


An analysis of the impact of information and communication technologies on non-maintenance shopping activities

Working Paper**Author(s):**

Bhat, Chandra R.; Sivakumar, Aruna; Axhausen, Kay W. 

Publication date:

2002

Permanent link:

<https://doi.org/10.3929/ethz-a-004347569>

Rights / license:

In Copyright - Non-Commercial Use Permitted

Originally published in:

Arbeitsberichte Verkehrs- und Raumplanung 97

An Analysis of the Impact of Information and Communication Technologies on Non-Maintenance Shopping Activities

Chandra R. Bhat

Dept of Civil Engineering, ECJ Hall, Suite 6.8

University of Texas at Austin, Austin, Texas, 78712

Tel: 512-471-4535, Fax: 512-475-8744, Email: bhat@mail.utexas.edu

Aruna Sivakumar

Dept of Civil Engineering, ECJ Hall, Suite 6.8

University of Texas at Austin, Austin, Texas, 78712

Tel: 512-471-4535, Fax: 512-475-8744, Email: arunas@mail.utexas.edu

Kay W. Axhausen

Verkehrsplanung (IVT), HIL F 32.3

ETH Hönggerberg, CH - 8093 Zürich

Tel: +41-1-633 3943, Fax: +41-1-633 1057, Email: axhausen@ivt.baug.ethz.ch

An Analysis of the Impact of Information and Communication Technologies on Non-Maintenance Shopping Activities

Chandra R. Bhat, Aruna Sivakumar, and Kay W. Axhausen

ABSTRACT

This paper examines the use and travel impacts of two forms of Information and Communication Technologies (ICTs): mobile telephones and computers. The travel impacts are examined in the context of participation in out-of-home non-maintenance shopping activities over a multiweek period through the modeling of the duration between successive shopping activity participations. The empirical analysis uses a continuous six-week travel survey collected in the cities of Halle and Karlsruhe in Germany in the Fall of 1999. The results indicate that the effects of ICTs on activity-travel patterns are mediated by individual sociodemographic and locational factors, as well as by unobserved individual characteristics. The results also show that the substitution between mobile phone use and shopping travel is grossly underestimated if the effects of common unobserved factors affecting mobile phone use and shopping travel are not considered. In addition, there is quite substantial intra-individual variation in intershopping duration.

Keywords: Information and communication technologies, sample selection, random-coefficients, unobserved heterogeneity, hazard-based duration model, multiday analysis, activity-travel behavior, shopping behavior.

1. INTRODUCTION

The rapid innovations and advances in information and communication technologies (ICTs) since the early 1990s have had a profound impact on the behavior of businesses and individuals in today's society. Businesses are increasingly harnessing the potential of ICTs to facilitate and consummate business-to-business transactions and business-to-consumer transactions. In particular, it is fairly routine today for businesses to manage the production and distribution activities of their services and products (supply-chain management), as well as promote the purchase of their services and products (electronic enabled commerce), through the use of the internet. Examples include the tracking of vehicle fleets by courier delivery providers such as Fed-Ex and United Parcel Services (UPS), and the electronic web sites of many retailing firms. Individuals and households are also substantially more likely today than ten years ago to use computers at home with web access and/or to use mobile telephony services, due in large part to the increasing affordability and functionality of these technologies. Projections suggest that technology improvements will further fuel the adoption and use of internet computing and mobile communication devices by individuals and households in the future. For example, broadband internet connections (cable modems and digital subscriber lines) to homes in the U.S. facilitate faster access to information, and the number of such connections is projected to increase by about thirtyfold between 2000 and 2007 (Pioneer Consulting, 1999). Similarly, the penetration of mobile telephones in the U.S. population is projected to increase from about 25% today to about 55% in 2004 (Forrester, 2000).

The impacts of ICT adoption and use are likely to be far-reaching, with the potential to fundamentally alter the life styles of businesses and individuals (see, for example, Droege, 1997, Graham and Marvin, 1996, Boden, 1999, French *et al.*, 1999 and Zimmerman *et al.*, 2001, for

broad discussions of the potential influence of ICTs on urban planning, medical care and services, education, and family responsibilities). An interesting aspect of ICT use from a transportation perspective is its impact on personal activity-travel behavior. Mokhtarian (1997) develops a typology for studies in the area of ICT use and personal activity-travel behavior interrelationships. From a time horizon standpoint, she identifies the impact of ICT use on individual activity-travel behavior as being *short-term direct* effects or *long term indirect* effects through changes in work arrangements, residential locations choices, and car ownership levels. Most empirical studies to date have focused on the *short-term direct* effects, though there have been a few studies directed toward the *long term indirect* effects on activity-travel behavior (see Lund and Mokhtarian, 1994; Salomon, 1996; Graham and Marvin, 1996). In terms of breadth of analysis, Mokhtarian classifies earlier studies into *comprehensive* studies that attempt to uncover the interrelationships between ICT use and overall activity-travel behavior of individuals, or *limited* studies that focus on a small subset of choices characterizing ICT use and/or activity-travel impacts of ICT use. Almost all earlier empirical studies may be classified under the category of limited analysis studies, though some relatively comprehensive studies have been undertaken recently (Harvey and Taylor, 2000 and Mokhtarian and Meenakshisundaram, 1999). Finally, in the context of the scale of analysis, Mokhtarian classifies studies as *macro-scale* (regional, national, or international levels of analysis) or *micro-scale* (individual-level). Both scales of analysis have been used quite widely in the past.

In this study, we focus on the *short-term direct* interrelationship between ICT use and individual activity-travel behavior. Our study is also *limited* to the use of two kinds of ICT; mobile telephony and personal computer use; and to out-of-home shopping activities of individuals. We use a *micro-scale* level in the analysis.

In the next section, we position the current study in the context of earlier studies from a substantive perspective. In Section 1.2, we highlight the methodological characteristics of our modeling framework.

1.1 The Current Research in the Context of Earlier Research

There have been several earlier studies of ICT use and the impact of ICT use on personal activity-travel behavior. These studies have provided important and useful insights into the interrelationships between ICT use and individual activity-travel patterns. The focus of this paper is to contribute to this growing body of ICT-related research. In addition, the current study may be distinguished from previous *short-term, limited analysis, micro-scale* ICT-related studies in several ways. First, the study focuses on an analysis of ICT use as well as the generation of out-of-home shopping activities in a joint framework. Most earlier studies, on the other hand, have either focused only on ICT use or only on the impact of ICTs on activity-travel behavior¹. These earlier studies do not account for the possible endogeneity of ICT use decisions in analyzing activity-travel patterns and, therefore, may not capture the true impact of ICT use on activity-travel patterns. For example, it is possible that an individual who has an active lifestyle may be more likely to use mobile phones, as well as be more likely to participate in (out-of-home) shopping activities. If ICT use is considered exogenous to the analysis of out-of-home shopping participation, one might find a “spurious” dependence of ICT use on shopping activity generation due to the active lifestyle characteristic. This, of course, can imply inappropriate

