4.68*	–2.41	*–5.36*	–2.26	*–5.30*	–2.04	*–3.81*	–1.94	*–13.60*
Recreation	–0.98	*–2.08*	–0.30	*–0.57*	–0.52	*–1.16*	–1.12	*–2.43*	–0.88	*–2.06*	–0.90	*–1.54*	–0.50	*–3.29*
Social	–1.01	*–2.19*	–0.05	*–0.10*	–0.45	*–0.92*	–0.83	*–1.99*	–0.72	*–1.62*	–0.89	*–1.69*	–0.36	*–2.51*
Others	–1.85	*–2.01*	–1.61	*–1.99*	–1.08	*–1.53*	–1.00	*–1.37*	–1.07	*–1.40*	–1.46	*–1.95*	–1.03	*–4.12*
Age Dummy: Generic Variable														
21–30	–1.99	*–3.45*	–1.58	*–2.75*	0.18	*0.45*	–0.99	*–1.77*	–1.06	*–2.09*	–1.09	*–1.83*	–0.80	*–5.24*
31–40	–2.15	*–3.46*	–1.51	*–2.47*	–0.60	*–1.19*	–0.93	*–1.42*	–0.63	*–1.01*	0.22	*0.33*	–0.60	*–3.34*
41–45	–2.91	*–4.44*	–1.76	*–2.76*	–1.16	*–2.11*	–1.61	*–2.37*	–1.32	*–2.00*	–0.88	*–1.19*	–1.25	*–6.41*
46–50	–1.51	*–2.41*	–1.30	*–1.88*	0.72	*1.39*	–0.43	*–0.66*	–0.27	*–0.42*	–0.12	*–0.18*	–0.20	*–1.06*
51–55	–3.22	*–4.47*	–1.82	*–2.85*	–0.43	*–0.84*	–1.45	*–2.16*	–0.67	*–1.08*	–0.61	*–0.89*	–1.04	*–5.61*
56–60	–3.28	*–4.76*	–1.76	*–2.55*	–0.75	*–1.47*	–1.15	*–1.71*	–0.90	*–1.36*	–0.69	*–0.94*	–1.03	*–5.24*
61–65	–3.21	*–4.33*	–2.14	*–2.79*	–1.00	*–1.64*	–1.30	*–1.93*	–1.27	*–1.80*	–1.03	*–1.24*	–1.24	*–5.70*
65+	–3.69	*–5.02*	–2.06	*–2.66*	–1.17	*–1.95*	–2.12	*–2.86*	–1.98	*–2.87*	–1.59	*–1.95*	–1.70	*–7.37*

