Modelling Individuals' Frequency and Time Allocation Behaviour for Shopping Activities Considering Household Level Random Effects

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ABSTRACT

The paper describes a comprehensive frequency and time allocation modelling system for shopping activities. The modelling system is person-based but explicitly considers fixed and random household effects. It has three components: a weekly shopping frequency model, a daily shopping frequency model, and a time allocation model for individual shopping episodes. The frequency models consider activity generation as a latent response, the *propensity* to participate in shopping activities. This latent response is modelled using an ordinal response model. Both the weekly and daily frequency models are multilevel ordinal logit models, where the household is the highest level and the individual person is the lowest level. The multilevel ordinal logit models incorporate household level influences on an individual's shopping behaviour in term of fixed effects and a random intercept. The time allocation models are hazard duration models that consider household-level random heterogeneity. The entire modelling system is sequential from the weekly frequency component to the time allocation component. The outputs of the earlier components enter as inputs to the later components: weekly frequency is the input to the daily frequency model; weekly and daily frequencies are input to the time allocation model. The system is designed to overcome the deficiencies of household-level information in the personal-level activity diary data that are used to develop the model.

INTRODUCTION

Activity-based modelling systems are divided into two broad types: activity program generation and activity scheduling.[*1*] The activity program can also be defined as an activity agenda.[*2*] Agenda formation (activity program generation) is a critical part of activity-based modelling because it includes issues that are partly latent; i.e., we cannot fully observe the agenda of an individual person.[*3*] Chapin (1974) defines this activity generation process by four attributes: *propensity, opportunity, appropriateness of timing and circumstances, environmental context*.[*4*] These are basically defined by motivational and constraining factors experienced by the individual.[*5*] The household within which the individual resides provides many of these motivational and containing factors.[*6*] Household-level effects on individual's activity behaviour are often latent in nature. This latency is exaggerated by the way data are generally collected in activity surveys. Despite their length and detail, household-level information generally is incomplete in these surveys, especially if all members of the household do not participate in the survey.[*7, 8*] But, being nested within the household the individual's activity generation is influenced by the household as a whole. Modelling activity generation and time allocation requires attention to this issue. Researchers often recognize household-level effects on an individual's activity behaviour by incorporating household-level information as exogenous variables,[*9*] or by proposing detailed household-based modelling systems that require comprehensive data.[*1, 6*] Recognizing the existence of incomplete household-level information in activity survey data and household-level latent effects on individual's activity behaviour is a major research challenge. The multilevel modelling approach is a promising tool in this purpose.[*8*] This paper describes a comprehensive frequency and time allocation modelling system for individuals' shopping activity that recognizes household-level latent effects. The generation of shopping activities is defined by the frequency corresponding to the latent variable *propensity* to participate in shopping activities. The temporal level of frequency is divided into two parts: weekly frequency and daily frequency. In the shopping activity generation model the individual is considered nested within the household. In addition to household-level covariates (fixed effects), the latent household influence is recognized by incorporating household-level random effects. Given the weekly and daily frequency, the time allocated to individual shopping episodes is modelled as a hazard-based duration model.

The paper is organized as follows. The motivations and the approaches of the paper are described in the next section, followed by sections describing individual modelling techniques, data used for the analysis and interpretations of the models developed. The paper ends with some conclusions.

MODELLING SHOPPING ACTIVITIES

Reichman (1976) defines shopping activities as maintenance type activities required to acquire goods for the needs of the person as well as the household.[*10*] Miller (2005) recognizes shopping activities as an individual activity type nested within different projects (where a project is a group of activities with a common goal).[*11*] Thus, the shopping activity is not always directed by an individual's personal needs; household-level latent factors play a significant role in generation and time allocation processes for this type of activity. Modelling shopping activities is not new in the literature. However, efforts to model this type of activity explicitly and comprehensively are rare. Some of the works in this area are discussed here.

The conceptual framework of Bhat and Koppelman (1993) makes some types of shopping activity generation conditional to household auto availability and describes shopping activities as temporally more flexible than other activities.[*1*] Therefore an individual's shopping activity is often modelled as temporally opportunistic type behaviour.[*12*] Bhat *et al* (2004) model the shopping activity generation indirectly by modelling the inter-shopping duration distribution considering the individual's affinity or dislike for shopping activities.[*13*] Bhat and Misra (1999) and Bhat (1998) model shopping activities combined with other out-of home activities. Although some of this research recognizes the household influence on individuals' shopping activity,[*14, 12*] they consider the household effect either directly by incorporating household level socio-economic variables or propose very comprehensive modelling approaches that are often not supported by the data available from activity diary surveys.[*7, 8*] The explicit recognition of household-based latent influences on individuals' shopping activity generation - time allocation process is missing in these studies. To overcome these issues, this paper proposes a comprehensive frequency and time allocation modelling system for shopping activities.

The generation stage of the proposed modelling system is divided into two parts: weekly frequency and daily frequency. Weekly frequency enters the daily frequency model as a covariate, recognizing the fact that the daily shopping frequency is not strictly conditional on the weekly shopping propensity. The weekly frequency represents the weekly propensity to shop, reflecting the individual's shopping affinity or aversion to shopping, given the household- and person-level constraints and opportunities. The daily frequency represents the daily propensity to shop that reflects both time pressure as well as household-level needs and constraints. Both daily and weekly frequencies enter into the time allocation model as covariates. Thus, the overall design of the frequency-time allocation system is modular: the individual components are estimated separately. The weekly and daily frequency models assume that shopping frequency is ordinal in nature. Although activity frequency is often modelled as a count variable,[*15, 16*] the basic limitation of this approach is the assumption of independence among the consecutive events. This assumption is very restrictive for shopping activity *per se*. An individual's shopping frequency within a time frame (week or day) is cumulatively dependent rather than independent. On the other hand, inter-shopping duration distribution models require multi-week activity diary data because, in single-week activity diary, the maximum observations of inter-shopping duration remain either left- or right-censored. So, the ordinal response variable model is more appropriate for single-week activity diary data. In this paper, the frequency models are ordinal response variable models. They assume the individual of concern is nested within the household, and, hence, a multilevel modelling approach is required. In multilevel ordinal response models, in addition to the household level covariates as fixed effects, the household is assumed to have a latent influence on individual's shopping propensity. This latent influence is modelled as a random intercept term within the models.