¹ Examples of studies of ICT use include Yen and Mahmassani (1998), Mokhtarian and Salomon (1997) and Mannering and Mokhtarian (1995) in the context of telecommuting, and Koppelman *et al.* (1991) and Manski and Salomon (1987) in the context of teleshopping/other ICT use. Examples of the impact of ICTs on activity-travel behavior include Henderson and Mokhtarian (1996), Pendyala *et al.* (1991), Koenig *et al.* (1996) and Mokhtarian and Varma (1998) in the context of the impact of telecommuting on commute-related activity-travel patterns, and Viswanathan and Goulias (1999), Tacken (1990), Gould and Golob (1997), Kilpala *et al.* (2000), Martens and

conclusions about the substitution or complementary effects of ICT use on shopping activity generation. Second, the current study allows the effect of ICT use to vary across individuals. Specifically, it allows the effect of ICT use to be in opposite directions for different individuals, so that ICT use substitutes for shopping trips for some individuals and complements shopping trips for others. Further, within the group of individuals for whom there is a substitution effect (or for whom there is a complementary effect), the current study accommodates heterogeneity in responsiveness to ICT use (the reader is referred to Chamberlain, 1980, Hsiao, 1986 and Diggle *et al.*, 1994, for a detailed discussion of heterogeneity-related issues in statistical models that are non-linear in the model parameters). Third, the current study uses a multi-week activity-travel diary collected in Germany in the Fall of 1999 to evaluate the effects of ICT use on out-of-home shopping activity episodes. The study is, therefore, able to accommodate intra-individual variations in activity travel patterns over a multiday period. The analysis of such intra-individual variation is important to examine the frequency of exposure of different sociodemographic and travel segments to policy scenarios (see Jones and Clark, 1988). Fourth, the current study focuses on examining the impacts of two different kinds of interactive ICT activities (computer use and mobile phone use) on non-maintenance shopping trips (*i.e.*, trips not associated with grocery shopping, medical drug shopping, *etc.*). Previous studies have mainly focused on the effect of a single ICT, generally associated with work-related computer use.² Further, as noted by Handy and Yantis (1997), the impact of ICTs on nonwork travel “has been largely ignored by researchers so far”. The one exception is the area of teleshopping; however, much of this

Korver (2000), Yim (2000), and Handy and Yantis (1997) in the context of the impact of computing, internet access, and mobile technology on non-work activity-travel behavior.

² Two recent studies have considered the impact of multiple ICTs, including mobile telephony (see Mokhtarian and Meenakshisundaram, 1999 and Viswanathan and Goulias, 2001); however, these studies do not distinguish between activity purposes. The current study focuses specifically on the interrelationship between non-maintenance shopping activities and ICT-use.

teleshopping literature has concentrated on the interaction between online grocery shopping and out-of-home grocery shopping (see Golob, 2000). There has been little to no empirical research on the effect of ICTs on non-maintenance shopping behavior. Fifth, the current study examines shopping activity participation behavior by analyzing the duration between successive out-of-home shopping activity participations of individuals. The intershopping duration is measured in days, since almost all individuals have no more than a single shopping activity participation on any given day. The duration-based structure used in this paper recognizes the dynamics of intershopping duration; that is, it recognizes that the likelihood of participating in shopping activity depends on the length of elapsed time since the previous participation. The traditional “number of trips” formulation is unable to accommodate such dynamics. The duration formulation also allows different individuals to have different participation rhythms in shopping behavior and it can be used to predict the effects of ICT on shopping activity participation behavior over any period of time (such as a day, a week, or a month).

An important point to note here is that our representation of ICT use is constrained by the ICT-related data collected in the six-week German diary data. Specifically, mobile telephone use is represented by the availability (*i.e.*, adoption) of a mobile telephone. Similarly, home computer use is broadly represented by whether the individual has access to personal e-mail at home. These representations of ICT use are not as rigorous as those of some earlier studies that use detailed diary data on the number and attributes of communication activities by ICT type (see Moberg, 1993; Spittje, 1994; Zumkeller, 1996; Mokhtarian and Meenakshisundaram, 1999).

1.2 Methodological Characteristics of Modeling Framework

The current paper uses a hazard-based model to examine the effect of ICTs on intershopping duration, while controlling for sociodemographic attributes of individuals and their residential location attributes (see Hensher and Mannering, 1994 and Bhat, 2000 for an extensive discussion of hazard-based duration models and transportation-related applications). The hazard formulation developed and applied in this paper extends the hazard formulations of Han and Hausman (1994) and Bhat (1996) in several ways. First, the paper accommodates sample selection in duration based on multiple criteria (in the application in the paper, the multiple criteria for sample selection are associated with the adoption of multiple ICTs). Second, the paper recognizes that the criteria for sample selection are individual-specific, but that the resulting sample selection affects all intershopping durations of the individual. This is an important difference from usual “cross-sectional” sample selection models in which both the criteria and variable of interest are associated with the same unit of observation (for example, see Greene, 2000; Pages 926-936). Third, the paper accommodates heterogeneity in sensitivity to ICTs due to observed as well as unobserved individual attributes. Fourth, the model in the paper allows unobserved heterogeneity across individuals and across spells of the same individual in intershopping duration. To our knowledge, this is the first formulation and application of a duration model in econometric literature to consider the above issues in a comprehensive, unifying, framework. Fifth, the estimation of the duration model requires simulation techniques to evaluate the multidimensional integral in the estimation criterion function. In the current paper, we use a simulation technique based on “intelligent” quasi-random draws rather than “random draws”.

The remainder of this paper is structured as follows. The next section discusses the model structure and estimation technique. Section 3 presents the data source and describes the sample

used in the analysis. Section 4 discusses the empirical results. The final conclusion section summarizes the important findings from the study and identifies directions for further research.

2. MODEL STRUCTURE

In the following presentation, we will first discuss the hazard-based model structure for intershopping duration without considering the sample selection based on ICT use. We will then introduce the modeling of ICTs along with the specification for the sample selection of intershopping duration based on ICT use.

2.1 Hazard-Based Duration Structure

Let t_{qi} be an index representing the i^{th} intershopping duration of individual q ($t_{qi} = 1, 2, \dots, k, \dots, K$, where k is in days). Let $\lambda_{qi}(\tau)$ represent the hazard on the τ^{th} day since the previous shopping activity participation for the i^{th} intershopping duration spell of individual q ; *i.e.*, $\lambda_{qi}(\tau)$ is the conditional probability that individual q 's $(i + 1)^{th}$ shopping episode will occur on the τ^{th} day after her/his i^{th} participation, given that the episode does not occur before the τ^{th} day:

$$\lambda_{qi}(\tau) = \lim_{\Delta \rightarrow 0^+} \frac{P(\tau < t_{qi} < \tau + \Delta \mid t_{qi} > \tau)}{\Delta} \quad (1)$$

Next, we relate the hazard rate, $\lambda_{qi}(\tau)$, to a baseline hazard rate, $\lambda_0(\tau)$, a scalar α_q capturing socio demographic and other attributes of individual q , a vector of ICT-use covariates, x_q , and a spell-specific unobserved component ϖ_{qi} (ϖ_{qi} corresponds to random noise across different intershopping durations). We accomplish this by using a proportional hazard formulation as follows:

$$\lambda_{qi}(\tau) = \lambda_0(\tau) \exp(-\alpha_q - \beta'_q x_q + \varpi_{qi}), \quad (2)$$

where β_q is a vector of individual specific ICT-use coefficients. For reasons that will become clear later, we assume a gamma distribution for $\exp(\omega_{qi})$. The exponential specification in equation (2) guarantees the positivity of the hazard function without placing constraints on the sign of α_q and the elements of the vector β_q .

