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An Analysis of Multiple Interactivity Durations Using a Unifying Multivariate Hazard Model

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ABSTRACT

This paper jointly examines the length between successive participations in several activity purposes using a 1999 multi-week travel survey conducted in the German cities of Halle and Karlsruhe. A multivariate hazard model that accommodates a flexible duration dynamics structure, recognizes the effects of covariates, incorporates the variation in interactivity duration due to unobserved individual-specific factors and variation in interactivity duration within spells of the same individual, and considers the joint nature of participation in the various activities is proposed and applied. The variables considered in the analysis include demographics, access to the internet, location characteristics, and day of week variables.

1. INTRODUCTION

The activity-based approach to travel demand modeling emphasizes activity participation and focuses on sequences or patterns of activity behavior (using the whole day or longer periods of time as the unit of analysis). Consequently, it offers a sound behavioral basis to assess the potential travel responses of individuals to policy actions through an examination of how people modify their activity participations (see Bhat and Misra, 2002 and Waddell *et al*., 2002 for recent discussions of the activity-based approach).

The activity-based analysis approach has seen substantial development in the past few years. However, almost all earlier studies have focused on a single day as the time period for analysis of activity-travel patterns. Such single day analyses have at least three inter-related limitations. First, there is an implicit assumption of uniformity and/or behavioral independence in activity decisions from one day to the next. Clearly, while there may be some amount of uniformity in decisions associated with work-related patterns, many activities (such as grocery shopping or recreational pursuits) are likely to have a longer cycle for participation. In fact, even within the context of work activity and travel, there may be rather substantial variation in patterns from day-to-day in such dimensions as the number of non-work stops during the commute, location of commute-related non-work stops, departure time to work, and commute route choice (see, for example, Mahmassani *et al*., 1997 and Bhat and Zhao, 2002). In addition to the assumption of uniformity implied in single-day analyses, the assumption of behavioral independence in activity decisions across days is also quite untenable, since, for example, an individual's likelihood of participation in shopping on any given day will tend to increase the longer s/he has not participated in such an activity (due to food inventory depletion effects; see Kim and Park, 1997). Ignoring the issue of day-to-day variation in behavior and the dynamics in behavior across days can, and in general will, lead to biased estimations of the effect of demographic and other individual/household attributes on activity-travel choices (see Hirsh *et al.*, 1986; Bhat *et al.*, 2002). This, in turn, has implications for accurate travel demand forecasting in response to changing demographic profiles in the population. Second, single day analyses are unable to reflect changes in the activity-travel patterns of individuals over a period longer than a day in response to policy actions. Thus, a workweek compression scheme is likely to lead to a multi-day response in activity-travel pattern shifts that cannot be captured using a single day model (Hirsh *et al.*, 1986). Third, single day models ignore information regarding the distribution of participation over multiple days, which can have an important impact on how an individual responds to a policy measure on a shorter-term day-to-day basis. For example, an individual who has to drop off a child on one day of the week while traveling to work may "stick" with the auto mode for all days of the workweek. This individual would be reluctant to switch to other travel modes, in response to a policy action such as congestion pricing, even on days s/he is not dropping the child (see Jones and Clark, 1988 for an extensive discussion of the need for multiday analysis to examine the response to policy actions).

1.1 Earlier Multi-day Research and Substantive Focus of Current Research

The appropriateness of a single day as the time period of analysis has been the subject of debate for a long time and is certainly not a new issue. Some of the early studies to question single day analyses and explicitly analyze multiday activity-travel data for travel demand modeling are the works of Hanson and Huff (Hanson and Huff, 1986; 1988a; 1988b and Huff and Hanson, 1986; 1990), Pas and Koppelman (Pas, 1988; Pas and Koppelman, 1987), and Hirsh *et al*. (1986). Hanson and Huff used the 1971 multiweek travel survey conducted in Uppsala, Sweden in their analysis, while Pas and Koppelman used the 1973 seven-day activity diary survey conducted in Reading, England. These researchers found quite substantial day-to-day variability in activity-travel patterns from one day to the next, and questioned the ability of travel demand models based on a single day of data to produce good forecasts and accurately assess policy actions. The studies by Hanson and Huff indicated that even a period of a week may not be adequate to capture much of the distinct activity-travel behavioral patterns manifested over longer periods of time. Hirsh *et al*. used a one-week activity diary collected in 1983 in Israel to examine the dependence among the shopping activity participations of individuals across different days of the week, and concluded that there is not only substantial day-to-day variation in shopping patterns but also significant dependence in activity decisions across days.

A few more recent studies along the same vein as the studies discussed above include Kunert (1994), Ma and Goulias (1997), Pas and Sundar (1995), Muthyalagari *et al*. (2001), and Schlich (2001). Kunert used a one-week travel diary collected in Amsterdam and Amstelveen in 1976 to examine interpersonal and intrapersonal variations in trip rates for sixteen life cycle groups. Kunert found that the average intrapersonal variance is about 60% of the total variation in trip rates and concluded that "even for well-defined person groups, interpersonal variability in mobility behavior is large but has to be seen in relation to even greater intrapersonal variability". Ma and Goulias examined activity and travel patterns using data from the Puget Sound (Seattle) Transportation Panel, and suggested that activity patterns show even greater day-to-day variation than travel patterns. Pas and Sundar examined day-to-day variability in several travel indicators and across household members using a three-day travel diary data collected in 1989 in Seattle, while Muthyalagari *et al.* studied intrapersonal variability using GPS-based travel data collected over a period of six days in Lexington, Kentucky. The study by Muthyalagari *et al.* study found larger day-to-day variability estimates than those obtained by Pas and Sundar, suggesting that GPS-based data collection may be recording short and infrequent trips better than traditional surveys. Finally, Schlich has recently used a sequence alignment method to analyze intrapersonal variability in travel behavior using a 6-week travel survey conducted in Germany in the Fall of 1999.

All the studies discussed thus far examine day-to-day variations in the context of both regular daily activities (such as work-commute patterns) as well as non-daily activities (such as grocery shopping participation and related patterns). A few other studies, on the other hand, have specifically focused on day-to-day variations in regular work activities. Mahmassani *et al*. (1997) descriptively examined the effect of commuter characteristics and the commuter's travel environment on the likelihood of changing departure time and route choice from one day to the next for the morning home-to-work trip. Hatcher and Mahmassani (1992) focused on the same travel dimensions as Mahmassani *et al*. (1997), except that their emphasis was on the evening work-to-home commute rather than the morning home-to-work commute. A ten-day diary data of morning and evening commute characteristics collected in Austin in 1989 is used in both these studies. Bhat (2000a) examined interpersonal and intrapersonal variation in the context of work commute mode choice, while Bhat (2001) studied interpersonal and intrapersonal variation in the context of the number of non-work commute stops made by commuters. A multiday travel survey data collected in the San Francisco Bay area in 1990 is used in both these studies.

The above studies have contributed to our understanding of multiday activity-travel behavior. However, they have mainly focused on either descriptively examining the extent of interpersonal and intrapersonal variations in activity-travel behavior or on examining day-to-day variations in the context of regular daily work activity. In this research, we focus on a rigorous modeling approach to examine the rhythms of individuals over a multiweek period. In addition, an important contribution of this research is to distinguish between participation in different activity types using multiweek data and to accommodate the dependencies in the participation across activity types. Specifically, the current study examines the participation of individuals, and the dependence in participation of individuals, in five different non-work activity purposes: recreation, social, personal business, maintenance shopping (groceries, laundry, *etc*.), and non-maintenance shopping (buying clothes, window shopping, *etc*.). A continuous six-week travel survey collected in the cities of Halle and Karlsruhe in Germany in the Fall of 1999 is used in the analysis.

1.2 Methodological Focus of Current Research

An examination of the participation of individuals in different activity types across multiple days is achieved in the current paper by analyzing the duration between successive activity participations of individuals in each activity type. The interactivity duration is measured in days, since a vast majority of individuals had no more than a single activity participation in each of the activity types on any given day. The methodology uses a hazard-based duration model structure since such a structure recognizes the dynamics of interactivity duration; that is, it recognizes that the likelihood of participating in an activity depends on the length of elapsed time since the previous participation. The hazard duration formulation also allows different individuals to have different rhythms in behavior and is able to predict activity participation behavior (both frequency and distribution of the activity participations) over any period of time (such as a day, a week, or a month).

Hazard models are seeing increasing use in the transportation field (see Bhat, 2000b for an extensive discussion of hazard-based duration models and transportation-related applications). In the context of examining interactivity durations from multiweek data, there have been three recent applications of hazard models: Schönfelder and Axhausen (2000), Kim and Park (1997), and Bhat *et al*. (2002). However, all these studies focus on the single activity purpose of shopping. Other activity purposes, and the dependencies across activity purposes, are not considered. Further, these earlier studies do not consider intra-individual variations in intershopping duration. In the current study, we develop a formulation that (a) accommodates a very flexible structure to account for the dynamics of participation decisions across multiple days within each activity purpose, (b) includes the effect of demographic, locational, computer use, and day-of-week attributes on interactivity durations, (c) recognizes the presence of unobserved individual-specific attributes affecting interactivity durations, (d) incorporates intra-individual variations in interactivity duration due to unobserved characteristics, and (e) recognizes the dependence among interactivity durations of each type due to unobserved individual-specific characteristics. To our knowledge, this is the first formulation and application of a generalized multidimensional duration modeling framework that accommodates all the issues discussed above.