Satiation Parameter of Specific Activities Only, φ														
Constant														
Basic need	2.57	*12.98*	3.23	*14.91*	2.55	*11.45*	2.41	*12.09*	2.87	*15.91*	2.81	*13.92*	2.57	*39.97*
Work and school	2.86	*5.92*	7.43	*11.64*	6.23	*7.77*	6.49	*7.76*	3.63	*7.30*	3.54	*7.34*	3.77	*22.34*
Drop off and pick up	3.90	*15.58*	3.22	*16.69*	2.14	*10.85*	1.95	*7.16*	1.97	*9.86*	2.83	*13.70*	2.52	*36.06*
Shopping	2.13	*9.17*	2.62	*10.88*	1.91	*9.00*	2.58	*9.49*	1.56	*7.30*	1.44	*6.70*	1.90	*24.39*
Services and private business	1.27	*5.64*	2.44	*12.75*	1.11	*5.92*	1.50	*6.35*	1.72	*9.64*	1.32	*7.28*	1.42	*21.60*
Recreation	3.68	*3.65*	2.54	*3.51*	1.96	*4.71*	2.41	*2.92*	2.21	*3.48*	1.88	*3.37*	1.93	*15.72*
Social	3.19	*6.00*	2.47	*6.72*	3.18	*4.68*	1.94	*4.10*	2.13	*7.55*	2.48	*5.31*	1.97	*25.53*
Others	4.84	*1.28*	3.13	*1.73*	4.24	*2.01*	3.79	*2.76*	2.97	*1.72*	2.75	*0.51*	3.54	*8.75*
Travel Ratio														
Basic need	–0.44	*–4.36*	–0.70	*–6.98*	–0.88	*–9.86*	–0.29	*–6.29*	–0.40	*–5.81*	–0.54	*–8.75*	–0.48	*–25.62*
Work and school	–0.71	*–2.93*	–4.09	*–11.96*	–3.16	*–8.12*	–4.03	*–7.97*	–1.09	*–7.98*	–1.44	*–7.19*	–1.58	*–27.88*
Drop off and pick up	–0.76	*–14.89*	–0.67	*–13.11*	–0.48	*–15.73*	–0.67	*–11.08*	–0.25	*–9.09*	–0.51	*–13.50*	–0.50	*–40.18*
Shopping	–1.01	*–7.99*	–1.17	*–8.55*	–0.98	*–10.47*	–1.19	*–7.66*	–0.69	*–7.35*	–0.37	*–4.94*	–0.87	*–23.49*
Services and private business	–0.56	*–7.28*	–0.85	*–11.72*	–0.41	*–7.72*	–0.58	*–5.33*	–0.54	*–13.77*	–0.32	*–6.40*	–0.51	*–27.22*
Recreation	–1.34	*–1.66*	–0.45	*–0.88*	–0.01	*–0.05*	–0.30	*–0.49*	–0.03	*–0.08*	0.00	*0.02*	0.00	*0.06*
Social	–1.30	*–3.37*	–0.51	*–2.11*	–1.54	*–2.80*	–0.32	*–0.88*	–0.15	*–1.05*	–0.52	*–1.33*	–0.28	*–10.14*
Others	–1.43	*–0.42*	–0.86	*–0.80*	–1.18	*–1.00*	–0.96	*–2.69*	–1.55	*–1.42*	–1.38	*–0.25*	–0.91	*–5.26*
Number of People Involved														
Basic need	0.14	*7.18*	0.13	*5.53*	0.18	*7.01*	0.12	*4.93*	0.13	*5.58*	0.12	*5.44*	0.14	*16.97*
Work and school	0.46	*6.48*	0.32	*4.09*	0.25	*2.70*	0.51	*6.39*	0.51	*5.58*	0.55	*7.54*	0.50	*16.59*
Drop off and pick up	0.11	*1.77*	0.27	*5.03*	0.32	*5.21*	0.57	*6.31*	0.42	*5.60*	0.28	*4.08*	0.31	*14.00*
Shopping	0.20	*7.11*	0.16	*5.55*	0.16	*4.52*	0.09	*2.99*	0.24	*7.87*	0.13	*3.93*	0.16	*14.81*
Services and private business	0.39	*8.31*	0.24	*6.74*	0.28	*7.35*	0.30	*7.65*	0.25	*6.05*	0.32	*7.52*	0.30	*20.35*
Recreation	0.19	*1.97*	0.29	*2.73*	0.14	*1.64*	0.16	*2.34*	0.17	*1.50*	0.28	*1.94*	0.21	*6.33*
Social	0.20	*4.88*	0.23	*4.27*	0.24	*4.93*	0.19	*4.84*	0.21	*3.84*	0.17	*4.40*	0.21	*12.59*
Others	–0.05	*–0.08*	0.25	*0.29*	–0.19	*–0.19*	0.39	*0.75*	1.42	*2.00*	0.46	*0.37*	0.15	*1.01*
Satiation Parameter of Composite Activity, ρ														
Constant	–1.32	*–28.38*	–1.44	*–31.82*	–1.03	*–22.11*	–1.14	*–31.85*	–1.41	*–33.89*	–1.33	*–30.73*	–1.21	*–103.87*
Married (dummy)	0.00	*–0.10*	0.01	*0.67*	0.00	*–0.07*	0.00	*0.07*	0.01	*0.73*	0.01	*0.42*	0.00	*0.66*
Ln (No. of household members)	0.03	*1.89*	–0.02	*–1.20*	–0.04	*–2.17*	–0.02	*–1.19*	–0.01	*–0.66*	–0.02	*–1.03*	–0.01	*–1.84*
Household vehicle (≥ 2)	0.04	*1.63*	0.01	*0.66*	0.02	*0.61*	–0.01	*–0.50*	0.03	*1.56*	0.01	*0.35*	0.02	*2.07*

NOTE: Par = parameter, *t* = *t* statistics, CBD = central business district.

of children in the household would demand more income and influence household members to spend more time working. This behavior is consistent across the weeks.