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

$$s_{qi}^* = \ln \int_{\tau=0}^{t_{qi}} \lambda_0(\tau) d\tau = \alpha_q + \beta_q' x_{qi} - \omega_{qi} + \varepsilon_{qi}, \quad (3)$$

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

A number of different specifications may be used for the coefficient vectors α_q and β_q in equations (2) and (3). The simplest specification is $\alpha_q = 0$ and $\beta_q = 0$ for all individuals, and $\omega_{qi} = 0$ for all intershopping duration spells. This, of course, corresponds to the Kaplan-Meier sample hazard. A second specification is to write α_q as a deterministic function of an observed vector w_q of individual sociodemographic and residential location attributes ($\alpha_q = \delta' w_q$), and to allow heterogeneity across individuals in the effect of ICT use on the intershopping hazard due to observed individual characteristics by specifying the ICT use coefficient β_{ql} ($l = 1, 2, \dots, L$) as a function of an observed vector y_{qi} of individual attributes: $\beta_{ql} = \vartheta_l + \gamma_l' y_{qi}$. The spell-specific error term ω_{qi} is included in this formulation. The variance of ω_{qi} captures the level of heterogeneity in intershopping hazard across all spells. We will refer to this specification as the deterministic coefficients duration (DCD) model. A third specification superimposes random

(unobserved) individual heterogeneity over the deterministic (observed) heterogeneity of the DCD model: $\alpha_q = \delta'w_q + v_q$ and $\beta_{ql} = \vartheta_l + \gamma_l'y_{ql} + \eta_{ql}$, where v_q and η_{ql} are assumed to be normally distributed across individuals; [$v_q \sim N(0, \sigma_v^2)$; $\eta_{ql} \sim N(0, \sigma_{\eta_l}^2)$]. In addition, we assume that v_q is independent of each η_{ql} random term ($l = 1, 2, \dots, L$) and that the η_{ql} terms are independent of each other; v_q and η_{ql} represent individual-specific unobserved factors associated with overall preferences for shopping and sensitivity to ICT-use, respectively; the variance of ϖ_{qi} in this third specification captures within-individual heterogeneity in the intershopping hazard. We will refer to the random specification above as the random coefficients duration (RCD) model.

2.2 Sample Selection with Hazard Based Duration Structure

In the previous section, ICT use was considered exogenous to intershopping duration. However, as indicated earlier in Section 1.1, considering ICT use to be exogenous may lead to an incorrect assessment of the effect of ICT use on intershopping duration. This is because the intershopping hazard model of the previous section does not disentangle the true effect of ICT adoption from the spurious effect of ICT adoption. The latter effect corresponds to common unobserved factors that influence ICT adoption as well as the intershopping hazard. In this section, we discuss a sample selection model structure that considers the endogenous nature of ICT use.

For ease in presentation, we present the sample selection model structure considering only two ICT adoption variables; mobile phone use and computer use at home (these are also the two ICT adoption variables used in our empirical analysis). However, the framework is general and can be extended to multiple ICT-use variables without any conceptual or practical difficulty.

The equation system for the sample selection model structure comprises three equations: one equation each for the mobile phone and computer use choices, and a third equation for the intershopping duration modeling. Considering the form of the proportional hazard formulation in equation (3) for intershopping duration, the equation system may be written as follows:

$$\begin{aligned}
m_q^* &= \theta' h_q + \zeta_q + \upsilon_q, m_q = 1 \text{ if } m_q^* > 0, m_q = 0 \text{ if } m_q^* \leq 0 \\
p_q^* &= \mu' r_q + \xi_q + \omega_q, p_q = 1 \text{ if } p_q^* > 0, p_q = 0 \text{ if } p_q^* \leq 0 \\
s_{qi}^* &= \alpha_q + \beta_q' x_q \pm \zeta_q \pm \xi_q - \overline{\omega}_{qi} + \varepsilon_{qi}, t_{qi} = k \text{ if } \Psi_{k-1} < s_{qi}^* < \Psi_k, \Psi_k = \ln \int_{\tau=0}^k \lambda_0(\tau) d\tau, x_q = [m_q, p_q]',
\end{aligned} \tag{4}$$

where m_q^* and p_q^* are latent propensities to use mobile telephones and computers, respectively, and m_q and p_q are dummy variables representing whether or not an individual uses mobile phones and computers, respectively. h_q and r_q are column vectors of exogenous variables affecting mobile telephone use and computer use, and θ and μ are corresponding column vectors to be estimated. υ_q and ω_q are standard normal variables with a correlation ρ . This correlation term captures common unobserved factors that affect the propensity to use mobile telephones and a personal computer at home. ζ_q is a normal random error term that captures common unobserved factors influencing mobile phone use propensity and the intershopping hazard [$\zeta_q \sim N(0, \sigma_\zeta^2)$]. This term causes “spurious” dependence in mobile phone use and the intershopping hazard. The ‘ \pm ’ sign in front of ζ_q in the hazard equation indicates that the correlation in unobserved factors between mobile phone use and intershopping hazard may be positive or negative. If the sign is ‘+’, it implies that individuals who use mobile phones are also intrinsically more likely to have a lower intershopping hazard (see the correspondence between

equations 2 and 3). Equivalently, it implies that individuals who use mobile phones are intrinsically more likely to have longer intershopping durations, or fewer shopping trips. If the sign is ‘-’, it implies that individuals who use mobile phones are intrinsically more likely to have a higher intershopping hazard, *i.e.*, they are more likely to have shorter intershopping durations or undertake more shopping trips. Of course, if such correlations are ignored, they “corrupt” the “true” dependence of the intershopping hazard on mobile phone use. This issue is discussed in more detail in the empirical results section. ξ_q is a normal random term that similarly captures common unobserved factors influencing personal computer use propensity and the intershopping hazard; $\xi_q \sim N(0, \sigma_\xi^2)$.