The rest of this paper is structured as follows. Section 2 presents the model structure and estimation details. Section 3 describes the data. Section 4 discusses the empirical results. Finally, Section 5 concludes the paper.

2. THE MODEL

2.1. Hazard-Based Duration Structure

Let T_{qmi} be an index representing the i^{th} interactivity spell of activity purpose m for individual q. Let τ represent some specified time on the continuous time scale. Let $\lambda_{qmi}(\tau)$ represent the hazard at continuous time τ since the previous activity participation in purpose m for the i^{th} intershopping duration spell of individual q; *i.e.*, $\lambda_{qmi}(\tau)$ is the conditional probability that individual q's $(i + 1)^{th}$ episode of activity purpose m will occur at continuous time τ after her/his i^{th} participation, given that the episode does not occur before time τ:

$$\lambda_{qmi}(\tau) = \lim_{\Delta \to 0^+} \frac{P(\tau < T_{qmi} < \tau + \Delta \mid T_{qmi} > \tau)}{\Delta}, \; q = 1, 2, \ldots, Q; \; m = 1, 2, \ldots, M; \; i = 1, 2, \ldots, I_{qm} \quad (1)$$

Next, we relate the hazard rate, $\lambda_{qmi}(\tau)$, to a baseline hazard rate, $\lambda_{m0}(\tau)$, a vector of demographic, locational, and episode-specific covariates, x_{qmi}, an individual-specific unobserved factor v_{qm} capturing miscellaneous individual attributes affecting interactivity duration (for example, an intrinsic preference for shopping or recreation), and a spell-specific unobserved component ϖ_{qmi}. We accomplish this by using a proportional hazard formulation as follows:

$$\lambda_{qmi}(\tau) = \lambda_{m0}(\tau)\exp(-\beta'_m x_{qmi} - v_{qm} + \varpi_{qmi}), \quad (2)$$

where β_m is a vector of covariate coefficients. The reader will note that the variance of ϖ_{qmi} captures unobserved intra-individual variation (or heterogeneity) in the interactivity hazard. The term v_{qm}, on the other hand, captures idiosyncratic individual specific effects. The variance of v_{qm}, therefore, captures unobserved inter-individual variations (or unobserved inter-individual heterogeneity) in the interactivity hazard. In this paper, we assume that v_{qm} is normally distributed across individuals and that ϖ_{qmi} is independent of v_{qm} (m = 1, 2,…, M). For reasons that will become clear later, we assume a gamma distribution for exp(ϖ_{qmi}).

The proportional hazard formulation of Equation (2) can be written in the following equivalent form (see Bhat, 2000b):

$$s^{*}_{qmi} = \ln \int_{\tau=0}^{T_{qmi}} \lambda_{m0}(\tau) d\tau = \beta'_m x_{qmi} + v_{qm} - \varpi_{qmi} + \varepsilon_{qmi}, \tag{3}$$

where ε_{qmi} is a random term with a standard extreme value distribution: Prob($\varepsilon_{qmi} < z$) = $F_{\varepsilon}(z)$ = 1-exp[-exp(z)].

Now, consider the case when the continuous variable T_{qmi} is unobserved. However, we do observe the discrete time intervals of interactivity duration, where the discrete interval is in the unit of a day. Let t_{qmi} represent the i^{th} interactivity duration of activity purpose m (in days) for individual q and let k be an index for days (thus, t_{qmi} = 1, 2,…k,… K_m, where k is in days). Defining τ^k as the continuous time representing the upper bound of the k^{th} day, we can write

$$\begin{aligned} s^{*}_{qmi} &= \ln \int_{\tau=0}^{T_{qmi}} \lambda_0(\tau) d\tau = \beta'_m x_{qmi} + v_{qm} - \varpi_{qmi} + \varepsilon_{qmi}, \\ t_{qmi} &= k \text{ if } \psi_{m,k-1} < s^{*}_{qmi} < \psi_{m,k}, \text{ where } \psi_{m,k} = \ln \int_{\tau=0}^{\tau^k} \lambda_{m0}(\tau) d\tau. \end{aligned} \tag{4}$$

Equation (4) applies to each individual activity purpose m (m = 1, 2, …, M). If there were no dependence between the random terms v_{qm} across activity purposes, the interactivity models can be estimated separately for each activity purpose. However, it is quite possible that individuals have similar (or opposite) participation preferences for a certain subset of activity purposes. For example, an individual predisposed to a higher participation rate in recreational activities because of her/his intrinsic preferences may also be predisposed to a higher participation rate in social activities (*i.e.*, an individual with a lower duration length between successive recreational activity participations may also have a lower duration length between successive social activity participations). To accommodate such dependencies among activity purposes, we allow the v_{qm} terms to be correlated across purposes for each individual *q*. Let $v_q = (v_{q1}, v_{q2}, ..., v_{qm})'$, so that v_q is distributed multivariate normal: $v_q \sim N(0, \Omega)$. Also, let $c_{qmi} = \exp(\varpi_{qmi})$, which is gamma-distributed by assumption as indicated earlier, have a mean one (an innocuous normalization for identification purposes) and a variance σ_m^2 (σ_m^2 provides an estimate of unobserved intra-individual heterogeneity in the interactivity hazard).

2.2 Model Estimation

The parameters to be estimated in the multivariate hazard model include the β_m and ψ_m vectors ($\psi_m = [\psi_{m,1}, \psi_{m,2}, ..., \psi_{m,K_m-1}]'$) for each purpose *m*, the scalar σ_m for each purpose, and the matrix Ω. To develop the appropriate likelihood function for estimation of these parameters, we begin with the likelihood of individual *q*'s *i*$^{\text{th}}$ interactivity duration in purpose *m*. This can be written from Equation (4), and conditional on v_{qm} and ϖ_{qmi}, as:

$$L_{qmi} \mid v_{qm}, \varpi_{qmi} = \left[\left(\exp\left\{-B_{(t_{qmi}-1)} \exp(\varpi_{qmi})\right\}\right) - \left(\exp\left\{-B_{t_{qmi}} \exp(\varpi_{qmi})\right\}\right)\right] \text{ , where} \quad (5)$$

$$B_{t_{qmi}} = \exp\left\{\psi_{t_{qmi}} - [\beta_m x_{qmi} + v_{qm}]\right\}.$$

Next, the likelihood function for individual *q*'s *i*$^{\text{th}}$ interactivity duration spell of purpose *m*, unconditional on ϖ_{qmi}, may be written as:

$$L_{qmi} \mid v_{qm} = \int_0^\infty \left[\exp\left\{-B_{t_{qmi}-1} \cdot c_{qmi}\right\} - \exp\left\{-B_{t_{qmi}} \cdot c_{qmi}\right\}\right] \text{, where } c_{qmi} = \exp(\varpi_{qmi}) \quad (6)$$

Using the moment-generating function properties of the gamma distribution (see Johnson and Kotz, 1970), the expression above reduces to:

$$L_{qmi} \mid v_{qm} = G_{(t_{qmi}-1)} - G_{t_{qmi}}, \text{ where } G_{t_{qmi}} = \left[1 + \sigma_m^2 B_{t_{qmi}}\right]^{-\sigma_m^{-2}} \tag{7}$$

The gamma distribution for c_{qmi} is convenient because it results in a closed-form expression in Equation (7). The likelihood function for all the interactivity duration spells of purpose *m* for individual *q*, conditional on v_{qm}, is:

$$L_{qm} \mid v_{qm} = \prod_{i=1}^{I_{qm}} (L_{qmi} \mid v_{qm}) . \tag{8}$$

Collecting all the purpose-specific error terms v_{qm} into a single vector v_q for individual *q*, we can write the likelihood of the entire string of spells of all purpose types for individual *q* as:

$$L_q \mid v_q = \prod_{m=1}^{M} \prod_{i=1}^{I_{qm}} (L_{qmi} \mid v_{qm}) , \tag{9}$$

and the unconditional likelihood can be written as:

$$L_q = \int_{v_q} \prod_{m=1} \prod_{i=1}^{I_{qm}} (L_{qmi} \mid v_{qm}) \, dF(v_q) . \tag{10}$$

where *F* is the multivariate cumulative normal distribution. Finally, the log-likelihood function is $L_q = \sum_q \ln L_q$. The dimensionality of the integration in Equation (10) is equal to the number of activity purposes *M*. In the empirical context of the current paper, we examine five purposes, resulting in a five-dimensional integral in the likelihood function for each individual. To maximize this likelihood function and estimate the parameters, we apply simulation techniques that approximate the individual likelihood function L_q in Equation (10) by computing the integrand in the equation at different realizations of v_q drawn from a multivariate normal distribution, and computing the average over the different values of the integrand. The convergent parameter vector is estimated as the value that maximizes the simulated function as computed above. Under rather weak regularity conditions, the maximized (log) simulated likelihood (MSL) estimator is consistent, asymptotically efficient, and asymptotically normal (see Hajivassiliou and Ruud, 1994; Lee, 1992).