The time allocation for an individual shopping episode is modelled using a continuous time hazard model. Being opportunistic and temporally flexible in nature, the start time and durations of shopping activities supports continuous time modelling better than models with discrete time representation. The continuous time hazard models are shared frailty models. The individual is considered nested within the household and household-based random effects are assumed to have a particular distribution (the Gamma distribution is considered for computational convenience).

MULTILEVEL ORDINAL LOGIT MODEL

The ordinal response model is basically a latent response model, where the actual dependent variable is latent. The observed dependent variables are specific values corresponding to the values of the latent variables exceeding certain threshold limits. In this case activity propensity is the latent variable. The number of activity episodes per day or number of days per week is observed as an integer number, defined by the term activity frequency. This frequency corresponds to the latent variable, propensity. If the propensity of an individual *i* in household *j* is defined by Y_{ij}^* and the corresponding frequency is Y_{ij} and τ_n (n=1, 2, 3, ….N) represents the threshold values, then [*17*]

$$Y_{ij} = \begin{cases} 1 \quad if \qquad Y_{ij}^* \le \tau_1 \\ 2 \quad if \;\; \tau_1 < Y_{ij}^* \le \tau_2 \\ 3 \quad if \;\; \tau_2 < Y_{ij}^* \le \tau_3 \\ . \\ \\ N \quad if \qquad \tau_{N-1} < Y_{ij}^* \end{cases} \tag{1}$$

In case of such an ordered categorical response, the outcome is cumulative. For example, if the probability of the frequency of shopping, *N*, for the i^{th} person of the j^{th} household is denoted by $Z^{(N)}$ then

$$0 < Z^{(1)} < Z^{(2)} < Z^{(3)} < .... < Z^{(N)} = 1$$

It is interesting to note that the probabilities for frequencies are cumulated upward but the ordered frequencies are cumulated downwards. This indicates the underlying threshold parameter τ_i varies from -∞ to +∞,

$$-\infty < \tau_1 < \tau_2 < \tau_3 < .... < \tau_{N-1} < +\infty$$

So,

$$Z^N = \Pr(\tau_{N-1} < Y_{ij}^* < \tau_N)$$

Now, the latent variable of concern, the propensity of shopping activity, is defined by a linear in parameters equation:

$$\boldsymbol{Y_{ij}^* = \vartheta_{ij} + \varepsilon_{ij}} \tag{2}$$

Where ϑ_{ij} can be expressed as a function of variables (fixed effects) and corresponding coefficients and ε_{ij} is the error term. If the cumulative probability of ε_{ij} is defined by F(.) then

$$\Pr(Y_{ij} \le N) = F(\tau_N - \vartheta_{ij})$$

$$\Pr(Y_{ij} = N) = F(\tau_N - \vartheta_{ij}) - F(\tau_{N-1} - \vartheta_{ij})$$

Equivalently it can be written as,

$$g(P(Y_{ij} < N)) = \tau_N - \vartheta_{ij} \tag{3}$$

Here the *g(.)* is an inverse function of *F(.)* and ($\tau_N - \vartheta_{ij}$) is its linear predictor. This inverse function is termed the *Link Function* of a multilevel model. If the error term of the linear equation for the latent variable Y_{ij}^* is assumed to have a logistic distribution, then

$$\Pr(Y_{ij} \le N) = \Pr(Y_{ij}^* \le \tau_N) = \eta_{ijN} = \frac{\exp(\tau_N - \vartheta_{ij})}{1+\exp(\tau_N - \vartheta_{ij})} \quad (4)$$

So, the cumulative probabilities becomes cumulative logits and we get a proportional odds model conditional on the latent and observed explanatory variables,

$$\log\left(\frac{\Pr(Y_{ij} \le N)}{\Pr(Y_{ij} > N)}\right) = \log\left(\frac{\Pr(Y_{ij} \le N)}{1-\Pr(Y_{ij} \le N)}\right) = \tau_N - \vartheta_{ij} \quad (5)$$

This proportional odds model expresses the ordered response of ζ categories (ζ=1, 2, 3……, N) in terms of ζ-1 cumulative category comparisons or ζ-1 cumulative log odds. Because of this cumulative assumption, the conditional probability of a response in category N is obtained as a difference of two conditional cumulative probabilities, (η_{ijN} - η_{ijN-1}).

Now, the link function *g(.)* represents the conditional expectation of the observed outcome given the explanatory variables and higher level effects. For a multilevel structure where the individual *i* is nested in the household *j*, the latent response variable Y_{ij}^* can be expressed as:

$$Y_{ij}^* = \vartheta_{ij} + u_j + \varepsilon_{ij} = \beta X_{ij} + u_j + \varepsilon_{ij} \quad (6)$$

The u_j represent the random intercept for the household cluster, *j,* in the latent response model. X_{ij} denotes a set of independent variables and β denotes corresponding coefficients. The typical assumption for the cluster specific random intercept is the multivariate normal distribution with 0 mean and σ^2 variance, $u_j \approx N(0,\sigma^2)$. So, the residual of equation (6) stands as

$$\chi^{/} = u_j + \varepsilon_{ij} \quad (7)$$

If the variance of the logistic distribution of ε_{ij} is $\pi^2/3$, then the variance of the residual

$$Var(\chi^{/}) = \sigma^2 + \pi^2/3 \quad (8)$$

Where the $\pi^2/3$ is level-one variance and the σ^2 is the level-two variance. For example, the covariance between the total residuals $\chi_{1j}^{/}$ and $\chi_{2j}^{/}$ of two individuals 1 and 2 within household *j* is σ^2 and intra-household correlation is,

$$\varphi = cor(\chi^{/}{}_{1j}, \chi^{/}{}_{2j}) = \frac{\sigma^2}{\sigma^2 + \pi^3/3} \quad (9)$$