2.3 Model Estimation

The parameters to be estimated in the sample selection model with a random coefficient duration (RCD) structure include the θ and μ vectors, the δ , ϑ , and γ vectors in the duration model, the ψ thresholds in the duration model that provide information regarding the baseline intershopping hazard profile, the ρ correlation parameter capturing the effect of common unobserved factors that affect the propensity to use mobile telephones and computers at home, the scalar variance terms σ_v^2 , σ_ζ^2 , σ_ξ^2 , and the vector variance term σ_η^2 . Let Ω represent a vector that includes all these parameters to be estimated, and let $\Omega_{-\sigma}$ represent a vector of all parameters except the variance terms. Define $g_q = 2m_q - 1$ and $n_q = 2p_q - 1$. Then the likelihood function for a given value of $\Omega_{-\sigma}$ and the error terms ζ_q , ξ_q , η_q , v_q , and ϖ_{qi} may be written for an individual q 's i^{th} intershopping duration spell as:

$$L_{qi}(\Omega_{-\sigma}) | \zeta_q, \xi_q, \eta_q, \nu_q, \varpi_{qi} = \Phi_2 [g_q \cdot (\theta' h_q + \zeta_q), n_q \cdot (\mu' r_q + \xi_q), g_q n_q \rho] \times \left[\exp\{-B_{(k_{qi-1})} \exp(\varpi_{qi})\} - \exp\{-B_{k_{qi}} \exp(\varpi_{qi})\} \right], \quad (5)$$

where k_{qi} is the actual intershopping duration of individual q in the i^{th} spell, $\Phi_2(\cdot)$ is the bivariate cumulative standard normal distribution, and

$$B_{k_{qi}} = \exp \left\{ \Psi_{k_{qi}} - \left[\delta' w_q + \sum_l (\vartheta_l + \gamma_l y_{ql} + \eta_{ql}) x_{ql} \pm \zeta_q \pm \xi_q + \nu_q \right] \right\}. \quad (6)$$

Assuming that $c_{qi} [= \exp(\varpi_{qi})]$ is distributed as a gamma random variable with a mean one (a normalization) and variance σ_c , the likelihood function for individual q 's i^{th} intershopping duration spell, unconditional on ϖ_{qi} , may be written as:

$$L_{qi}(\Omega_{-\sigma}) | \zeta_q, \xi_q, \eta_q, \nu_q = \Phi_2 [g_q \cdot (\theta' h_q + \zeta_q), n_q \cdot (\mu' r_q + \xi_q), g_q n_q \rho] \cdot \left\{ \int_0^{\infty} [\exp\{-B_{k_{qi-1}} \cdot c_{qi}\} - \exp\{-B_{k_{qi}} \cdot c_{qi}\}] f(c_{qi}) dc_{qi} \right\} \quad (7)$$

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

$$L_{qi}(\Omega_{-\sigma}) | \zeta_q, \xi_q, \eta_q, \nu_q = \Phi_2 [g_q \cdot (\theta' h_q + \zeta_q), n_q \cdot (\mu' r_q + \xi_q), g_q n_q \rho] \cdot [G_{(k_{qi-1})} - G_{k_{qi}}], \quad (8)$$

where $G_{k_{qi}} = [1 + \sigma_c^2 B_{k_{qi}}]^{-\sigma_c^{-2}}$. The gamma distribution for c_{qi} is convenient because it results in a closed-form expression in Equation (8). Next, define the following standard normal variables:

$$f_{qv} = \frac{\nu_q}{\sigma_\nu}, \quad f_{q\zeta} = \frac{\zeta_q}{\sigma_\zeta}, \quad f_{q\xi} = \frac{\xi_q}{\sigma_\xi}, \quad \text{and} \quad f_{q\eta l} = \frac{\eta_{ql}}{\sigma_{\eta l}} \quad (l = 1, 2; \text{ the range of } l \text{ corresponds to the number}$$

of ICTs). Also, define $f_{q\eta} = (f_{q\eta 1}, f_{q\eta 2})'$. Then the likelihood function for a given value of the parameter vector Ω and for an individual q with I_q intershopping duration spells can be written

conditional on $f_{q\zeta}, f_{q\xi}, f_{qv}$, and the $f_{q\eta}$ random terms as:

$$L_q(\Omega) | f_{q\zeta}, f_{q\xi}, f_{qv}, f_{q\eta} = \prod_{i=1}^{I_q} \left\{ \Phi_2 \left[g_q \cdot (\theta' h_q + f_{q\zeta} \sigma_\zeta), n_q \cdot (\mu' r_q + f_{q\xi} \sigma_\xi), g_q n_q \rho \right] \cdot \left[G_{(k_{qi}-1)} - G_{k_{qi}} \right] \right\}$$

$$\text{where } G_{k_{qi}} = [1 + \sigma_c^2 B_{k_{qi}}]^{-\sigma^2} \quad (9)$$

$$\text{and } B_{k_{qi}} = \exp \left\{ \psi_{k_{qi}} - \left[\delta' w_q + \sum_l (\rho_l + \gamma_l y_{ql} + f_{q\eta l} \sigma_{\eta l}) x_{ql} \pm f_{q\zeta} \sigma_\zeta \pm f_{q\xi} \sigma_\xi + f_{qv} \sigma_v \right] \right\}$$

The unconditional likelihood for individual q with I_q intershopping durations may finally be written as:

$$L_q(\Omega) = \int_{f_{q\zeta}=-\infty}^{+\infty} \int_{f_{q\xi}=-\infty}^{\infty} \int_{f_{qv}=-\infty}^{\infty} \int_{f_{q\eta}=-\infty}^{\infty} [L_q(\Omega) | f_{q\zeta}, f_{q\xi}, f_{qv}, f_{q\eta}] \cdot d\Phi(f_{q\zeta}) d\Phi(f_{q\xi}) d\Phi(f_{qv}) d\Phi(f_{q\eta}). \quad (10)$$

The log-likelihood function is $\mathcal{L}(\Omega) = \sum_q \ln L_q(\Omega)$.

The likelihood function in Equation (10) involves the evaluation of an $(L+3)$ -dimensional integral, where L is the number of ICTs modeled in the analysis. In the current empirical analysis, there are two ICTs, leading to a five-dimensional integral. This five-dimensional integration cannot be accomplished using general purpose numerical methods such as quadrature, since quadrature techniques cannot evaluate the integrals with sufficient precision and speed for estimation via maximum likelihood (see Hajivassiliou and Ruud, 1994).

We apply simulation techniques to approximate the integrals in the individual-specific likelihood function and maximize the logarithm of the resulting individual-specific simulated likelihood function across individuals with respect to Ω . The simulation technique approximates the individual likelihood function in Equation (10) by computing the integrand in the equation at different realizations of $f_{q\zeta}$, $f_{q\xi}$, f_{qv} , and $f_{q\eta}$ drawn from standard normal distributions, and computing the individual likelihood function by averaging over the different values of the integrand across the different realizations. Notationally, if $SL_q^d(\Sigma)$ is the realization of the

individual likelihood function in the d th draw ($d = 1, 2, \dots, D$), then the individual likelihood function is approximated as:

$$SL_q(\Omega) = \frac{1}{D} \sum_{d=1}^D SL_q^d(\Omega), \quad (11)$$

where $SL_q(\Omega)$ is the simulated likelihood function for the q th individual's sequence of intershopping episodes, given the parameter vector Ω . $SL_q(\Omega)$ is an unbiased estimate of the actual likelihood function $L_q(\Omega)$. Its variance decreases as D increases. It also has the appealing properties of being smooth (*i.e.*, twice differentiable) and being strictly positive for any realization of the draws.