In the current paper, we use a quasi-Monte Carlo (QMC) method to draw realizations for v_q from the multivariate normal distribution. Specifically, we use 150 draws of the Halton sequence (details of the Halton sequence are available in Bhat, 2001; 2003).

One additional issue needs discussion at this point. The Halton draws do not reflect the desired correlation matrix Ω of the multivariate distribution of v_q. They are rather univariate draws for each dimension. To translate the univariate Halton draws to the multivariate Halton draws, we apply the Cholesky decomposition of the variance-covariance matrix Ω to the univariate draws. In addition, to ensure the positive-definitiveness of the correlation matrix Ω, we parameterize the likelihood function in terms of the elements of the Cholesky decomposed-matrix of Ω rather than using the elements of Ω directly. After obtaining the convergent parameter values in terms of the Cholesky decomposed-matrix of Ω, we obtain the equivalent convergent values of Ω.

3. THE DATA

3.1 Data Source

The data source for the current study is a 6-week travel survey conducted in Karlsruhe (West Germany) and Halle (East Germany) as part of the MobiDrive study funded by the German Ministry for Research and Education (see Axhausen *et al.*, 2002, for a detailed description of this data source). The main objective of this travel survey data collection was to facilitate a better understanding of the rhythms, routines, and habits of individuals over an extended time period of several weeks. The data collection effort was initiated by contacting a sample of households randomly selected from a phonebook database in each of the two cities. A subsample of this larger sample of households was selected for administration of the travel survey, based on eligibility considerations and willingness to participate (only households who did not plan to take a vacation of more than a week during the survey period and who did not have children under the age of 6 years were deemed eligible).

Axhausen *et al.* (2002) have examined the multiweek MobiDrive survey data for systematic biases in the types of households participating in the survey, households dropping out after a few days, item non-response, and fatigue effects in reporting over time. Their study indicates that there are no substantial differences in key sociodemographic attributes between respondent and non-respondent households. Households also very rarely dropped out during the six-week period, and item non-response was literally non-existent because respondents were called back over the telephone to clarify errors/ambiguities and to fill in missing entries. Finally, Axhausen *et al.* (2002) and Fraschini and Axhausen (2001) have examined fatigue effects, both descriptively and using formal modeling techniques. Their studies do not find any significant evidence of fatigue effects in several dimensions of travel, including the shares of mobile and immobile days within each week, and the number of weekly reported work and nonwork journeys and trips.

The final sample from the survey included information on 361 individuals from 162 households. Of these, 44 individuals from 23 households in Karlsruhe participated in a pretest survey, and 317 individuals from 139 households in Karlsruhe and Halle participated in the main survey. The structure and administration procedures were identical in the two surveys. The pretest travel survey was administered between May 31st and July 25th , and the main survey was administered between September 13th and November 14th. In addition to the six-week continuous travel diary, information on the sociodemographic characteristics of households and their members, car fleet size and composition, and attitudes toward different modes of transport was also collected (the reader is referred to Schlich *et al.* (2000) for a detailed description of the survey).

3.2 Sample Used and Description

Five non-work activity purposes are considered for the multivariate interactivity duration analysis in the current paper: (1) maintenance shopping (grocery shopping, medical drug shopping, *etc*.), (2) other shopping (buying clothes, shoes, window shopping, *etc*.), (3) social (meeting friends and family, group/club meetings, and participation in restaurant, culture, and spectator sports activities), (4) recreation (active sports, walk/stroll, culture and nature excursions, short vacation, garden/cottage activities, cinema, *etc*.), and (5) personal business.

The sample used in the current analysis includes the interactivity duration spells of 192 adult individuals (an adult individual is defined as a person whose age is equal to or over 16 years). We confined the analysis to only those adult individuals who pursued at least two episodes of each of the five activity purposes defined earlier (this provides at least one completed interactivity duration spell of each activity purpose).

Table 1 provides aggregate statistics (range and mean) on the number and length of interactivity duration spells for each activity type. The second column indicates a substantial range in the number of interactivity spells contributed by individuals. The mean values (in parenthesis) show that participation in maintenance and recreational activity purposes is generally more prevalent in the sample of individuals than participation in other purposes. The participation in "other shopping" is the least among all activity types, on average. The third column indicates substantial variation in the length of interactivity duration spells for each activity purpose. The reader will note that this variation is both because of difference in spell lengths across individuals and within individuals. The empirical analysis in this paper disentangles the inter-individual and intra-individual variations in spell length, and also attributes the variation to systematic (due to observed characteristics) and unobserved factors. The mean values (in parenthesis) of the spell lengths reflect our observations from the statistics on number of spells per person. Specifically, the mean interactivity spell length for maintenance and recreation are smaller than for other activities, and the mean interactivity spell length for "other shopping" pursuits is largest. The fourth column presents the upper end cut-off of the interactivity duration length used in the current empirical analysis. This upper end cut-off is needed in estimation because of the very few spells beyond a certain duration length. For example, there are only 23 spells out of 2262 spells, or 1% of spells, with a length of more than 16 days in the sample for maintenance shopping. Consequently, it is not possible to estimate a non-parametric hazard for each day beyond 16 days, and so spell lengths of 16 days or more are collapsed into a single "16 or more days" category. The numbers in the fourth column of Table 1 provide the cut-off used for each purpose and the percentage of spells in the sample with a length longer than the cut-off value (in parenthesis). For all activity types, the percentage of spells above the cut-off is less than or equal to 1% of the entire sample.

Table 1 provides information on the range and mean values of the length of interactivity duration spells, but does not provide details of the distribution of spell lengths. One way to descriptively examine the spell length distribution is to plot the sample hazards for each activity purpose. The sample hazard value for day *d* is the share of interactivity durations ending at day *d* from the set of all interactivity durations that have not terminated until day *d* (see Kiefer, 1988).

The sample hazards are presented in Figure 1 (for maintenance and other shopping activity purposes) and in Figure 2 (for the social, recreation, and personal activity purposes). All the sample hazards are relatively high in the first few days, reflecting the high number of short intershopping durations in the sample. Beyond these first few days, the profile is non-monotonic without a clear positive (snowballing) or negative (inertial) duration dependence. This "randomness" in the hazard distributions is because the sample hazard does not consider the effect of covariates and the variations in the hazard due to unobserved intra-individual and inter-individual factors. The baseline hazard that considers the effect of covariates and recognizes the presence of unobserved factors provides a better picture of duration dynamics, and will be presented later in Section 4.1. However, even the sample hazard reveals small spikes at 7 and 14 days for all activity purposes (especially for the non-shopping purposes in Figure 2), indicating a certain level of rhythmic weekly activity participation in all activities.

3.3 Variable Specifications

The choice of variables for potential inclusion in the model was guided by previous research and intuitive arguments regarding the effect of exogenous variables on activity participation. Four broad sets of variables were considered: individual and spouse characteristics, household characteristics, location and trip-making characteristics, and day of week variables.

Individual and spouse characteristics explored in our specifications included dummy variables for sex, ethnicity, education level, vehicle license holding, marital status, employment status (part-time employed, full-time employed, self-employed, and not employed), and linear and non-linear representations of work hours per week and age. Household characteristics considered in the model included household size, family structure, the number and employment status of household adults, household income, household tenure status (own or rent), household dwelling type (single family unit, duplex, apartment, *etc.*), number of motorized vehicles, number of dogs, and communication-related connections (such as number of telephones, number of private e-mail addresses, number of fax machines, and access to internet at home). Location and trip-making characteristics included whether the household is located in Karlsruhe or Halle, the population density of zone of residence, area type variables classifying the residential zone of households into one of four categories (urban, urban-suburban, suburban, and rural), the most frequently used mode for activity participation, the percentage of episodes of each type chained with other activities, and accessibility to transit. The day of week effect was represented by a series of dummy variables for each day (with one of the days being the base category).

We arrived at the final specification based on a systematic process of eliminating variables found to be insignificant in previous specifications and based on considerations of parsimony in representation. Table 2 provides a list of individual-level exogenous variables included in the final specification and their descriptive statistics in the sample.