The individual's age was a highly significant variable in influencing baseline utility perception. Age was considered as a cohort-specific dummy variable in the models to capture nonlinear effects. It is clear that older people have lower baseline utility in all out-of-home activities than younger people, and this behavior was consistent across the random weeks.

φ Parameter

The φ parameter captures activity-travel behavior by translating time to ensure corner solutions and also addresses the satiation effects in time expenditure to specific out-of-home activities. This parameter is further expressed as an exponential function of a number of activity-specific variables. The higher the value of the φ parameter, the lower will be the time expenditure on the specific out-of-home activity; in other words, a higher φ value indicates lower willingness to spend more time on the specific activity. The constant term of the φ parameter captures the unexplained behavior in satiation effect. All constants in all models across the weeks are highly significant. Although there are variations in parameter values, the general trend is the same across the random weeks. It is clear that work and school activity has higher constant values. This indicates that work and school activity is more a part of regular or skeleton-type activities and that time allocation to this type of activity is more or less fixed. In contrast, service and private business activities have lower constant values, indicating that people are willing to spend more time on this type of activity, although this research always has different constraints (as reflected in the baseline utility component; this activity type has lower baseline marginal preference). Similarly, shopping and recreation-type activities have lower constant values, indicating people's willingness to spend more time on these activities. Conversely, the "others" activity type contains a variety of different types of activities that were not included in the general classification and shows low satisfaction in spending more time with this activity.

Travel ratio captures the influence of transportation system performance on an individual's activity-travel behavior. It has a negative sign for all out-of-home activities for all random weeks. In addition, for all cases, it has highly significant parameter values. In all cases this variable has a negative effect on the φ parameter, indicating that a higher value of travel ratio reduces satisfaction in spending time on specific out-of-home activities. The variable has consistent effects across the random weeks.

The number of people involved in the specific out-of-home activities increases the φ parameter values, indicating increasing satisfaction in spending time. This variable also has highly significant coefficients for all specific out-of-home activities and for all random weeks except for the "other" type. Although variations in coefficient values are visible across the random weeks, the general trends are the same for the same out-of-home activities across the random weeks.

ρ Parameter

The ρ parameter is purely a satiation factor that defines the marginal rate of utility gain or loss in spending each additional unit of time on the activity types under consideration. This parameter is the same for all activities, including the composite activity. In the utility function formulation used in this paper, this parameter obtains a balancing effect from the satiation parameter for the composite activity (*20*). However, the requirement for this parameter is that it must be less than 1 and hence is specified as mentioned in Equation 1. Although different socioeconomic variables were tested within the specification, it was difficult to get statistically significant parameter values. This may be because the satiation effects are already captured by the φ parameters for all specific out-of-home activities with respect to the composite activity. However, the constant term in the ρ parameter specification is highly significant and has the same sign and almost the same values across the random weeks. The reason for there being a highly statistically significant constant parameter in the ρ specification without any significant number of socioeconomic variables may be that there are some behavioral elements not captured by the variables collected in the survey.

CONCLUSIONS

This paper uses a Kuhn–Tucker demand system model to analyze variations in weekly time expenditure behavior among all possible activities. Activities were first classified into two general types: at-home and out-of-home activities. Out-of-home activities were then further classified into eight general activity types. MobiDrive data, which is a 6-week travel diary data for two cities in Germany, were used for the investigation. The main objective of this paper was to investigate whether a typical random week modeling time frame can capture sufficient rhythms of activity-travel behavior or not. Although it is almost impossible to quantify the rhythm of activity-travel behavior very precisely, comparing estimated model parameters for a number of individual weeks provides insight into the extent to which activity pattern rhythms can be captured with a typical week.