The simulated log-likelihood function is constructed as:

$$S_{\text{QL}}(\Omega) = \sum_q \ln[SL_q(\Omega)]. \quad (12)$$

The parameter vector Ω is estimated as the value that maximizes the above simulated function. Under rather weak regularity conditions, the maximum (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 $f_{q\zeta}$, $f_{q\xi}$, f_{qv} , and $f_{q\eta}$ from their population normal distributions. The QMC approach uses “cleverly” crafted non-random and more uniformly distributed sequences within the domain of integration. The underlying idea of the method is that it is really inconsequential whether the discrete points are truly random; of primary importance is the even distribution (or maximum spread) of the points in the integration space. The sequences used in the quasi-Monte Carlo (or QMC) method are labeled as quasi-random sequences, though this is a misnomer since randomness plays no part in the construction of the sequences. Within the broad framework of

QMC sequences, we specifically use 125 draws of the Halton sequence in the current analysis. Details of the Halton sequence and the procedure to generate this sequence are available in Bhat, (2001). Bhat has demonstrated that the Halton simulation method out-performs the traditional pseudo-Monte Carlo (PMC) methods for mixed logit model estimation. Subsequent studies by Train (1999) and Hensher (1999) have confirmed this result.

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.*, 2000, 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).

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. Both the

pretest and main surveys were conducted in two waves to capture seasonal variation. 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.

3.2 Sample Used and Description

The sample used in the current analysis comprises 1144 intershopping duration spells of 255 adult individuals (an adult individual is defined as one whose age is equal to or over 16 years; we restricted the empirical analysis to adult individuals on the basis that children are likely to be accompanied by adults for shopping activities, and are not likely to be decision-makers themselves). The intershopping spells correspond to participation in non-maintenance shopping activities (*i.e.*, not including grocery shopping, medical drug shopping, *etc.*).

The number of intershopping duration spells over the course of the survey varies between 1 and 18 across individuals, with an average of 4.74 spells. The length of the intershopping duration varies between 1 and 40 days. However, there were very few intershopping spells larger than 23 days, and so we collapsed all these intershopping durations to 23 days (only 14 intershopping spells out of 1144, or 1.2% of spells, were longer than 23 days).

Table 1 provides descriptive information on intershopping duration. The column titled “Risk Set” provides information on the number of intershopping episodes which are “at risk” of termination in period t ; that is, it provides the number of episodes whose length extends at least up to the beginning of period t . The column labeled “# terminated” indicates the number of

episodes that terminate in period t . The sample hazard associated with each period is computed using the Kaplan-Meier (KM) nonparametric estimator as the number of terminated episodes in period t divided by the risk set in period t (see Kiefer, 1988). The sample hazard values are provided in the fourth column of Table 1, and are also plotted in Figure 1. The hazard reveals spikes at 7, 18, and 21 days, indicating a certain level of rhythmic interpurchase durations among shoppers. However, the overall hazard profile is quite flat, suggesting a substantial amount of randomness in interpurchase durations when the effect of covariates and unobserved heterogeneity are ignored (see discussion under Equation (3)).

3.3 Variable Specification and Model Formulation

Three broad sets of variables were considered in the analysis: individual characteristics, household characteristics, and location characteristics.

Individual characteristics explored in our specifications included dummy variables for sex, ethnicity, education level, and employment status, and linear and non-linear representations of work hours per week and age. It also included the following two individual trip-making attributes: the most frequently used mode for shopping activity-participation and the percentage of shopping episodes chained with other activities. 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 vehicles, and communication-related connections. Location and trip-making characteristics included whether the household is located in Karlsruhe or Halle, and whether the household is located in an urban area, an urban-suburban area, a suburban area, or a rural area.

A number of different model structures were also estimated in the analysis. These included the following: (1) Exogenous models for ICT use (mobile phones and computer use) with the sample hazard specification for intershopping hazard, (2) Exogenous models for ICT use with a deterministic-coefficients specification for the intershopping hazard, (3) Exogenous models for ICT use with a random coefficients specification for the intershopping hazard, (4) Endogenous models for ICT use with the sample hazard specification for intershopping hazard, (5) Endogenous models for ICT use with a deterministic-coefficients specification for the intershopping hazard, and (6) Endogenous models for ICT use with a random coefficients specification for the intershopping hazard. In each of the latter three structures, we attempted four different model formulations for introducing the endogeneity in ICT use. These four formulations corresponded to different correlation patterns in unobserved factors affecting ICT-use propensity and the intershopping hazard (see discussion in Section 2.2). Thus, in all, we estimated 15 different model formulations.

In this paper, we present the results of the final variable specification for three model formulations. The three model formulations are: (1) Exogenous models for ICT use with a deterministic-coefficient specification for the intershopping hazard and with unobserved interpell heterogeneity, (2) Exogenous models for ICT use with a random coefficient specification for the intershopping hazard, and (3) Endogenous models for ICT use with a random coefficient specification for the intershopping hazard, and with ‘-’ signs on the ζ_q and ξ_q terms in the hazard structure of Equation (4). We adopt a negative sign on the error ζ_q and ξ_q terms because this combination provided a better data fit than the other three sign combinations on ζ_q and ξ_q (*i.e.*, the [+ , +], [+ , -], and [- , +] combinations). The ‘-’ signs imply that individuals who use mobile phones and/or computers at home are intrinsically more likely to have a higher

intershopping hazard; that is, individuals who use mobile phones and/or computers at home are intrinsically more likely to undertake shopping activities than individuals who do not use ICTs. As we will indicate empirically later, ignoring this correlation in ICT use and intershopping duration will, in general, lead to incorrect estimates of the impact of ICT use on intershopping duration.

Table 2 provides the definitions and sample statistics for the variables used in the final model specifications.

4. EMPIRICAL RESULTS

The results are presented in four broad sections. The first section presents the results for the ICT use models. The second section discusses the results of the intershopping duration hazard model, and presents the sample selection and unobserved heterogeneity parameters. The reader will note that the estimation of the ICT use models, the duration hazard, and the sample selection and unobserved heterogeneity parameters are all achieved simultaneously. They are discussed in separate sections for presentation ease. The final section discusses model fit statistics.

4.1 ICT Use Estimation Results

Tables 3 and 4 provide the estimation results for mobile phone use and home computer use, respectively. As can be observed from these tables, the coefficient estimates do not vary substantially among the three model structures (*i.e.*, the exogenous ICT use-deterministic-coefficient hazard model, the exogenous ICT use-random coefficient hazard model, and the endogenous ICT use-random coefficients hazard model). This is to be expected since the ICT use

coefficients are consistently estimated regardless of whether a deterministic or random coefficient specification is adopted for the hazard model and independent of whether or not sample selection of the duration model, based on the ICT use variables, is accommodated. The next two subsections discuss the results for mobile phone use and home computer use, respectively, in greater detail.

4.1.1 Mobile phone use results

The impact of individual characteristics on mobile phone use propensity in Table 3 indicates that employed individuals are more likely to use mobile phones relative to unemployed individuals. Similarly, individuals with high education are more likely to use mobile phones relative to individuals with low education. The impact of age is interesting. The results indicate that the highest level of mobile phone use is among teenage adults (16-19 years of age). Among individuals above 19 years, middle-aged individuals (30-50 years) are the most likely to use mobile phones.

The effects of household attributes indicate that individuals in high income households use mobile phones more than individuals in low income households, as expected. In addition, individuals in households with several adults tend to be less likely to use mobile phones, perhaps because reaching an adult in such households in the case of emergencies is easier using conventional telephones than reaching an adult in households with few adults. The flexibility and convenience offered by mobile telephones would also facilitate the more efficient realization of family and personal responsibilities, which would be particularly important for households with fewer adults. Finally, among household characteristics, nuclear family households are much more likely to use mobile phones compared to other types of households.