The estimation of the parameters (threshold parameters, parameters corresponding to the explanatory variables) and variances of such a multilevel model is not straightforward because the likelihood function is not closed form. Two types of distributions are involved in such a model. The first one is the *link function* as described above that maps the mean values of the responses to the linear predictors. In our case this is an ordinal logit function. On the other hand, to deal with the response variables, another function should be defined: the *family function*. Since in this case the response is binary for each ordinal class the family function is the binomial distribution, [for details see *18*]. The overall likelihood is then conditional upon the higher-level random effects. The general form of likelihood function of the two-level model is

$$L = \prod_J \int \left\{ \prod_i f(Y_{ij} \mid X_{ij}, U_j) \right\} g(U_j) dU_j \quad (10)$$

Here $f(Y_{ij} \mid X_{ij}, U_j)$ is the conditional density of the response variable given the latent and independent variables and *g(Uj)* is the prior density of the latent variable (corresponding to the household-level latent effect). For multivariate normally distributed latent effect ($u_j \sim N(0,\sigma^2)$), u is expressed as a linear combination of uncorrelated random effects $\boldsymbol{v}$, $\boldsymbol{u=Lv}$, where $\boldsymbol{L}$ is Cholesky decomposition of the covariance matrix. Due to insufficient locations under the peak of the integrand of equation (10), adaptive quadrature is used instead of Gaussian quadrature to ensure a positive semi-definite covariance matrix. The contribution of the second-level household unit to the likelihood function shown in equation (10) is found by integrating the product of contributions from the person- level inside the household over the household-level random effect distribution. The parameters are estimated by using GLLAMM function of STATA that uses the d0 method to maximize likelihood [for details see, *21*]. The d0 method uses Newton Raphson algorithm to solve the parameters iteratively [for details see, *19*].

The test for the statistical significance of the variance component of the household random effect is not easy. The Wald test is not fully justified because the null value is on the border of the parameter space. On the other hand, in case of likelihood ratio test, the test statistics no longer have the conventional chi-square distribution under the null hypothesis. Given these concerns, both tests are used in this paper.

HAZARD-BASED DURATION MODEL FOR TIME ALLOCATION

For continuous time hazard models, two classes of models are considered: semiparametric hazard model and parametric hazard model. The basic difference between these two types is the treatment of the baseline hazard rate. The semiparametric model makes the proportional hazard assumption (covariates have multiplicative effects) and uses the partial likelihood method to estimate the parameters [for details see *20*]. The baseline hazard rate is estimated nonparametrically and separately from the covariates' parameter estimation process. The parametric hazard models assume a distribution for the baseline hazard rate and the parameters are estimated by the full information likelihood method. Parametric models can be both proportional hazard models and accelerated time models (the time scale is expressed as a function of covariates). Inherent in the estimation process, the semiparametric hazard model recognizes the baseline hazard distribution but neglects the direct interaction of the covariates with the baseline distribution. On the other hand, the parametric hazard model parameterizes the baseline rate together and explicitly recognizes the interactions. Detailed comparison of different types of hazard models in terms of underlying theories and applications to activity based modelling are available in [*3*]. In this paper, both semiparametric and parametric models are developed and results are compared. The technical details of the estimations and likelihood functions for these models are available in [*21*].

The semiparametric hazard model used in this paper has the form

$$h_{ij} = h_0(t)\alpha_j \exp(x_{ij}\beta) \tag{11}$$

Where $h_0(t)$ is the baseline hazard rate, α_j is the random effect on the individual i of the household j , x_{ij} represents the covariate matrix of individual i in household j, β represents corresponding parameters and t represents time. The hazard rate, h_{ij} can be transformed to get the survival function of duration of the event [for details, see *3*]:

$$S = \exp\left(-\int_0^t h_{ij}\,dt\right) \tag{12}$$

In this model, the group level random effect, α_j is assumed to have a Gamma distribution with mean value 1 and variance θ. This assumption gives the closed form for the likelihood function, thereby making the estimation process easier. Here the individual observations are clustered according to households, and individuals within the households are correlated because they share the same frailty. The variance of the random distribution, θ, measures the degree of within-household correlation. If the α_j of equation (11) is expressed as a logarithmic function (i.e., let $\log(\alpha_j) = \nu$) then the hazard becomes,

$$h_{ij} = h_0(t)\exp(x_{ij}\beta + \nu) \tag{13}$$

which is analogous to the standard linear model. This model does not contain any constant term because it is homogeneous to degree 0 in number of covariates. The signs of the coefficients in the semiparametric model are direct to the hazard rate. For example, an increasing value of positive signed covariates increases the hazard rate but decreases the duration and vise versa.

The parametric representation of the accelerated time hazard model starts with the representation of the duration of the event as a log-linear function of covariates

$$\ln t_{ij} = x_{ij}\beta + \psi_{ij} \tag{14}$$

The distributional assumptions of the error term, ψ_{ij} gives different types of parametric hazard model. For example the normal distribution assumption gives a lognormal model, the logistic distribution assumption yields a log-logistic model, the extreme value distribution assumption gives an exponential or weibull model, etc. In this paper the weibull, log-logistic and lognormal models are reported. The survival functions of the reported distributions are:

$$\textit{Weibull}, \quad S = \exp(-\exp(-px_{ij}\beta)t^{p}{}_{ij}) \tag{15}$$

$$\textit{Logistic}, \quad S = \{1 + (\exp(-x_{ij}\beta)t_{ij})^{1/\gamma}\}^{-1} \tag{16}$$

$$\textit{Lognormal}, \quad S = 1 - \Phi\{\frac{\ln(t_{ij}) - x_{ij}\beta}{\sigma}\} \tag{17}$$

Here p, γ and σ are corresponding ancillary parameters. The consideration of unobserved heterogeneity of these accelerated time models is also considered as multiplicative as in the semiparametric hazard model

$$h_{ij} = \alpha_j h_{ij}(t) \tag{18}$$

Here $h_{ij}(t)$ is the individual hazard model given the covariates x_{ij}, $h(t|x_{ij})$. The α_j is any positive distribution. Similar to the semiparametric model, it is considered as Gamma distributed with mean value 1 and variance θ. The θ measures the degree of within-household correlation. It is worth mentioning that the coefficients' signs of the covariates in parametric hazard model are opposite to the effects of corresponding explanatory variables on hazard rate but direct to the duration. For example, a positive coefficient variable in a parametric hazard model increases the duration and decreases the hazard and vise versa.