4. EMPIRICAL RESULTS

The results are presented in four sections. The first section discusses the baseline hazard estimates for each of the activity types. Section 4.2 interprets the covariate effects. Section 4.3 presents and intuitively explains the unobserved heterogeneity effects. The reader will note that the baseline hazard, the covariate effects, and the unobserved heterogeneity effects are all estimated simultaneously, but are discussed in separate sections for presentation ease. Also, all these effects are estimated jointly across the various activity types. The final section (Section 4.4) discusses model fit statistics.

4.1 Baseline Hazard

The baseline hazard functions for the two shopping activities are shown in Figure 3, and the baseline functions for the other three non-shopping activity purposes are presented in Figure 4. The baseline hazards for the two shopping activities indicate a general and distinct upward trend. That is, individuals are more likely to engage in shopping as the time elapsed since the previous participation increases. This can be attributed to a “depletion of inventory” effect for food items and other non-grocery items. The baseline hazards for the social, recreational, and personal business activities do not show a clear distinct upward trend as do the hazards for the shopping categories. On the other hand, there are clear spikes at 7 and 14 days for the non-shopping activity purposes in Figure 4, suggesting a rhythmic weekly pattern of participation in the non-shopping activities (there is also a spike at 12 days for the recreation activity purpose). While there is some evidence of similar weekly rhythms for the shopping activities in Figure 1, they are not as pronounced as for the non-shopping activities.

The reader will note the clear differences between the baseline hazard profiles in Figures 3 and 4, and the corresponding sample hazard profiles in Figures 1 and 2. First, the baseline hazards are either flat or increasing between 1 to 5 days while the sample hazards are decreasing during the same period. Second, the baseline hazard for the shopping categories reveals a general increasing trend while the sample hazard shows a general decreasing or flat trend for these categories. Clearly, the baseline trend is more intuitive and reasonable because of inventory depletion effects. Third, the weekly rhythms (spikes at 7 and 14 days) as reflected in the baseline hazard are much more pronounced than in the sample hazard. These differences between the baseline and sample hazards emphasize the need to recognize the variations in interactivity duration due to covariates and intra-individual/ inter-individual differences.

To summarize, two general conclusions may be drawn from the above results. First, the shopping hazards show positive duration dependence and a mild weekly rhythmic pattern; the non-shopping hazards show a relatively flat profile, but with very prominent weekly rhythmic pattern. Thus, inventory depletion appears to drive shopping patterns, while weekly rhythm appears to drive the non-shopping patterns. Second, the hazard functions are anything but smooth and monotonic. Consequently, parametric hazard functions used commonly in transportation are not suitable for interactivity duration analysis. A non-parametric approach is more appropriate for accommodating non-monotonic and multi-spike profiles, and is also able to handle multiple participation episodes during the sample day (*i.e.*, ties in interactivity duration).

4.2 Covariate Effects

In this section, we discuss the effect of covariates on the duration hazard for all the five activity purposes. It should be observed from Equation (2) that a positive coefficient on a covariate implies that the covariate lowers the hazard rate, or equivalently, increases the intershopping duration (decreases shopping frequency). Alternatively, a negative coefficient on a covariate implies that the covariate increases the hazard rate, or equivalently, decreases the intershopping duration (increases shopping frequency).

Table 3 shows the estimated covariate effects for the final model specification. These effects are discussed by variable category in the subsequent sections.

4.2.1. Effect of Individual and Spouse Characteristics

The effects of employment-related variables within the class of individual and spouse characteristics indicate that individuals who work full-time (greater than 20 hours per week) have a lower hazard (*i.e.* higher interactivity duration or lower frequency of participation) for non-maintenance shopping activities relative to other individuals (however, there are no systematic variations in the non-maintenance shopping hazard among full-time employed individuals based on number of work hours). The results also show that individuals who work longer have a lower hazard (*i.e.* a higher interactivity duration) than individuals who work shorter durations for maintenance activities. These employment-related effects on shopping activity participation are likely to be manifestations of tighter time constraints for individuals who are employed full-time and work long hours. The effects of the employment variables (full-time employed dummy variable and number of work hours) for the recreational activity purpose are interesting. The positive coefficient on number of work hours indicates that longer hours of work implies a lower hazard or longer inter-recreation duration, presumably because of time constraints. But this time constraint effect is tempered for full-time employed individuals (note that the overall coefficient on work hours is positive even for full-time employed individuals: the magnitudes of the coefficients on the full-time employed dummy variable and the number of work hours suggests that the coefficient on work hours is positive beyond 21 hours for full-time employed individuals, which is exactly the threshold point for defining a full-time employed individual). A possible reason for the tempering effect of time constraints for full-time employed individuals is that these individuals are intrinsically more dynamic “go-getters”, who place a premium on physical and mental activity/relaxation. Finally, within the group of employment variables, spousal employment leads to a higher interactivity hazard for maintenance shopping, possibly due to higher responsibilities for household maintenance shopping if an individual's spouse is employed (we also explored the interaction effects of employment status and weekend participation on the interactivity hazards for all the activity types to examine any differential preferences between employed and unemployed individuals for weekend activity pursuits; the only interaction effect that turned out to be significant was for the recreational activity purpose, and we discuss this effect under day of week effects).

The effect of age is included as a non-linear effect (the non-linear specification turned out to be better than a linear representation). The results show that teenagers are less likely to participate in maintenance shopping, recreation, and personal business activities, and more likely to participate in social activities, compared to other adults. This is not unexpected, since teenagers are likely to "hang out" with their friends in a social setting and share less of the maintenance responsibilities of the household compared to their older counterparts. The only other age-related effect is the higher hazard (or lower interactivity duration /higher participation rate) of seniors (age > 65 years) in personal business activities.

The impacts of other variables within the class of individual and spousal characteristics show the higher participation rate of women in maintenance shopping (a recurring finding in the literature; see Frusti *et al.*, 2003), and the higher participation rates of retired individuals in maintenance and personal business activities. The results also show that women and married individuals are less likely to participate in recreational activities.

4.2.2. Effect of Household Characteristics

The effect of household characteristics indicates that individuals in nuclear family households have a higher hazard for maintenance shopping compared to other households. This may be attributed to the higher household responsibilities and maintenance needs of nuclear family households. On the other hand, individuals in nuclear family households have a lower hazard for recreational pursuits, perhaps again due to the higher household responsibilities and biological demands of young children. The influence of income on the hazard of “other (non-maintenance) shopping” and recreational activities is intuitive, and reflects the higher expenditure potential of high income households for discretionary activities. Interestingly the results show that the number of motorized vehicles does not have any statistically significant effect on participation rates in each (and all) activity purposes. This may be because of one or both of the following reasons. First, the urban transit level of service is quite good in German cities, and this leads to less general dependence on motorized vehicles for transport. Second, individuals and households may locate themselves based on their mobility preferences and motorized vehicle ownership desires. For example, individuals and households who are unable to, or choose not to, own motorized vehicles may locate themselves in areas with very good transit services so that their mobility desires are fulfilled. This self-selection in residential location gets manifested as a lack of impact of motorized vehicle ownership on activity participation rates. The impact of single family or duplex dwelling shows that individuals residing in such dwellings have a lower hazard for maintenance shopping and recreational activity participation. The effect on maintenance shopping is, however, only marginally significant. The effect on the recreational activity purpose may be a consequence of neighborhoods around single family/duplex dwellings being less pedestrian and non-motorized friendly, leading to fewer physically active recreation activities (such as walking or bicycling around the neighborhood). The last two variables under household characteristics reflect a substitution effect of access to the internet on non-maintenance shopping and the substantial positive impact of the presence of dogs in a household on the recreational activity pursuits (such as walking the dog) of individuals in the household. Of course, both these results must be interpreted with caution. Specifically, these effects may not be true causal effects. For example, the impact of number of dogs on higher recreational participation may simply be an artifact of individuals who are recreational activity-inclined to have dogs in the household.

4.2.3. Effect of Location and Trip-Making Characteristics

The effects of location and trip-making characteristics may be interpreted as follows: (a) Individuals residing in Karlsruhe have a higher hazard (lower interactivity duration) for participation in social and personal business activities compared to individuals in Halle, (b) Individuals who use a car as the primary mode to participate in shopping (especially maintenance shopping) have a lower intershopping hazard (higher intershopping duration or less frequent shopping) than those who use other modes (this may reflect the ability to carry large amounts of groceries if a car is used, resulting in less need to shop frequently), (c) Individuals who chain participations with other activity stops are more likely to participate in all activity purposes, except recreation (perhaps due to the relative ease of participating in activities if the activity is chained with other activities; however, none of these effects are very statistically significant), and (d) Suburban residents and residents of locations with excellent transit service have higher hazards (or lower interactivity durations/higher participation rates) in personal business activities.

4.2.4. Effect of Day of Week Variables

The final set of covariates corresponds to day of week effects. These effects suggest the higher likelihood of participation in maintenance shopping on Fridays and over the weekend, the higher participation rate in other (non-maintenance) shopping on Sundays, the higher participation rates in social activities on Mondays, and the higher participation rates of employed individuals in recreational activities over the weekends.