The results of locational characteristics show that households in Karlsruhe (in West Germany) are more likely to own mobile phones than those in Halle (in East Germany). Further, individuals in households in urban-suburban and suburban locations are more likely to use mobile phones than individuals in urban and rural areas.

4.1.2 Computer use at home

The pattern of the impacts of individual, household, and locational attributes on computer use at home are similar to the impact of these variables on mobile phone use. The one additional variable is the single-person household variable. The effect of this variable suggests that individuals living alone are not as likely to use computers at home as individuals in non-single households.

4.1.3 Correlation in use of ICTs

The correlation in unobserved factors affecting mobile phone propensity and computer use propensity is positive and statistically significant (see bottom of Table 4); that is, the same unobserved factors that make an individuals inclined to use one type of ICT also make the individual inclined to use the other type of ICT. This is an intuitive result.

4.2 Hazard-Based Duration Model Estimation Results

4.2.1 The baseline hazard

The baseline hazard functions for the three different model formulations are provided in Figure 2. The overall profiles of these hazard functions are similar with spikes at 7, 18, and 21 days. Also, there is a heightened hazard profile between 12-16 days, *i.e.*, around the two week

intershopping duration. Taken together, there is a rhythmic weekly or biweekly or triweekly intershopping duration (the spike at 18 days is a little surprising though).

There is one clear difference between the hazard functions in Figure 2 and the sample hazard function in Figure 1. Specifically, the hazard functions in Figure 2 show an increasing trend as the intershopping duration increases, reflecting a “snowballing” effect; that is, individuals are more likely to engage in shopping as the time elapsed since the previous participation increases.

4.2.2 Effects of individual and household characteristics on intershopping hazard

The effects of covariates on the intershopping hazard are provided in Table 5. 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. Alternatively, a negative coefficient on a covariate implies that the covariate increases the hazard rate, or equivalently, the covariate decreases the intershopping duration.

The effect of individual characteristics in Table 5 indicates that men have a lower hazard (*i.e.*, a higher intershopping duration) than women, and shoppers who use a car as the primary mode to participate in shopping have a lower hazard than those who use other modes. The latter effect may reflect the ability to carry large amounts of shopping items if a car is used, resulting in less need to shop frequently. The results also indicate that individuals who chain shopping participations with other activity stops are more likely to shop frequently.

The effect of household characteristics indicates that individuals in high income households have a higher intershopping hazard (*i.e.*, shop more frequently) than individuals in low income households. This is intuitive, and reflects the higher shopping expenditure potential

of high income households. Household structure also affects the intershopping hazard, with individuals in couple family households likely to have a higher intershopping hazard compared to nuclear family and other households. This may be attributed to the lower household responsibilities in couple families, and the consequent higher mobility levels of individuals in such households.

The impact of individual and household characteristics on the intershopping hazard are similar across the different models. However, the impacts of the ICT use variables are quite different across the models, especially between the third model and the other two models, as we discuss next.

4.2.3 Effect of ICT use variables

The effect of ICT use on the duration hazard, as estimated in each of the three models, is discussed in the subsequent three subsections. Within each subsection, the focus is on three issues: model coefficients, the percentage of individuals for whom ICT use has a substitution effect versus a complementary effect, and the mean percentage change in the hazard because of ICT use.

4.2.3.1 Exogenous ICT use-deterministic coefficients model

The parameters capturing the effect of mobile phone use in the exogenous ICT use-deterministic duration hazard model indicates that mobile phone use decreases the intershopping hazard (*i.e.*, increases the intershopping duration or decreases the number of shopping trips) for individuals with low education levels and living in Halle (see the coefficient on the constant under mobile phone use = 0.3937). Thus, mobile phone use has a substitution effect on shopping

trips for such individuals. This substitution effect extends to individuals with high education and living in Halle ($0.3937-0.2903 = 0.1034$), and individuals with low education and living in Karlsruhe ($0.3937-0.2894 = 0.1043$). However, the effect turns to one of complementarity for individuals with high education and living in Karlsruhe ($0.3937-0.2894-0.2903 = -0.186$). The effect of computer use on number of shopping episodes, on the other hand, is uniformly one of substitution across all individuals (as in the case of mobile phone use, we considered the mediating role of several sociodemographic characteristics on the impact of computer use, but none of these turned out to be statistically significant at the 10% level of significance).

There is no unobserved heterogeneity in the response to ICT use in the deterministic duration hazard model. Thus, the effect of mobile phone use on shopping episodes is estimated to be one of pure substitution for individuals in all groups except the highly educated Karlsruhe residents (for whom the effect is one of pure complementarity). The effect of computer use is estimated to be one of substitution for all individuals.

The overall mean effect of ICT use on the intershopping hazard may be assessed by computing the percentage change in hazard between ICT users and ICT nonusers. This can be written as $\{\exp(-\beta_i) - 1\} \times 100$. In the deterministic model, β_i is a function of only observed variables, and can be computed in a straightforward manner. These values are indicated in the first column in Table 6. The reader will note that a negative mean effect on the hazard implies a lower intershopping duration, or fewer shopping episodes (*i.e.*, an overall substitution effect). A positive mean effect implies an overall complementary effect. An interesting result from Table 6 is that the substitution effect of computer use is lower than mobile phone use for individuals with low education in Halle, but is higher than that of mobile phone use for individuals with higher education in Halle and low education in Karlsruhe. This result might reflect the higher comfort

level and intensity of use of computers for internet shopping among highly educated individuals and a better internet shopping infrastructure in Karlsruhe compared to Halle.

4.2.3.2 *Exogenous ICT use-random coefficient model*

Table 5 indicates that the mean coefficients of mobile phone use and computer use in the exogenous ICT use-random coefficients model are about the same as those obtained in the exogenous ICT use-deterministic coefficients model. Our results indicated virtually no variation in the effect of mobile phone use on the intershopping hazard due to unobserved individual factors and hence we do not include a random heterogeneity term for the effect of mobile phone use. However, the magnitude of the standard deviation characterizing the distribution of individual-specific effects of computer use on the intershopping hazard is sizeable compared to the mean computer use effect. This estimated standard deviation parameter is also significant at about the 7% level of significance.

The mean coefficient and the standard deviation on the computer use variable suggests that computer use has an overall substitution effect on number of shopping episodes; however, computer use has a complementary effect for about 22% of computer users.

To summarize, the exogenous ICT use-random coefficients model indicates homogeneity in the shopping behavior of mobile phone users, after controlling for their education levels and residential location. However, among computer users, 78% make fewer shopping trips than non-users, while 22% make more shopping trips than non-users.

The mean effect of ICT use on the intershopping hazard may be computed as $\{\overline{\exp(\beta_i)} - 1\} \times 100$, where $\overline{\exp(\beta_i)}$ is the mean value of the exponent of β_i . Now, since β_i is normally distributed in the random coefficients specification, $\exp(\beta_i)$ is log-normally distributed with mean:

$$\overline{\exp(\beta_i)} = \exp(\vartheta_i + \gamma_i' y_{qi}) \cdot [\exp(\sigma_{\eta_i}^2)]^{0.5}. \quad (13)$$

The resulting estimates of the mean impacts of ICT use are provided in the column under the exogenous ICT use-random coefficient model in Table 6. These results show a close similarity to those obtained from the deterministic coefficients model.