To test whether the household-based random effect is statistically significant or not, the null hypothesis (H_0: $\theta = 0$) is tested for all models. The likelihood ratio from two models, one considering the random effect and the other not considering the random effect, is chi-squared distribution with one degree of freedom, standard values of which for 95% confidence level is 3.84.

DATA

CHASE (Computerized Household Activity Scheduling Elicitor) survey data from the first wave of the Toronto Travel-Activity Panel Survey (TAPS) are used in this paper. The survey was conducted in Toronto, Canada in 2002-2003 with 271 households. The total participants are 426 adults out of 524 total adults in these households. Detailed descriptions of CHASE and TAPS are available in [*22, 23, 7*]. The CHASE survey is a multi-day, self-reporting survey, where the participants list the process of their activity scheduling over a period of 7 days. For each participant, the CHASE program tracks the activity episodes that are added first, then modified or deleted over time. It also identifies the implementation states of the episodes (added or modified). The *added* attribute of the episode indicates the first entry. At the end of 7-day period, it is seen that not all *added* episodes are implemented; some are modified and implemented; some are modified and deleted from the list or deleted at the first stage. So the episodes having the attributes, *added* are considered to have the least scheduling effects within them. These episodes are assumed to be the output of activity generation process.

CHASE divides all activities into nine major groups, of which shopping is one. CHASE collects a variety of attributes related to the activity type, the actor of the activity and the household within which the actor resides. In addition to this general information, some specific information about the activity is collected by actively prompting the respondent in an *End of Week Review* (EWR). EWR does a systematic query of subjects concerning spatio-temporal flexibilities, normal duration, and frequency, etc. of the activity type of concern. A detailed description of this EWR component of CHASE is available in [*24*]. Among the information collected by EWR, the most focused one for this paper is the response to the question "*About How Often Do You Do The Activity?*". The answer of this question is used to calculate the weekly shopping frequency in terms of *number of days per week*. This stated frequency is used to develop the models for weekly shopping frequency. The *added* shopping episodes of the participants who have answered this EWR question are then used to develop daily frequency and time allocation models.

After cleaning the data for missing attributes, a total of 167 persons from 98 households were selected for modelling. For the weekly frequency model, the number of persons is 167; for the daily frequency generation model, the total number of persons is 163 and for the time allocation model, the total number of *added* shopping episodes for these 163 persons is 621. Out of 167 persons, 4 persons are not used in the daily generation and time allocation models because of ambiguous or missing start time-duration information. In CHASE the shopping activities of these selected people are divided into 8 individual types: Convenience store, Major grocery (more then 10 items), Minor grocery (less than 10 items), Houseware, Clothing/Personal item, Drug store, Internet shopping. For the reason of insufficient number of observations, some types are collapsed together. For weekly frequency, the total number of observations is divided into Grocery-household related shopping and Nongrocery-personal types of shopping. For daily frequency, the total number of shopping as a whole is considered. For time allocation modelling, three major types: Grocery shopping, Nongrocery-household related shopping and all Other personal types of shopping are considered as attributes of the episodes. The maximum observed weekly frequency of these 167 individuals is 5 days per week and the minimum is 1 day per week. No person stated the frequency of 0 days per week. The weekly frequency data used in this paper is thus conditional to at least once a week shopping because the EWR is prompted only against the type of activity the participant listed at least once through out the whole week. In the case of the daily shopping frequency, the maximum frequency is 5 shopping episodes per day and the minimum is 0 episodes per day. The day-specific maximum frequency is 4 for Sunday, 3 for Monday, 4 for Tuesday, 4 for Wednesday, 4 for Thursday, 3 for Friday and 5 for Saturday. For the day-specific daily frequency model, the total number of individuals (163) under observation is same for each day, so the minimum daily frequency for any day is 0. Within the total 621 observations of shopping episodes, the minimum observed duration is 01 minute and the maximum duration is 740 minutes with the mean duration of 54.21 minutes and standard deviation of 59.15 minutes.

The attributes considered in the models can be divided into three broad categories: *activity specific attributes*, *person specific attributes* and *household specific attributes*. The *activity specific attributes* include start time, duration, temporal flexibility of the duration, spatial flexibility of the activity locations in terms of the number of possible locations of the activity, day of week of the activity, the total number of episodes of the day, the type of shopping activity and the total persons involved in the activity etc. The *person specific attributes* include: age (in years), sex, position in the household (single adult, adult with partner, adult child, other household adults), job specific attributes (full-time job, part-time job, self-employed person, retired person, household dependent person, at-home job, out-of-home job), yearly income in Canadian dollars, the use of a transit pass and the possession of a driving license. The *household specific attributes* include: household size (total number of people in household), number of adults, total number of children, number of teens, number of adult children, number of automobiles in the household and household internet availability. These broader divisions of attributes used in the models have their roots in theoretical aspects of activity behaviour that are complex and shaped by both opportunities and constraints dispersed over space and time. Since this paper deals with a general type of activity, shopping, the activity specific attributes in general cover the constraints and scope of shopping activity over temporal and spatial scales. The person specific attributes in general account for the individuals' behaviour and idiosyncrasies. The household specific attributes in general accommodate inter-household interactions, household level demands for shopping activities and the influence of household conditions on the individual's behaviour.