4.3 Unobserved Heterogeneity Results

The model system used in this paper accommodates (a) Variations in interactivity hazard due to unobserved individual-specific factors (inter-individual heterogeneity), (b) Covariation in the interactivity hazards of different activity types generated by unobserved individual-specific factors, and (c) Variations in interactivity hazard due to unobserved factors not related to individual characteristics (intra-individual heterogeneity). In the next section, we discuss the first two elements listed above. In the subsequent section, we present the results for unobserved intra-individual heterogeneity. In Section 4.3.3, the covariate effects and unobserved heterogeneity results are interpreted in the context of the fraction of variation in interactivity hazard explained by covariates and by unobserved factors.

4.3.1 Unobserved Inter-Individual Heterogeneity and Covariance Among Interactivity Hazards

The unobserved inter-individual heterogeneity for the different activity purposes and the covariance among interactivity hazards is captured by the variance-covariance matrix Ω of v_q (see Section 2.1). As indicated in Section 2.2, we do not estimate this variance-covariance matrix directly. Instead, we parameterize the likelihood function in terms of the Cholesky decomposition (say *S*) of Ω. After obtaining the estimates of *S*, the matrix Ω needs to be computed as $\Omega = S'S$. The relevant standard errors (and *t*-statistics) of the elements of Ω are computed by re-writing the likelihood directly in terms of Ω (Ω-parameterized likelihood function), computing the estimate of Ω from the estimate of S at convergence of the S-parameterized likelihood function, and maximizing the Ω-parameterized likelihood function. This "optimization" will immediately converge and provide the necessary standard errors for the elements of Ω.

The estimated variance-covariance matrix ($\hat{\Omega}$) is shown in Table 4. For ease of discussion, and because of the symmetric nature of the matrix, only the upper triangle is presented. The estimated parameters along the diagonal are highly statistically significant (except for the estimate of "other shopping"), indicating the significant presence of unobserved individual-specific factors affecting interactivity durations. Several of the off-diagonal estimates are also statistically significant at the 0.1 level of significance, indicating significant covariance among the interactivity hazards (the hypothesis of no covariance among all activity categories is strongly rejected by a likelihood ratio test; see Section 4.4). The covariance estimates indicate that the interactivity hazard for maintenance shopping is strongly correlated with the hazards for other shopping and personal business activities. That is, if an individual has an intrinsically low hazard (low participation frequency) for maintenance shopping, s/he will also have an intrinsically low hazard (low participation frequency) for other shopping and personal business activities. Equivalently, an individual with an intrinsically high hazard (high participation frequency) for maintenance shopping will also have an intrinsically high hazard (high participation frequency) for other shopping and personal business activities. On the other hand, there is a negative correlation between the hazard of maintenance shopping and those of social and recreational activity types (these, however, are not statistically significant). The hazard for "other" (non-maintenance) shopping is positively correlated with social and personal business activities (as well as maintenance shopping, as already discussed earlier). The results also show the statistically significant positive correlation between social and recreational activity participation.

Overall, four general conclusions may be drawn from Table 4. First, there are unobserved individual-specific factors that impact the hazard (participation rate) of activity engagement. Second, there is complementarity in participation in maintenance shopping, other shopping, and personal business activities due to unobserved individual factors (perhaps, a general inclination toward shopping, grooming, *etc*.). Third, there is a strong substitution effect between individual participation in maintenance shopping and social-recreational activities. Finally, there is a strong complementary effect in social and recreational activity participation due to unobserved individual factors (perhaps due to an overall inclination to participate in physically active and non-physically active leisure).

4.3.2 Unobserved Intra-Individual Heterogeneity

Unobserved intra-individual heterogeneity is captured by the variance of the gamma distribution term, c_{qmi}, for each activity purpose *m*. These values are estimated as follows (*t*-statistics are in parentheses): (1) maintenance shopping: 0.4490 (4.633), (2) non-maintenance shopping: 0.6825 (3.978), (3) social activities: 0.5596 (4.106), (4) recreation: 0.4248 (5.029), and (5) personal business: 0.3316 (2.244). Clearly, all these variance estimates are highly significant, suggesting the presence of statistically significant intra-individual heterogeneity for all activity purposes.

The unobserved inter-individual and intra-individual heterogeneity estimates indicate the presence of heterogeneity, but do not provide an intuitive sense of the magnitude of the different sources of unobserved heterogeneity and the effect of observed heterogeneity (*i.e.*, the effect of covariates). The next section translates the statistical estimates into more intuitive measures.

4.3.3 Variation Components of Interactivity Hazard

The covariate effects and the variances of the unobserved heterogeneity terms provide important information regarding the fraction of variation in the interactivity hazard explained by covariates and by unobserved factors. To see this, consider Equation (2) and take the logarithm of both sides of the equation to yield the following equation:

$$\ln \lambda_{qmi}(\tau) = \ln \lambda_{m0}(\tau) - \beta'_m x_{qmi} - v_{qm} + \ln c_{qi}, \text{ where } c_{qi} = \exp(\varpi_{qmi}). \tag{11}$$

Since the baseline hazard $\lambda_{m0}(\tau)$ is the same across all interactivity spells for each activity purpose *m*, the variance across spells of the (log) interactivity hazard for purpose *m* can be partitioned as follows:

$$Var\left[\ln \lambda_{qmi}(\tau)\right] = Var(\beta'_m x_{qmi}) + \left[Var(v_{qm}) + Var(\ln c_{qmi})\right], \tag{12}$$

where $Var(\beta'_m x_{qmi})$ represents the variance due to observed heterogeneity and the second term on the right hand side of the equation (shown in parenthesis) represents the variance due to unobserved heterogeneity. The variance due to unobserved heterogeneity for purpose *m* can be further partitioned into inter-individual and intra-individual heterogeneity. The extent of unobserved inter-individual heterogeneity is provided by $Var(v_{qm})$, while the extent of intra-individual unobserved heterogeneity is provided by $Var(\ln c_{qi})$.

The percentage of variation in the departure time hazard explained by each of the different variance components can be computed from the estimates of β_m and the estimated variance of the error components. These percentages are presented in Table 5. The percentage of variation captured by observed and unobserved factors is indicated first. Next, within unobserved heterogeneity, the percentage of variation captured by intra- and inter-individual heterogeneity is presented. Thus, the number associated with inter-individual heterogeneity in Table 5 indicates the percentage of unobserved heterogeneity captured by inter-individual heterogeneity. Several important observations may be drawn from this table. First, there are quite substantial differences in our ability to explain the interactivity hazard across activity types. The best prediction ability is for the maintenance shopping and recreational purposes, and the poorest is for participation in social activities. An alternative way to interpret these results is that there is substantial randomness in social activities (*i.e.*, spur-of-the-moment participations) in social activities compared to other activity types. Second, variation in the hazard (or equivalently, interactivity duration) due to unobserved factors is higher across individuals than within the spells of the same individual for all activity purposes except “other” (non-maintenance) shopping. Third, there is substantial intra-individual variations in the length of intershopping spells for the “other shopping” category. Fourth, the magnitude of both inter-individual and intra-individual unobserved heterogeneity is sizable for all activity purposes. This reinforces the need to collect multi-day data that can estimate and disentangle these two sources of unobserved heterogeneity, thus allowing the accurate and reliable effect of covariates to be estimated.

4.4 Model Fit Statistics

The log-likelihood at convergence for the multivariate hazard model estimated in this paper with 154 parameters is –17092.2. The corresponding number of parameters and likelihood values for other restrictive models are as follows: (1) Univariate hazard structures for each activity purpose separately, but with inter-individual heterogeneity and intra-individual unobserved heterogeneity (144 parameters) is –17124.7, and (2) Univariate naive hazard structure assigning a single hazard profile across all individuals (93 parameters) is –17836. A likelihood ratio test of the multivariate model estimated in the paper with restricted model (1) clearly indicates the significant presence of covariations in the interactivity hazards of the different activity purposes (the likelihood ratio statistic is 65, which is greater than the chi-squared value with 10 degrees of freedom at any reasonable level of significance). Similarly, comparisons of the model estimated in the paper with the model (2) indicates the need to recognize inter-individual unobserved heterogeneity and the significant influence of demographic, locational, and day of week factors on interactivity durations. Overall, the multivariate mixed hazard model estimated in this paper fits the data much better than any of the restrictive forms.