4.2.3.3 *Endogenous ICT use-random coefficient model*

The estimated coefficient on the mobile phone use constant in the endogenous ICT use-random coefficients model is higher in magnitude than those in the earlier models, as can be observed in Table 5. This reflects a substantially higher substitution effect due to mobile phone use than estimated in the earlier two models. This is an intuitive result, when viewed in combination with the estimated highly significant standard deviation ($= 0.4174$) of the common unobserved error component between the mobile phone use propensity and the duration hazard (see under sample selection and heterogeneity terms in Table 5). Specifically, as discussed earlier, the significant presence of unobserved factors common to the duration hazard and mobile phone use propensity implies that mobile phone users are intrinsically likely to be making more shopping trips than non-users. If this association is ignored, the intrinsic complementarity in mobile phone use and shopping trips (due to unobserved individual characteristics, such as say active and dynamic lifestyle) reduces the magnitude of the true substitution effect of mobile phone use on shopping trips. As a simple illustration of this effect, assume two groups of individuals with identical observed characteristics. The first group of individuals has unobserved characteristics that lead to mobile phone use and an overall desire for a higher number of shopping episodes than the second group of mobile phone non-users. If individuals in the first group were not using mobile phones, they would have made, say, 6 trips. Individuals in the

second group, however, make only 4 trips. Note that this difference in trip-making propensity is because of unobserved life-style related factors. If these unobserved factors are ignored, the implicit assumption is that both the first and second groups make only 4 trips. Now, because of mobile phone use in the first group of mobile phone users, we might actually observe individuals in this group making 3 trips. Thus, the true reduction in trips because of mobile phone use is from 6 trips to 3 trips, an overall substitution effect of 50%. However, if the unobserved factors that caused the first group to be more shopping-inclined were ignored, the (mis-)estimated reduction in trips because of mobile phone use would be from 4 to 3, an overall substitution effect of only 25%. While this is a simple illustration, it does capture the essence of the reason for the higher magnitude on the mobile phone use constant in the endogenous ICT use-random coefficient models.

The impact of home computer use on shopping episodes includes both substitution and complementary effects because of the random heterogeneity in responsiveness to home computer use in the random coefficient structure (the standard deviation parameter characterizing this random heterogeneity is significant at the 5% level). The estimated mean and standard deviation parameters indicate that, among computer users, 74% make fewer shopping trips than non-users and 26% make more shopping trips than non-users.

The estimated mean magnitudes of the effects of ICT use on the intershopping hazard in the endogenous ICT use-random coefficients model are provided in the final column of Table 6, and reflect the discussion indicated earlier. Specifically, the first two models underestimate the substitution effect of mobile telephone use considerably. In fact, the results of the endogenous ICT use-random coefficients model indicates a substitution effect for all sociodemographic groups, including the highly educated Karlsruhe residents.

4.2.4 Sample selection and overall unobserved heterogeneity results

The standard deviation of the error term generating sample selection in mobile phone use and the intershopping hazard is highly significant in the endogenous ICT use-random coefficient model. Ignoring this error term leads to a bias in the estimated effect of mobile phone use, as discussed in the previous section. However, the common error term between computer use and the intershopping hazard was not significant and is not included in the table.

The variances of the unobserved heterogeneity terms provide important information regarding the fraction of variation in the intershopping hazard explained by covariates and by unobserved factors. To see this, consider Equation (2) in the context of the most general endogenous ICT use-random coefficients specification for the duration hazard:

$$\begin{aligned}\lambda_{qi}(\tau) &= \lambda_0(\tau) \exp(-\alpha_q - \beta'_q x_q + \zeta_q + \xi_q + \omega_{qi}) \\ &= \lambda_0(\tau) \exp(-\delta' w_q - v_q - \sum_l [\vartheta_l + \gamma'_l y_{ql} + \eta_{ql}] x_{ql} + \zeta_q + \xi_q) c_{qi}, \text{ where } c_{qi} = \exp(\omega_{qi}) \\ &= \lambda_0(\tau) \exp(-\Pi' \tilde{x}_q - \sum_l \eta_{ql} x_{ql} - v_q + \zeta_q + \xi_q) c_{qi},\end{aligned}\quad (14)$$

where $\tilde{x}_q = (w'_q, x_{q1}, \dots, x_{qL}, y_{q1} x_{q1}, \dots, y_{qL} x_{qL})'$ and $\Pi = (\delta', \vartheta_1, \dots, \vartheta_L, \gamma'_1, \dots, \gamma'_L)'$.

Taking the logarithm of both sides of the above equation yields the following equation:

$$\ln \lambda_{qi}(\tau) = \ln \lambda_0(\tau) - \Pi' \tilde{x}_q - \sum_l \eta_{ql} x_{ql} - v_q + \zeta_q + \xi_q + \ln c_{qi}. \quad (15)$$

Since the baseline hazard $\lambda_0(\tau)$ is the same across all intershopping spells, the variance across spells of the (log) intershopping hazard can be partitioned as follows:

$$\text{Var}[\ln \lambda_{qi}(\tau)] = \text{Var}(\Pi' \tilde{x}_q) + [\text{Var}(\sum_l \eta_{ql} x_{ql}) + \text{Var}(v_q) + \text{Var}(\zeta_q) + \text{Var}(\xi_q) + \text{Var}(\ln c_{qi})], \quad (16)$$

where $\text{Var}(\Pi' \tilde{x}_q)$ represents the variance due to observed heterogeneity and the second term on the right hand side represents the variance due to unobserved heterogeneity.

The variance due to unobserved heterogeneity comprises only the term $Var(\ln c_{qi})$ in the exogenous ICT use-deterministic coefficients model. This term captures overall unobserved heterogeneity across intershopping duration spells and across individuals. The variance due to unobserved heterogeneity, however, can be further partitioned into intra-individual heterogeneity and inter-individual heterogeneity in the remaining two models. In both these models, the extent of intra-individual unobserved heterogeneity is provided by $Var(\ln c_{qi})$. In the exogenous ICT use-random coefficients model, the inter-individual unobserved heterogeneity comprises the unobserved variation in response to ICT use [$Var(\sum_l \eta_{ql} x_{ql})$] and intrinsic inter-individual unobserved heterogeneity [$Var(v_q)$]. In the endogenous ICT use-random coefficient model, the intrinsic inter-individual unobserved heterogeneity effect can be further partitioned into unobserved heterogeneity related to mobile phone use propensity [$Var(\zeta_q)$], unobserved heterogeneity related to home computer use propensity [$Var(\xi_q)$], and unobserved heterogeneity unrelated to ICT use propensity [$Var(v_q)$].