Instead of focusing on a specific activity type, this paper models all possible activity types jointly (*7*). The Kuhn–Tucker demand system model is designed to capture complex trade-offs in time expenditure on the activity types under consideration. The fundamental assumption of the formulation of the Kuhn–Tucker demand system model is that every individual maximizes his or her total utility in allocating time to all specific activity types under time budget constraints. The time budget is defined as the 7-day time period, or a typical week. The idea is to compare the model results developed for each individual week of the MobiDrive survey. All 6-week data are also pooled together to develop the pooled data model in order to capture the average week behavior.

In terms of fitting the observed data, the individual weekly models show excellent performance (adjusted rho-square values are above 0.2, which is very high considering the complexity of the models), which indicates the appropriateness of the modeling technique used in this paper. Most importantly, it is clear that the goodness-of-fit values are almost the same across the individual weeks of the 6-week travel diary survey, which supports the hypothesis that a typical week captures the rhythms of activity-travel behavior sufficiently, especially when interactivity interactions are modeled properly.

Interactivity interactions in time expenditure are modeled in several stages: baseline preference in spending time, to specific activity and satiation effect in spending time, to the specific activities. Satiation effects in time expenditure are captured in two ways: satiation effect combined with translating time (to ensure corner solutions) and pure satiation effects. All of these major elements of the models are further specified as functions of different socioeconomic and activity-specific variables. Comparing the model parameters of the individual models that are statistically significant, it is clear that individual weeks do have variations but that the general trend is similar across the weeks. It cannot be concluded that a typical week captures the complete rhythms of activity-travel behavior, but based on the results presented in this paper, it can be argued that considering a typical week as a random week captures the rhythms of activity-travel behavior sufficiently.

However, this study used travel diary survey data, not activity diary survey data. Given a detailed activity diary survey with more detailed behavioral information (spatial, socioeconomic, and activity-specific), including a more detailed classification of out-of-home activities, it can be expected that model results could be further improved.