5. CONCLUSIONS

This paper has focused on examining the interactivity durations of five activity purposes over a multi-week period using a continuous six-week travel diary collected in the German cities of Karlsruhe and Halle in the Fall of 1999. The methodology proposed and applied in the paper uses a hazard-based structure that addresses several econometric issues, including (1) allowing a non-parametric baseline hazard to account for non-monotonicity in the interactivity durations dynamics and spikes in the hazard based on weekly rhythm of participation in activities, (2) recognizing the interval-level nature of interactivity durations: that is, recognizing that a day is an interval of time, with several individuals having the same interactivity duration, (3) incorporating unobserved heterogeneity due to both inter-individual as well as intra-individual differences, and (4) accommodating the presence of common individual-specific unobserved factors that influence the interactivity duration hazard (or equivalently, participation rates) of multiple activity purposes. All of these econometric issues are considered within an efficient, unifying, framework that is easy to implement. The efficiency originates from the use of a gamma distribution for intra-individual unobserved heterogeneity, so that the probability of an interactivity spell terminating at a particular length, conditional on the error terms generating inter-individual unobserved heterogeneity and covariance among interactivity hazards, takes a closed form structure. The efficiency also is a consequence of a single underlying variance-covariance matrix forming the basis to capture both inter-individual heterogeneity in interactivity hazards as well as covariance in the different hazards for each individual. As a result, the dimensionality of integration during estimation is the same as the number of activity purposes in the analysis. Overall, the multivariate hazard model presented here represents a very efficient, powerful, structure for the joint analysis of multiple duration categories. To our knowledge, this is the first formulation and application of a multivariate non-parametric hazard structure in the econometric literature. The resulting model is estimated using a simulated maximum likelihood method.

The application of the multivariate model to examine interactivity durations in five activity purposes using the German MobiDrive data provides several important insights. First, individuals are more likely to engage in shopping activities (both maintenance shopping and no-maintenance shopping) as the time elapsed since their previous participation increases. However, there is no such clear duration dynamics for non-shopping activities. Second, there is a very distinct weekly rhythm in individuals' participation in social, recreation, and personal business. While there is a similar rhythm even for the shopping purposes, it is not as pronounced as for the non-shopping purposes. Thus, inventory depletion appears to drive shopping participation, while weekly rhythms appear to drive non-shopping participation. Third, individual and spouse attributes, household characteristics, residential location and trip-making variables, and day of week effects have a strong influence on interactivity duration. Among these, two particularly interesting findings are the substitution effects of access to internet at home on non-maintenance shopping activity participation and the strong positive influence of the number of dogs in the household on recreational activity participation. It is also interesting to note the lack of effect of number of motorized vehicles owned by the household and the residence location/transportation service characteristics on participation rates. This latter finding may be a reflection of relatively consistent and good quality of transit service across all neighborhoods in German cities and/or self-selection into residential locations based on preferences to own motorized vehicles and mobility desires. Fourth, there is significant and substantial unobserved inter-individual variation in the duration hazards for the different activity types (varying from 10 to 72% of total unobserved heterogeneity for activity purposes), as well as significant and substantial intra-individual variation (varying from 23 to 90% of total unobserved heterogeneity for activity purposes). Thus, there is a need to collect and analyze activity participation behavior using multi-day survey data. Fifth, there is a strong substitution effect between individual participation in maintenance shopping and social-recreational activities, and there is a strong complementary effect in social and recreational activities.

There are, as always, several avenues to extend the current research. First, there is no explicit accounting of the interaction among household members on individual activity participation behavior; rather, the effect of such interactions is accommodated implicitly using household-level variables such as marital status and spouse’s employment status. Second, several of the independent variables used in the analysis may be co-determined with interactivity duration. For example, the need to shop frequently may lead to a higher-level of chaining the activity with other activities. Thus, it would be more appropriate to model travel mode choice, activity chaining, internet-use, residential location, and interactivity duration jointly. Of course, there also needs to be the realization that it is not possible to model all dimensions of residential, activity, and travel jointly. Extensive empirical studies to establish a reasonable simplifying structure for activity-travel modeling always remains an area for further exploration.

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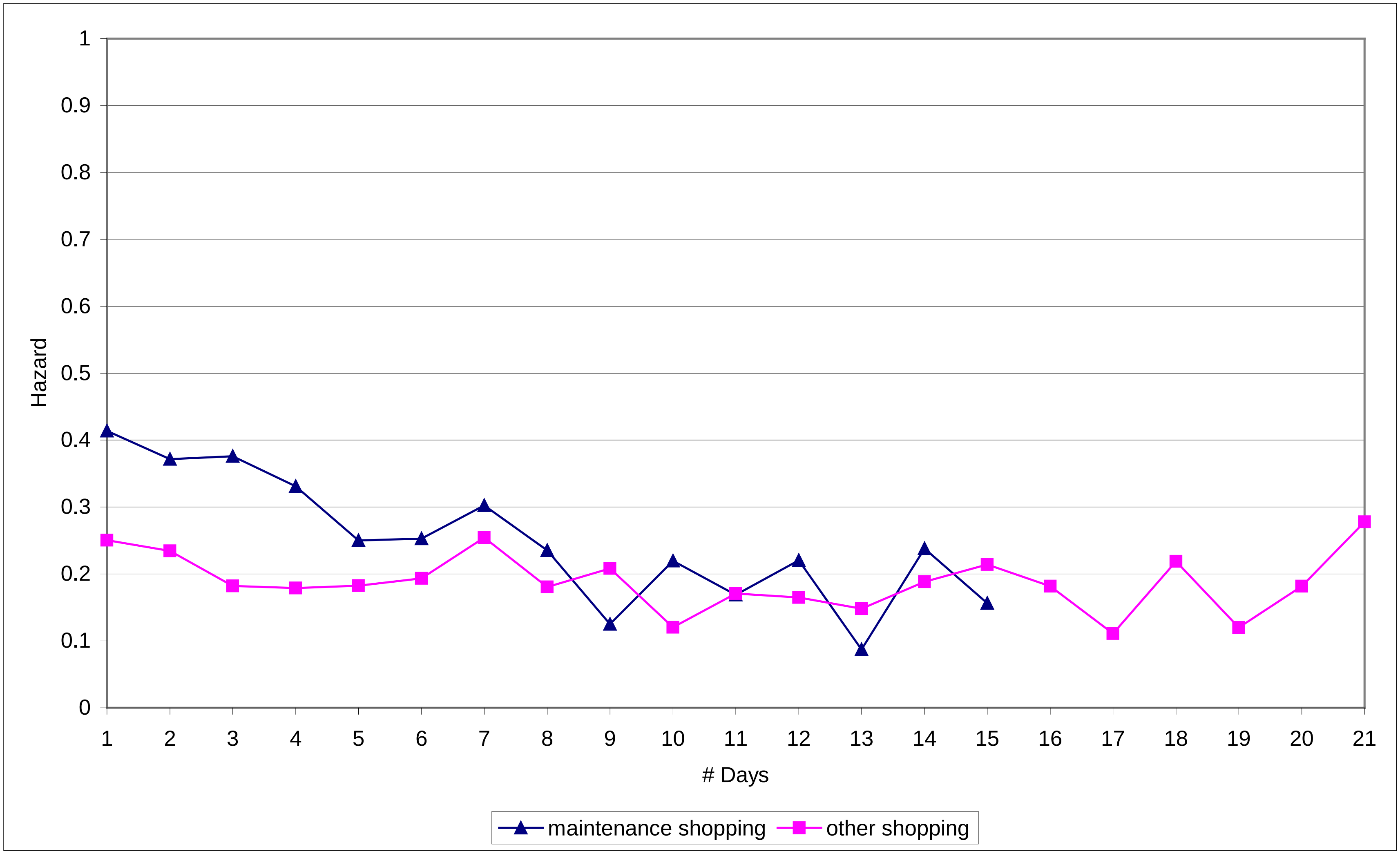