INTERPRETATIONS OF THE MODELS

This section discusses the details of the individual models. The estimated coefficients are considered statistically significant if the corresponding two-tailed 't' statistics satisfy the 90% confidence interval, ($t \geq 1.64$). Although some of the variables in the models reported in this paper are not significant by this criterion, they provide significant insight into the behavioural process and so are retained for purposes of discussion.

Weekly Shopping Frequency Models

Three sets of models for the weekly shopping frequency are reported in Table 1. The reported models are of the total weekly shopping frequency, the weekly frequency for Grocery-household related shopping and the weekly frequency for Nongrocery-personal shopping.

To test the null hypothesis for the household based random effect, single-level ordinal logit models are also reported adjacent to the corresponding multilevel models. As mentioned before, the basis for accepting the Null hypothesis in this case is first 't' test and if it fails then the likelihood ratio test. The null hypothesis is rejected only for the Grocery-household related shopping, but the household-related covariates as fixed effects enter in each model. This indicates that the influence of the household on the individual's shopping behaviour is more direct than random except for Grocery-household related shopping, which has both direct effects as well as random effects. Efforts were taken to incorporate random coefficient of the household-related attributes within the Grocery-household related shopping frequency model but this did not result in an improved model and hence these results are not reported here. This implies that the information required to capture the household influence on an individual's weekly Grocery-household related shopping frequency is not complete in the available data source. But the incorporation of the random intercept in a multilevel ordinal model captures the unobserved heterogeneities and improves the statistical significance of the fixed effects. The following paragraphs discuss the effects of the fixed-effect variables on weekly shopping frequencies.

For the activity-specific attributes, duration flexibility is not significant for Grocery-household related shopping model but it is significant for Nongrocery-personal shopping and total shopping frequency. For each model, the coefficient of this variable is negative, implying that the duration flexibilities of the shopping episode reduce the weekly frequencies of shopping activities. The spatial attributes of the activity, the number of possible locations the person goes to for shopping, is not significant in any model, but interestingly it has negative effect on Grocery-household related shopping compared to Nongrocery-personal shopping and Total shopping frequency. This implies that the spatially dispersed shopping locations increase the Nongrocery-personal shopping frequency but reduces the Grocery-household related shopping frequency. This is intuitive in that for dispersed shopping locations travel time increases, so for Grocery shopping people tend to buy larger amounts at specific locations, resulting in lower shopping episode frequencies. Non-grocery shopping on the other hand involves a variety of goods and purchased from a dispersed set of locations, resulting in an increase in this type of shopping frequency. For individual-level attributes, age is not significant in any model but the sign of the parameter indicates that younger people have higher weekly shopping frequency than older people. The variable indicating sex is also insignificant in all models, but the signs suggest that males do more Nongrocery-personal shopping compared to females. Females do more grocery shopping than males but the total shopping frequency is higher for males. Attributes indicating the status of the individual in the household indicate that compared to other adults in the household, single heads, adults with a partner and adult children have higher total weekly shopping frequencies. For Grocery-household related shopping type, the single head and the adult child in the household have higher weekly frequency compared to the adult with partner and other adults in the households. For Nongrocery-personal shopping, the single head of the household has lower weekly frequencies compared to the others. The job-related attributes of the individual are significant in total shopping frequency models. The references in this case are household dependents and unemployed persons. The negative coefficients of the other job-status attributes imply that the household dependent and unemployed persons are involved in shopping activities more than the others. Individual income has a negative effect, indicating that higher income people have lower weekly shopping frequencies. This is consistent with the assumption that higher income people typically spend more time working and on related responsibilities and hence might have less time for shopping activities. The locational attribute of the job indicates that people with home-based jobs have lower weekly shopping frequencies. This is may be explained by people with out-of-home job locations often go shopping on the way home from work while people working at home may not have this type of scheduling choice. The variable representing driving license possession is significant in the total frequency model, suggesting that the person having a driving license has a higher weekly shopping frequency. On the other hand, transit-pass users have higher Grocery-household related shopping and lower Nongrocery-personal shopping frequencies compared to non-transit-pass users.

For household-level fixed effects, the variable representing the total number of adults in the household is not significant, but it seems to have a positive influence on the weekly shopping frequency of all types of shopping. The variable representing the total number of teens in the household is significant in the Grocery-household related shopping frequency model only, and has opposite signs for Grocery and Nongrocery shopping. These two variables, total adults and total teens are compared to the total number of children in the household. Thus, the higher the number of teen in the household compared to children reduces Grocery-household related shopping but increases Nongrocery-personal shopping. On the other hand, more adults in the household compared to the number of children increases all types of weekly shopping frequencies. Other household-level fixed effects are: household automobiles and household internet availability. Higher automobile ownership increases Grocery-household related shopping but reduces Nongrocery-personal shopping. Household internet availability only enters the total shopping model and has complementary effects on weekly shopping frequency.