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REFERENCES

1. Axhausen, K. W., A. Zimmermann, S. Schönfelder, G. Rindsfüser, and T. Haupt. Observing the Rhythms of Daily Life. *Transportation,* Vol. 29, 2002, pp. 95–124.
2. Schönfelder, S. *Urban Rhythms: Modelling the Rhythms of Individual Travel Behavior.* PhD thesis. Institute of Transport Planning and Systems, Swiss Federal Institute of Technology, Zurich, Switzerland, 2006.
3. Schlich, R., and K. W. Axhausen. Habitual Travel Behavior. *Transportation,* Vol. 30, 2003, pp. 13–36.
4. Miller, E. J. Propositions for Modelling Household Decision-Making. In *Integrated Land Use and Transportation Models: Behavioural Foundations* (M. Lee-Gosselin and S. Doherty, eds.), Elsevier, New York, 2005.
5. Schönfelder, S., and K. W. Axhausen. Analyzing the Rhythms of Travel Using Survival Analysis. In *Jahrbuch 2000/2001 Schweizerische Verkehrwirtschaft* (C. Kaspar, C. Laesser, and T. Bieger, eds.), SVWG, St. Gallen, Switzerland, pp. 137–162.
6. Bhat, C. R., T. Frusti, H. Zhao, S. Schönfelder, and K. W. Axhausen. Intershopping Duration: An Analysis Using Multiweek Data. *Transportation Research Part B,* Vol. 38, 2004, pp. 39–60.
7. Habib, K. M. N., E. J. Miller, and K. W. Axhausen. How Reasonable Is The Typical Week Time Frame Approach in Activity-Based Travel Demand Modeling? Case Study Shopping Activity/Trip Using a Multi-Week Trip Diary Survey Data. In *Arbeitsberichte Verkehrs- und Raumplanung,* Vol. 443, IVT, ETH Zurich, Switzerland.
8. Habib, K. M. N., and E. J. Miller. Modelling Activity Generation: A Utility-Based Model for Activity-Agenda Formation. Presented at 11th International Conference on Travel Behaviour Research, Kyoto, Japan, August 2006.
9. Becker, G. A Theory of the Allocation of Time. *The Economic Journal,* Vol. 75, No. 299, 1965, pp. 493–517.
10. DeSerpa, A. C. A Theory of Economics of Time. *The Economic Journal,* Vol. 81, No. 324, 1971, pp. 282–846.
11. Evan, A. W. On the Theory of the Valuation and Allocation of Time. *Scottish Journal of Political Economy,* Vol. 19, No. 1, 1972, pp. 1–17.
12. Jara-Diaz, S. R. Time and Income in Travel Demand: Towards a Microeconomic Activity Framework. In *Theoretical Foundation of Travel Choice Modelling* (T. Gärling, T. Laitila, and K. Westin, eds.), Pergamon Press, Oxford, United Kingdom, 1998.
13. Miller, E. J. Project-Based Activity Scheduling for Household and Person Agents. In *Flow, Dynamics and Human Interactions: Proc., 16th International Symposium on Transportation and Traffic Theory* (H. Mahmassani, ed.), Elsevier, New York, 2005.
14. Habib, K. M. N., and E. J. Miller. Modeling Daily Activity Program Generation Considering Within-Day and Day-to-Day Dynamics in Activity Travel Behavior. Presented at 86th Annual Meeting of the Transportation Research Board, Washington, D.C., 2007.
15. Habib, K. M. N., and E. J. Miller. Modeling Skeletal Components of Workers' Daily Activity Schedules. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1985,* Transportation Research Board of the National Academies, Washington D.C., 2006, pp. 88–97.
16. Winston, G. C. Activity Choice: A New Approach to Economic Behavior. *Journal of Economic Behavior and Organization,* Vol. 8, 1987, pp. 567–588.
17. Kuhn, H. M., and A. W. Tucker. Nonlinear Programming. In *Proc., Second Berkeley Symposium on Mathematical Statistics and Probability* (J. Neyman, ed.), University of California Press, Berkeley, 1951.
18. Wales, T. J., and A. D. Woodland. Estimation of Consumer System of Binding Nonnegativity Constraints. *Journal of Econometrics,* Vol. 21, 1982, pp. 263–285.
19. von Haefen, R. H., and D. J. Phaneuf. Kuhn–Tucker Demand System Approach to Non-Market Valuation. In *Application of Simulation Methods in Environmental and Resource Economics* (R. Scarpa and A. Alberini, eds.), Kluwer Academic Publishers, Norwell, Mass., 2004.
20. Bhat, C. R. A Multiple Discrete-Continuous Extreme Value Model: Formulation and Application to Discretionary Time-Use Decisions. *Transportation Research Part B,* Vol. 39, 2005, pp. 679–707.
21. Bhat, C. R. The Multiple Discrete Continuous Extreme Value (MDCEV) Model: Role of Utility Function Parameters, Identification Considerations, and Model Extensions. *Transportation Research Part B,* Vol. 42, No. 3, 2008.
22. Hicks, J. R. *Value and Capital.* Oxford University Press, Oxford, England, 1968.
23. *GAUSS 7.0.* Aptech Systems Inc., Black Diamond, Wash., 2007.
24. Ag, P. T. V., B. Fell, S. Schönfelder, and K. W. Axhausen. MobiDrive Questionnaires. *Arbeitsberichte Verkehrs und Raumplanung,* Vol. 52, Institut für Verkehrsplanung, Transporttechnik, Strassen und Eisenbahnbau, ETH Zürich, Zürich, Switzerland, 2000.
25. Chalasani, V. S., S. Schönfelder, and K. W. Axhausen. Archiving Travel Data: The MobiDrive Example. *Arbeitsbericht Verkehrs und Raumplanung,* Vol. 129, Institut für Verkehrsplanung und Transportsysteme, ETH Zürich, Zürich, Switzerland, 2002.
26. Ettema, D. Latent Activities: Modeling the Relationships Between Travel Time and Activity Participation. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1926,* Transportation Research Board of the National Academies, Washington D.C., 2005, pp. 171–181.
27. Jara-Díaz, S., M. Munizaga, P. Greeven, and R. Guerra. The Unified Expanded Goods-Activity-Travel Model: Theory and Results. Presented at 11th World Conference on Transportation Research, Berkeley, Calif., 2007.

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