Figure 1. Sample hazard for shopping activities

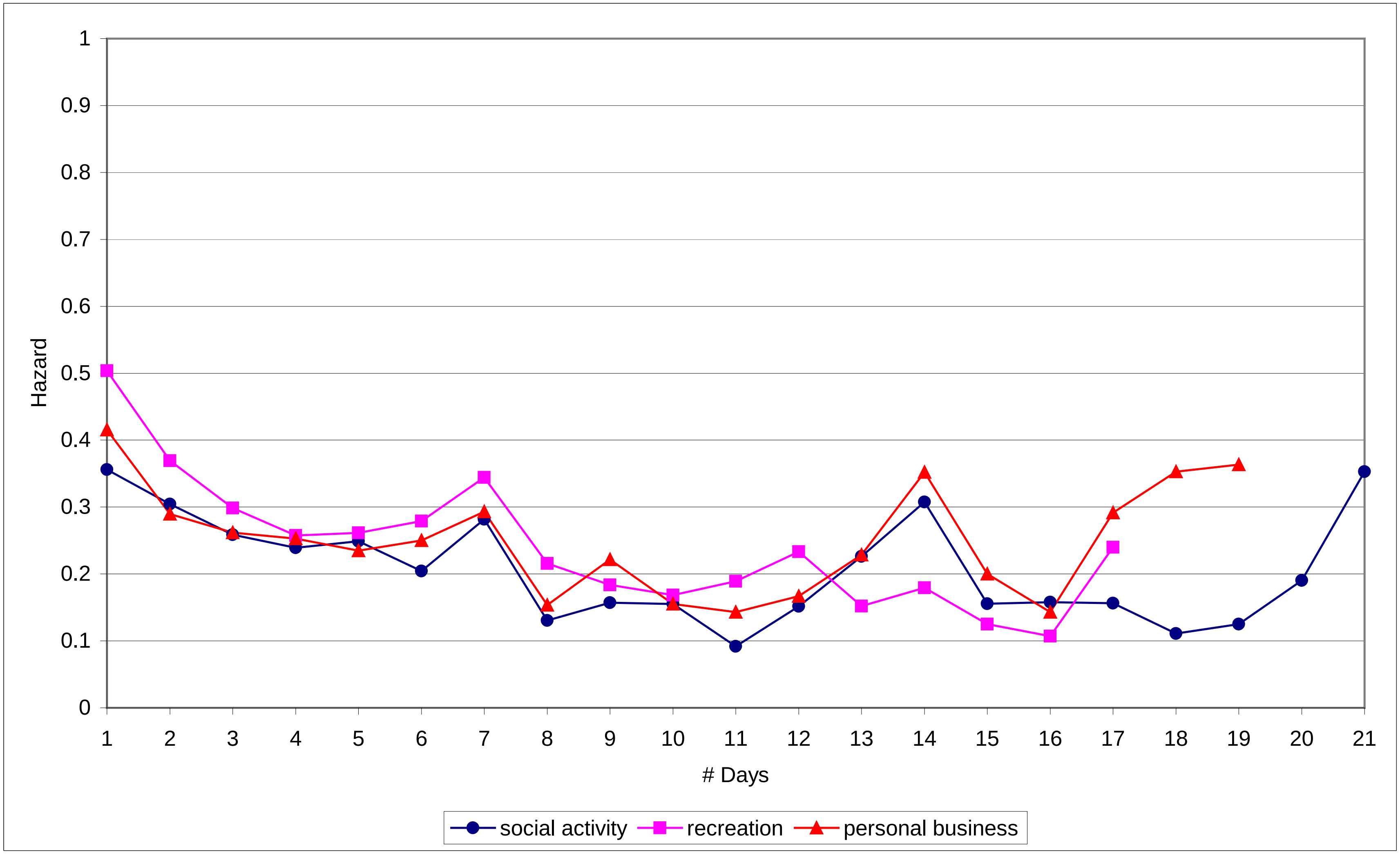

Figure 2. Sample hazard for non-shopping activities

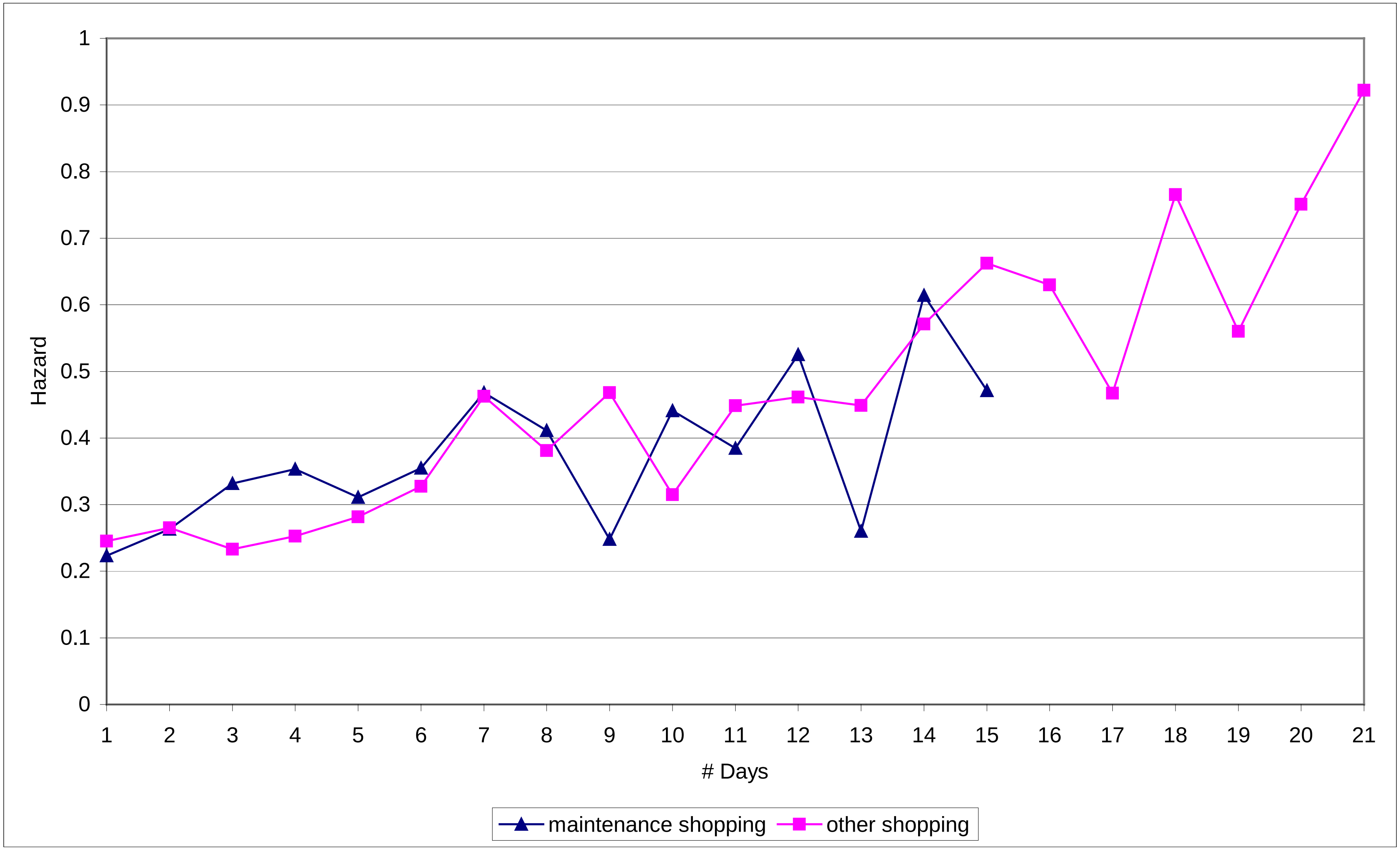

Figure 3. Baseline hazard for shopping activities

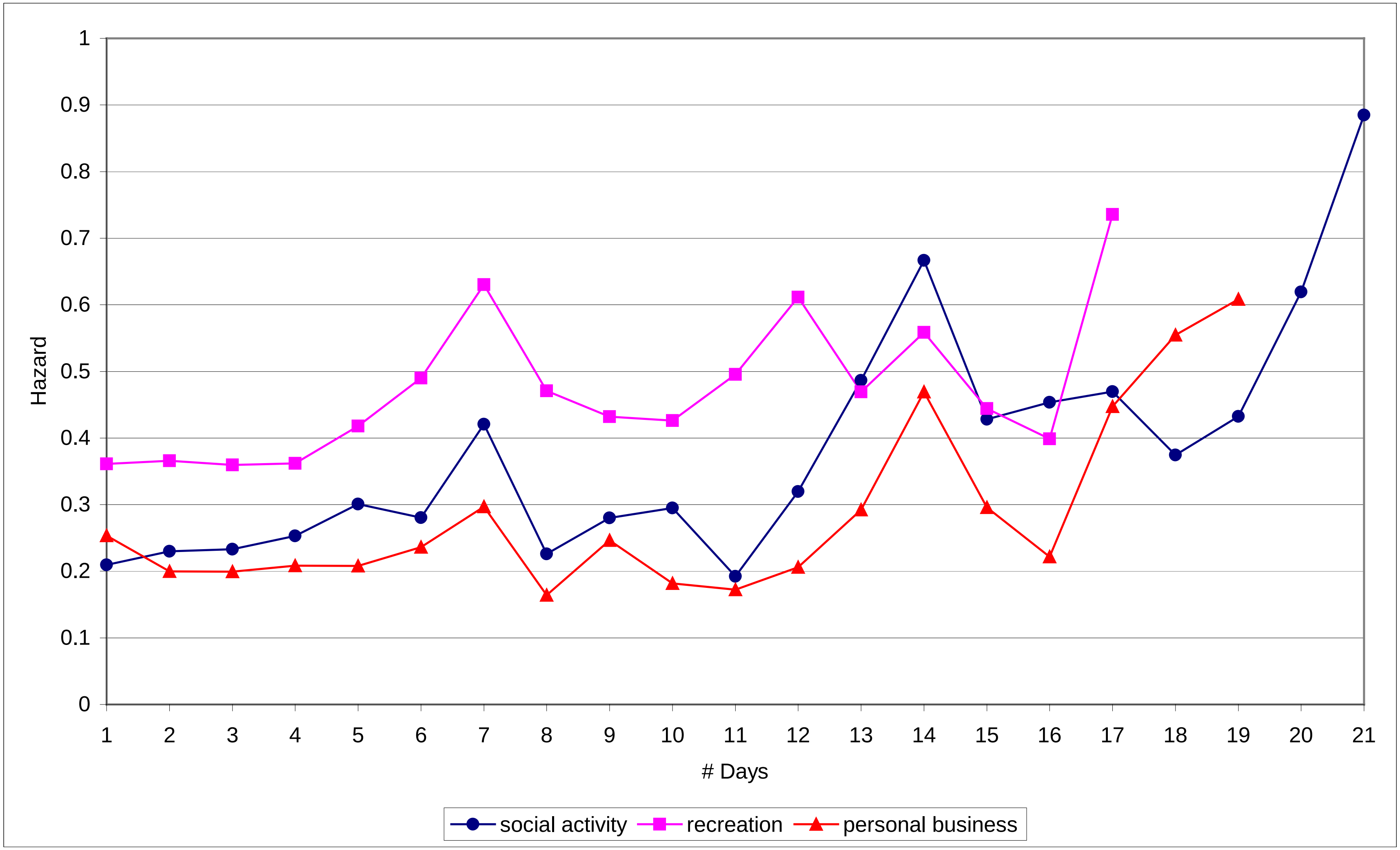

Figure 4. Baseline hazard for non-shopping activities

Table 1. Number and Range of Interactivity Duration Spells

Activity type	Number of interactivity duration spells per person: range (mean value)	Interactivity duration spell length: range (mean value)	Upper end cut-off of interactivity duration length for empirical analysis (percentage of spells over cut-off value)
Maintenance shopping	1 to 36 (11.78)	1 to 31 days (2.87 days)	16 days (1.0%)
Other shopping	1 to 18 (5.64)	1 to 38 days (4.84 days)	22 days (0.8%)
Social activities	1 to 34 (8.45)	1 to 37 days (3.70 days)	22 days (0.7%)
Recreation	1 to 40 (12.71)	1 to 38 days (2.71 days)	18 days (0.7%)
Personal business	1 to 37 (9.87)	1 to 26 days (3.31 days)	20 days (0.3%)

Table 2. Individual-Level Variable Definitions and Sample Statistics (Number of Individuals = 192)

Variable	Definition	Mean	Std. Dev.
Individual and spouse characteristics			
Full-time employed	1 if the individual works more than 20 hours per week, 0 otherwise	0.4948	0.5013
Number of work hours (x10^{-1})	Number of work hours per week (divided by 10)	2.1661	2.0631
Spousal employment	1 if spouse is employed, 0 if spouse is not employed or person is not married	0.4479	0.4986
Age less than 20 years	1 if the age of the individual is less than 20 years, 0 otherwise	0.0781	0.2691
Age greater than 65 years	1 if the age of the individual is greater than years, 0 otherwise	0.0833	0.2771
Female	1 if the individual is a female, 0 otherwise	0.5313	0.5003
Retired	1 if the individual is retired, 0 otherwise	0.2031	0.4034
Married	1 if the individual is married, 0 otherwise	0.6300	0.4850
Household Characteristics			
Nuclear Family	1 if family includes parents and one or more children, 0 otherwise	0.3854	0.4880
Income (000s)	Monthly household income (in 1000s of Deutche Marks)	4.3050	2.0703
Number of motorized vehicles	Number of motorized vehicles in the household	1.2100	0.7170
Single family or duplex dwelling	1 if the household lives in a single family or duplex dwelling unit, 0 otherwise	0.2135	0.4109
Access to internet at home	1 if the individual has private access to e-mail, 0 otherwise	0.2292	0.4214
Presence of dogs	1 if dogs are present in household, 0 otherwise	0.0900	0.2920
Location and trip-making characteristics			
Karlsruhe	1 if the household is in Karlsruhe, 0 otherwise	0.6250	0.7057
Car is the primary mode for:			
Maintenance shopping	1 if car is the most frequently used mode for maintenance shopping, 0 otherwise	0.4427	0.4980
Other shopping	1 if car is the most frequently used mode for other shopping, 0 otherwise	0.6042	0.4903
Social activities	1 if car is the most frequently used mode for social activities, 0 otherwise	0.6458	0.4795
Recreation	1 if car is the most frequently used mode for recreation, 0 otherwise	0.5312	0.5003
Personal business	1 if car is the most frequently used mode for personal business, 0 otherwise	0.5313	0.5003
Percentage of episodes chained for:			
Maintenance shopping	Percentage of maintenance shopping episodes chained with other activities	0.4646	0.3099