Daily Shopping Frequency Model

Daily frequency models are summarized in Table 2. The same variables are used in all models so that the variations of statistical significance of the same variable across the models can be compared. The first column of the table summarizes a conditional daily frequency model. This model is conditional on the decision of going to shopping in the particular day, where individual days are covariates of the model. The other columns summarize the unconditional daily frequency models. The day-specific covariates in the conditional model suggest that the daily frequency is the highest on Saturday compared to the other days. Weekly frequency is significant for the Sunday and Monday models. This suggests that higher weekly frequency increases daily shopping frequency on Sunday but reduces it for Monday, implying the typical weekday-weekend trade-off for shopping activities. The locational flexibility variable is significant in the Monday, Wednesday and Saturday models but the sign is positive for Wednesday only. This indicates a type of weekly rhythm for shopping activity, similar to many other activities. Duration flexibility and age are both only significant in the Sunday model. This indicates that duration flexibility increases the Sunday shopping frequency and older people go shopping on Sunday more than younger people. Sex is significant for the Wednesday model and is positive, indicating that males shop in the middle of the week more than females do. The individual's status in the household is not significant in any model except for Sunday. It seems that the single adults in the household have lower Sunday shopping frequencies than other types of people. Driving license has a positive effect on daily shopping frequency. Full-time employed people have lower daily shopping frequencies and the opposite sign of this variable in the Friday and Sunday models indicates the typical weekday-weekend trade-off in shopping activities for full-time employed people. For household level fixed effects, the models include only two variables, 'household automobile' and 'household internet' and both are insignificant in all models. Thus, it is clear that there are not many household-related variables or fixed effects available in the data set that explain daily shopping frequency variations. But the household-based random effect is statistically significant in all models. Both the Wald test (t statistics) and Likelihood ratio test justify the household-level random influence on individual daily shopping frequencies. This indicates that individual's daily frequency of shopping is significantly influenced by household level factors not captured by activity diary data. The hierarchical approach of multilevel models captures the superimposed constraints/opportunities that influence household members' daily shopping behaviour. In contrast to weekly shopping frequency, the significance of household based random effects in daily shopping frequency also indicates that the weekly frequency is derived by more from the individual's affinity/aversion towards shopping activity than due to household level constraints/opportunities, whereas the converse tends to hold for daily shopping frequency.

Time Allocation Models For Shopping Episodes

The hazard models for allocating time to individual shopping episodes are summarized in Table 3. The models consider the weekly frequency and daily frequency as covariates and both are significant in all models. For day-specific dummy variables Saturday is considered as the reference. For multiple episodes per day, the duration of the previous episode also enters into the models as a covariate. The household-based random effects are significantly different from zero in all models presented in this table (i.e., the null hypothesis is rejected for all models).

According to the hazard models presented in the Table 3, people spend more time shopping on Saturday than other days of the week. Higher daily frequency reduces the duration of individual episodes, while higher weekly frequency results in spending more time per episode. For multiple shopping episode days, the durations of earlier episodes positively influence the duration of later episodes. The start time dummies show that morning episodes are longer than afternoon and evening episodes. Travel time significantly influences shopping duration. People allocate more time for shopping episodes that require longer travel times. This is reasonable in that the greater effort involved in traveling longer encourages people to shop for larger amounts per trip in order to reduce number of shopping activities. This is consistent with the trends found in weekly and daily shopping frequencies described in the previous sections. People having a driving license and higher number of household autos normally spend more time shopping than other people. Grocery and Nongrocery household shopping takes more time than Personal and other types of shopping. Joint shopping activities take more time than single shopping activities. More feasible shopping locations and duration flexibility both encourage more allocation of time for shopping. Males allocate less time compared to the females for shopping. Higher income people allocate more time for shopping, and more autos per household positively influence the shopping time allocation by the individual.

The pseudo R^2 goodness of fit values show that the semiparametric model gives the poorest fit to the observed data, while the parametric models all yield similar results. One possible reason for this is the different parameter estimation methods of the two models. Although the semiparametric model recognizes the baseline distribution, the partial likelihood method used for estimating parameters cannot recognize the interaction between the baseline pattern and the covariate effects. The poor goodness of fit of the semiparametric hazard model compared to the parametric hazard models indicates that the time allocation to shopping activity does have an underlying distributional pattern.

In all of three components of the person-based shopping frequency-time allocation modelling system the household is considered to generate a random effect in addition to the fixed effects. The random effects are considered in terms of random intercepts, which are found to be statistically significant in all three components. The sequential design of the modelling process is ensured by incorporating the output of each earlier part as an input into the next part. The weekly frequency enters as a covariate in daily frequency, and both weekly and daily frequencies enter into the hazard based time allocation models as covariates. The statistical significances of these apparently endogenous variables in the lower-level models justify the assumption of latency of activity propensity in the generation-time allocation process for shopping activities.

CONCLUSIONS

This paper describes the component models of a comprehensive frequency and time allocation modelling system for the shopping activities. The models are developed at the individual personal level with the incorporation of household-level fixed and random effects. The weekly and daily *propensities* of participating in shopping activities are modelled as multilevel ordinal logit models. In multilevel ordinal logit models the household-level influence is modelled using fixed and random effects. In the hazard-based duration model for time allocation to individual shopping episodes, the household-level influence is modelled by fixed covariates and household-based random heterogeneity. The modelling system is sequential: weekly frequency enters the daily frequency model as input, and weekly and daily frequency enters the time allocation model as inputs. The sequential approach supports the assumptions that the weekly propensity influences the daily propensity, and both weekly and daily propensity influences duration, but none of these are strictly conditional to one another. The paper discusses the details of the individual components of the modelling system. Some important insights are: duration flexibility of the shopping type reduces weekly shopping frequency but increases time allocation to the particular shopping episode. The weekly and daily frequencies have opposite effects on the time allocation behaviour. Compared to females, males have higher weekly shopping frequencies but lower daily frequency and shorter shopping episodes. Having a driving license results in higher weekly shopping frequency and longer shopping durations.

In terms of application, the use of the estimated models will provide detailed input to the activity scheduler. At the same time it will increase the policy sensitivities of the overall activity-travel demand model. For instance, the current model TASHA [see *25*] uses random draws from observed distributions of shopping frequencies and durations to generate shopping episodes and their attributes. Such an input system makes the overall activity/travel scheduling process insensitive to policy impacts at this very bottom level of the behavioural process. The model presented in this paper provides the potential to go beyond the use of static distributions to dynamically generate activity episodes as input for an activity/travel scheduler and thereby enhance the behavioural validity and policy sensitivity of the model.

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TABLE 1: **Multilevel and Single Level Ordinal Logit Models for Weekly Shopping Frequency**

Covariates	Individual = 167 nos Household = 98 nos		Individual = 122 nos Household = 93 nos		Individual = 94 nos Household = 68 nos	
	All Types of Shopping		**Grocery and Household Related Shopping**		**Nongrocery-Personal Shopping**	
	Multilevel With Household Random Effect	Single Level Without any Random Effect	Multilevel With Household Random Effect	Single Level Without any Random Effect	Multilevel With Household Random Effect	Single Level Without any Random Effect
	Coeff ('t')	***Coeff ('t')***	***Coeff ('t')***	***Coeff ('t')***	***Coeff ('t')***	***Coeff ('t')***
Duration flexibility	-0.78(-2.4)	-0.79(-2.45)	-0.18 (-0.42)	-0.20 (-0.53)	-0.95 (-1.90)	-0.93 (-2.19)
Space fixed	0.091(1.33)	0.09(1.34)	-0.14 (-1.54)	-0.11 (-1.49)	0.12 (0.94)	0.13 (1.27)
HH Adults			0.38 (1.10)	0.33 (1.16)	0.25 (0.95)	0.27 (1.31)
HH. Teens			-1.03 (-2.36)	-0.95 (-2.56)	0.57 (0.97)	0.54 (1.17)
HH. Autos	-0.31(-1.21)	-0.32 (1.35)	1.15 (2.85)	1.03 (3.11)	-1.06 (-2.18)	-0.79 (2.42)
HH. Internet	0.70(1.43)	0.7 (1.41)				
Age	-0.02 (-1.39)	-0.02 (-1.39)	-0.02 (-1.48)	-0.02 (-1.52)		
Male	0.51(1.42)	0.52 (1.43)	-0.31 (-0.65)	-0.20 (-0.47)	0.48 (0.97)	0.46 (1.04)
Single Head in Home	2.85(3.1)	3.1 (2.9)	2.04 (2.40)	1.84 (2.55)	-1.23 (-1.07)	-0.72 (-0.83)
With partner in Home	2.26(3.0)	2.3 (3.1)				
Adult child in Home	2.79(3.0)	2.82 (3.0)	0.46 (0.44)	0.48 (0.53)	2.45 (1.61)	1.72 (1.67)
Fulltime Job	-2.82(-2.93)	-2.85 (-2.98)				
Part time Job	-2.76(-2.62)	-2.78 (-2.64)	-0.37 (-0.50)	-0.32 (-0.48)		
Self-employed	-2.95(-2.56)	-3.0 (-2.61)	-0.77 (-0.90)	-0.81 (-1.0)		
Retired	-2.71(-2.88)	-2.75 (-2.94)	0.17 (0.28)	0.10 (0.20)	0.76 (1.12)	0.66 (1.17)
Income	-4.13E-6 (-0.83)	-4.71E-6 (-0.98)	5.4E-6 (0.90)	5.0E-6 (0.86)		
At Home Job			-0.77 (-0.97)	-0.75 (-1.10)	-0.79 (-0.88)	-0.74 (-0.78)
Driving license	1.36(2.02)	1.38 (2.1)				
Transit Pass User			1.12 (1.10)	0.97 (1.00)	-1.33 (-0.61)	-1.06 (-0.61)
Threshold Parameters						
Threshold_11	-4.98	-4.96	-4.22	-3.89	-6.58	-5.68
Threshold_12	-2.85	-2.82	-3.48	-3.16	-4.30	-3.51
Threshold_13	-0.71	-0.69	-1.67	-1.41	-1.80	-1.34
Threshold_14	0.29	0.31	0.43	0.48	-0.29	-0.10
Threshold_15			1.85	1.73		
Variance of Household Random Intercept for Multilevel Ordinal Logit Model						
Second Level: household	1.64E-18 (13E-10)		1.12 (0.88)		1.12 (0.93)	
Loglikelihood	-199.85	-199.94	-114	-122	-114	-115
H_0: No Random Effects	Accepted		Rejected		Accepted	

TABLE 2: Multilevel Ordinal Logit Models for Daily Shopping Frequency

	Conditional frequency (at least 1 on the specific day)	**Unconditional Daily Frequency According to Day of the Week**						
		Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Covariates	***Coeff ('t')***	***Coeff ('t')***	***Coeff ('t')***	***Coeff ('t')***	***Coeff ('t')***	***Coeff ('t')***	***Coeff ('t')***	***Coeff ('t')***
Sunday	-1.04 (-2.84)							
Monday	-1.15 (-3.08)							
Tuesday	-0.65 (-1.76)							
Wednesday	-1.06 (-2.87)							
Thursday	-0.69 (-1.74)							
Friday	-0.85 (-2.25)							
Weekly frequency	-0.06 (-0.53)	0.34 (2.47)	-0.40 (-2.78)	0.09 (0.60)	-0.00 (-0.01)	-0.11 (-0.69)	0.11 (0.69)	0.06 (0.33)
Space fixed	-0.01 (-0.29)	0.04 (0.85)	-0.11 (-1.63)	0.00 (0.03)	0.15 (2.52)	0.03 (0.40)	-0.02 (-0.29)	-0.17 (-2.26)
Duration flexibility	0.15 (0.67)	0.06 (0.26)	-0.15 (-0.58)	-0.51 (-1.80)	0.19 (0.68)	0.32 (1.05)	0.24 (0.82)	0.05 (0.18)
Age	0.01 (0.22)	0.02 (1.94)	0.01 (0.92)	-0.01 (-0.46)	-0.01 (-0.14)	0.01 (0.32)	-0.01 (-0.72)	-0.02 (-1.13)
Male	-0.16 (-0.61)	-0.75 (-2.71)	0.05 (0.18)	-0.48 (-1.60)	0.98 (3.43)	0.001 (0.02)	0.24 (0.79)	-0.05 (-0.15)
Single adult in Home	-0.35 (-0.34)	-1.06 (-1.63)	-0.44 (-0.60)	-0.56 (-0.71)	0.69 (0.75)	-0.21 (-0.25)	1.14 (1.45)	0.81 (0.88)
Adult with Partner in Home	0.18 (0.21)	-0.43 (-0.83)	-0.65 (-1.09)	0.42 (0.72)	0.37 (0.49)	-0.16 (-0.22)	0.56 (0.86)	-0.10 (-0.14)
Driving license	1.64 (1.67)							
Fulltime Job	-0.61 (-1.78)	0.40 (1.5)	1.50 (0.01)	0.03 (0.10)	-0.32 (-0.95)	0.59 (1.65)	-0.87 (-2.63)	0.05 (0.15)
Income	3.76 E-7 (0.75)							
Household size	-0.63 (-2.45)							
Household autos	0.24 (0.53)	-0.23 (-1.13)	-1.13 (0.11)	-0.07 (-0.28)	0.41 (1.24)	0.22 (0.74)	-0.07 (-0.27)	0.04 (0.11)
Household internet	0.62 (0.66)	-0.24 (-0.55)	-0.55 (-0.53)	0.98 (1.54)	-0.12 (-0.17)	-0.70 (-1.21)	-0.02 (-0.03)	1.62 (1.63)
Threshold Parameters								
Threshold_11	0.21	3.10	-0.03	2.77	3.39	2.28	2.36	3.05 (2.37)
Threshold_12	2.23	3.91	0.89	3.50	4.19	3.07	3.10	3.90 (3.00)
Threshold_13	3.94	4.75	1.94	4.75	5.14	3.96	3.92	4.14 (3.18)
Threshold_14	5.37	6.09		5.82	6.64	4.77		4.21 (3.23)
Threshold_15								4.89 (3.71)
Variance of Household Random Intercept								
Second Level: household	5.08 (3.97)	0.28 (1.27)	0.58 (1.71)	0.52 (1.46)	1.74 (2.77)	0.95 (2.21)	0.58 (1.61)	2.28 (3.12)
Loglikelihood	-657.00	-391	-356	-327	-363	-298	-292	-356
H_0: No Random Effect	Rejected	Rejected	Rejected	Rejected	Rejected	Rejected	Rejected	Rejected