Other shopping	Percentage of other shopping episodes chained with other activities	0.5422	0.3300
Social activities	Percentage of social activity episodes chained with other activities	0.3780	0.2852
Recreation	Percentage of recreation activity episodes chained with other activities	0.4689	0.2721
Personal business	Percentage of personal business activity episodes chained with other activities	0.5410	0.2858
Suburban residence	1 if the household is in suburban area, 0 otherwise	0.1979	0.3995
Excellent transit service	1 if access to bus, light rail and heavy rail are all within 25 meters of home, 0 otherwise	0.1667	0.3737

Table 3. Multivariate Mixed Hazard Duration Model (Covariate Effects)

Covariates	Maintenance shopping		Other (non-maintenance) shopping		Social activities		Recreation		Personal business	
	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.
Individual and spouse characteristics										
Employment related										
Full-time employed	-	-	0.2507	2.51	-	-	-0.3357	-1.18	-	-
Number of work hours (x10^{-1})	0.0784	2.51	-	-	-	-	0.1684	2.29	-	-
Spousal employment	-0.1908	-1.55	-	-	-	-	-	-	-	-
Age related	-	-	-	-	-	-	-	-	-	-
Age less than 20 years	0.8806	3.79	-	-	-0.6318	3.02	0.4049	1.99	0.3028	1.82
Age greater than 65 years	-	-	-	-	-	-	-	-	-0.2013	-1.22
Other variables										
Female	-0.5305	-4.51	-	-	-	-	0.2670	2.32	-	-
Retired	-0.2895	-1.86	-	-	-	-	-	-	-0.2239	-1.75
Married	-	-	-	-	-	-	0.1532	1.16	-	-
Household Characteristics										
Nuclear Family	-2.0960	-1.65	-	-	-	-	0.3237	2.08	-	-
Income (000s of DM)	-	-	-0.0362	-1.31	0.0686	2.41	-0.1150	-3.28	-	-
Number of motorized vehicles	-	-	0.0954	1.28	-	-	-	-	-	-
Single family or duplex dwelling	0.2287	1.72	-	-	-	-	0.5882	3.97	-	-
Access to internet at home	-	-	0.3738	2.78	-	-	-	-	-	-
Presence of dogs	-	-	-	-	-	-	-1.2872	-5.98	-	-
Location and trip-making characteristics										
Karlsruhe	-	-	-	-	-0.4227	-3.32	-	-	-0.2310	-2.52
Car is the primary mode for activity	0.4547	3.89	0.0922	0.95	-	-	-	-		
Percentage of episodes chained	-0.2905	-1.84	-0.2837	-1.62	-0.3468	-1.59	-	-	-0.1395	-0.86
Suburban residence	-	-	-	-	-	-	-	-	-0.1569	-1.62
Excellent transit service	-	-	-	-	-	-	-	-	-0.2855	-2.54
Day of the week variables										
Friday	-0.3308	-4.56	-	-	-	-	-	-	-	-
Saturday	-0.2302	-3.00	-	-	-	-	-	-	-	-
Sunday	-0.3999	-1.75	-0.3234	-1.35	-	-	-	-	-	-
Monday	-	-	-	-	-0.2332	-1.78	-	-	-	-
Employed*weekend	-	-	-	-	-	-	-0.1971	-2.24	-	-

Table 4. Variance-Covariance of Interactivity Hazards, Only Upper-Triangle Elements Presented (t-stats in parenthesis)

Activity type	Maintenance shopping	Other shopping	Social activities	Recreation	Personal business
Maintenance shopping	0.5621 (5.36)	0.1211 (2.61)	-0.0216 (-0.51)	-0.0575 (-1.40)	0.1632 (4.06)
Other shopping	-	0.064 (1.54)	0.0433 (1.65)	0.0032 (0.23)	0.1033 (2.82)
Social activities	-	-	0.4421 (4.13)	0.0738 (2.13)	0.0561 (1.66)
Recreation	-	-	-	0.661 (5.68)	-0.0319 (-.90)
Personal business	-	-	-	-	0.2105 (4.24)

Table 5. Percentage of Interactivity Hazard Variance Explained by Observed and Unobserved Factors

Heterogeneity source	**Maintenance shopping**	**Other shopping**	**Social activities**	**Recreation**	**Personal business**
Observed heterogeneity	**24**	**16**	**9**	**22**	**14**
Unobserved heterogeneity	**76**	**84**	**91**	**78**	**86**
Inter-individual	72	10	54	77	65
Intra-individual	28	90	46	23	35