TABLE 3: Hazard Based Duration Model for Time Allocation to Shopping Episodes Considering Household Level Random Effects

Covariates		Semiparametric Hazard with Gamma Frailty *Coeff ('t')*	Weibull Accelerated Life Shared-Gamma Frailty Model *Coeff ('t')*	Log logistic Accelerated Life Shared-Gamma Frailty Model *Coeff ('t')*	Lognormal Accelerated Life Shared-Gamma Frailty Model *Coeff ('t')*
Sunday		-0.08 (-0.47)	0.06 (0.57)		
Monday		0.23 (1.32)	-0.17 (-1.64)	-0.15 (-1.33)	-0.10 (-0.86)
Tuesday		-0.37 (-2.14)	0.27 (2.50)	0.35 (3.03)	0.30 (2.56)
Wednesday		0.07 (0.42)	-0.03 (-0.27)	-0.005 (-0.04)	-0.01 (-0.13)
Thursday		-0.12 (-0.64)	0.09 (0.81)	0.08 (0.63)	0.06 (0.45)
Friday		-0.22 (-1.22)	0.17 (1.54)	0.20 (1.68)	0.18 (1.5)
Episode per day		0.20 (3.72)	-0.11 (-3.42)	-0.15 (-4.60)	-0.14 (-4.24)
Weekly Frequency		-0.38 (-3.73)	0.25 (4.04)	0.27 (4.19)	0.25 (3.78)
Duration of Previous Episode		-0.004 (-2.14)	0.002 (1.87)	0.002 (1.79)	0.002 (1.78)
Start Time Dummy	9-10 am	-0.26 (-1.07)	0.16 (1.03)	0.27 (1.93)	0.31 (2.02)
	11-12 noon	-0.25 (-1.52)	0.14 (1.36)	0.09 (0.82)	0.12 (1.06)
	1-2 pm	-0.29 (-1.83)	0.19 (1.93)	0.15 (1.38)	0.18 (1.67)
	3-4 pm	0.24 (1.53)	-0.19 (-2.03)	-0.01 (-0.14)	-0.04 (-0.35)
	After 6 pm	0.53 (4.15)	-0.39 (-5.01)	-0.37 (-4.60)	-0.31 (-3.82)
Travel Time		-0.02 (-4.72)	0.01 (5.41)	0.01 (4.96)	0.02 (5.67)
Grocery Shopping		-0.30 (-2.31)	0.22 (2.76)	0.27 (3.26)	0.31 (3.60)
Nongrocery Household Needs		-0.67 (-4.85)	0.47 (5.52)	0.49 (5.71)	0.48 (5.37)
Total Persons Involved		-0.23 (-3.02)	0.15 (3.14)	0.17 (3.77)	0.19 (4.20)
Space fixed		-0.03 (-1.28)	0.03 (1.88)	0.004 (0.23)	0.02 (1.18)
Duration Flexibility		-0.12 (-2.11)	0.07 (2.07)	0.12 (2.99)	0.12 (3.09)
Adult Child in home		0.19 (0.78)	-0.15 (-1.02)	-0.02 (-0.16)	0.02 (0.14)
Male		0.28 (2.54)	-0.21 (-3.01)	-0.21 (-2.90)	-0.16 (-2.24)
At home Job		0.40 (1.23)	-0.25 (-1.19)	-0.24 (-1.23)	-0.26 (-1.28)
Income		-1.72E-06 (-0.97)	1.30E-06 (1.15)	1.24E-06 (1.16)	1.82E-06 (1.66)
Household autos		-0.12 (-1.16)	0.08 (1.03)	0.14 (2.62)	0.15 (2.66)
Driving license		0.28 (1.02)	-0.18 (-1.01)	-0.27 (-1.58)	-0.28 (-1.59)
CONSTANT			3.28 (12.28)	2.89 (10.68)	2.70 (9.94)
Ancillary Parameters					
σ					0.71
P			1.69		
γ				0.40	
θ		0.24	0.41	0.13	0.16
Loglikelihood		-3316.78	-700.78	-704.16	-703.37
Likelihood ratio		138.28	178.04	192.21	179.06
Pseudo R^2		0.02	0.11	0.12	0.11
$H_0: \theta=0$		Rejected	Rejected	Rejected	Rejected