The percentage of variation in the departure time hazard explained by each of the different variance components can be computed from the estimates of Π and the estimated variances of the many error components. These percentages are presented in Table 7. 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 intra-individual heterogeneity in Table 7 indicates the percentage of unobserved heterogeneity captured by intra-individual heterogeneity. Finally, the inter-individual heterogeneity component is partitioned into its various components. Several important observations may be drawn from this Table. First, the

percentage of hazard variation captured by observed factors increases from 11% in the Exogenous ICT use-deterministic coefficients model to 32% in the two random coefficients model. This is not surprising, since the better representation of inter-individual heterogeneity and sample selection factors allows the influence of observed covariates to be captured more accurately. Second, variation in the hazard due to unobserved factors is higher within the spells of the same individual than across individuals. Specifically, the results show that a little more than 70% of the total unobserved heterogeneity is due to intra-individual unobserved heterogeneity. Third, the results in the endogenous ICT use-random coefficients model indicate that 85% of the unobserved individual factors that affect the intershopping hazard also affect mobile phone use propensity. That is, there is a large overlap in unobserved individual factors affecting shopping behavior and mobile phone use propensity.

4.3 Model Fit Statistics

The log-likelihood value at convergence for the exogenous ICT use-deterministic coefficients model with 52 parameters is -3151.6 . The corresponding values for the exogenous ICT use-random coefficients model with 54 parameters and the endogenous ICT use-random coefficients model with 55 parameters are -3142.4 and -3141.41 , respectively. The log-likelihood value for the naive model that assigns sample shares for ICT use (*i.e.*, uses only constants in the ICT use equations) and adopts a single intershopping hazard profile across all individuals is -3218.2 . This naive model has 24 parameters. A likelihood ratio test of the three models estimated in this paper with the naive model clearly indicates the significant influence of sociodemographic, locational, and individual-specific unobserved factors on ICT-use and intershopping duration (the likelihood ratio test statistic is of the order of -133.0 , which is larger

than the chi-squared statistic with 28-30 degrees of freedom at any reasonable level of significance. Similarly, a likelihood ratio test between the exogenous ICT use-deterministic coefficients model and the exogenous ICT use-random coefficients model indicates the presence of statistically significant unobserved individual heterogeneity in intershopping duration (the likelihood ratio test statistic is 18.4, which is greater than the chi-squared statistic with 2 degrees of freedom at any reasonable level of significance). The difference between the exogenous ICT use-random coefficients and endogenous ICT use-random coefficients models is statistically significant from a data fit standpoint only at the 15% level of significance. However, the substantive implications regarding the effect of ICT use on intershopping hazard are substantially different between the two models, as has already been discussed. The fundamental difference between these two models is that the exogenous ICT use-random coefficients model does not allow the unobserved individual-specific determinants of the intershopping hazard to be related to ICT use. However, the endogenous ICT use-random coefficients model indicates that almost all the unobserved individual-specific determinants of intershopping hazard affect ICT use (see Table 7).

5. CONCLUSION

This paper has examined the use and travel impacts of two forms of Information and Communication Technologies (ICTs). The two forms of ICTs correspond to mobile telephone use and computer use at home. The travel impacts are examined in the specific context of participation in out-of-home non-maintenance shopping activities over an extended period of six weeks. This is achieved by analyzing the duration between successive shopping participations using a hazard-based structure that recognizes the dynamics of intershopping duration; that is,

the structure recognizes that the likelihood of participating in shopping activity depends on the length of time elapsed since the previous participation.

The econometric model structure developed in the paper accommodates the possible endogeneity of ICT use decisions when individuals make intershopping duration choices. Unlike typical sample selection models in which both the sample selection criteria and the variable of interest are associated with the same unit of observation, the proposed structure recognizes that the criteria for sample selection (*i.e.*, ICT use decisions) are individual-specific, while the resulting sample selection affects all intershopping durations of the individual. The structure also recognizes the interval-level nature of intershopping durations; that is, it recognizes that a day is an interval of time, with several individuals having the same intershopping duration. In addition, the structure allows the responsiveness of shopping activity behavior to ICT use to vary across individuals based on observed and unobserved covariates of the individual. Finally, the structure is able to accommodate unobserved heterogeneity due to both inter-individual as well as intra-individual differences in intershopping durations. To our knowledge, this is the first formulation and application of a duration model in econometric literature to address all the above issues in a comprehensive unifying framework. The resulting model is estimated using a maximum simulated likelihood technique.

The duration formulation is applied to examine ICT use and the impact of ICT use on intershopping duration using a continuous six-week travel survey collected in the cities of Halle and Karlsruhe in Germany in the Fall of 1999. Several results from the empirical analysis in the paper are noteworthy. First, sociodemographic and locational characteristics affect ICT use. Further, there is a strong positive correlation in mobile telephone use and home computer use. Second, the effects of ICTs on activity-travel patterns are mediated by individual

sociodemographic and locational factors, as well as by unobserved individual characteristics. Specifically, our results show that the impact of mobile telephones on intershopping duration is a function of the education level of the individual and the individual's residence location (*i.e.*, whether the individual resides in Halle or Karlsruhe). The impact of home computer use is mediated by unobserved individual factors, with computer use having a substitution effect on the number of shopping trips for about 78% of computer users and a complementary effect for about 22% of computer users. These results emphasize the need to recognize systematic and random variations across individuals in the effect of ICT use on activity-travel behavior. Third, unobserved factors that increase the likelihood of using ICTs are also likely to impact activity-travel behavior. Ignoring this sample selection can and, in general, will lead inappropriate evaluations of the effect of ICT use on activity-travel behavior. In the empirical analysis in the paper, the results showed that the substitution between mobile phone use and shopping travel is grossly underestimated if the effect of common unobserved factors affecting mobile phone use and shopping travel is not considered. Overall, the results suggest a beneficial effect of increasing mobile phone and home computer use penetration in reducing the number of individual trips for non-maintenance related shopping activities. Fourth, the baseline hazard profile indicates a generally increasing trend as the intershopping duration increases. This reflects a "snowballing" effect; that is, the longer the time that has elapsed since the previous shopping participation, the more likely it is to engage in shopping activity. However, the baseline hazard profile is not monotonic and smooth. There is a clear spike at 7 days, a generally elevated profile between 12-16 days, and large spikes at 18 days and 21 days. These results suggest a weekly, biweekly, or triweekly rhythm in shopping participation. Fifth, there is substantial intra-individual variation in intershopping duration. In particular, intra-individual variation represents

about 50% of the overall variation in intershopping hazard, and about 70% of the unobserved variation in intershopping hazard. This clearly points to the need to observe and analyze individual activity-travel behavior over a period of multiple days.

The analysis in this paper provides important insights into the factors influencing ICT use and the effect of ICT use on intershopping duration. However, there are several avenues to extend the analysis. First, the consideration of a comprehensive set of ICTs (rather than just home computer use and mobile telephone use) would provide a broader picture of ICT use effects on activity and travel behavior. Second, a more detailed representation of ICT use, obtained using a communication activity diary, would be valuable in better understanding the interactions between ICT use and activity-travel behavior. Third, extending the current analysis to include multiple activity purposes (such as grocery shopping and recreational activities) would allow consideration of the potential joint nature of participation decisions across activity purposes. Fourth, the analysis may be extended to include a study of the impacts of ICT use on other dimensions of activity-travel behavior, such as length of trips, time-of-day of trips, travel mode used, and activity duration of participation episodes. Fifth, capturing the interaction among household members in activity-travel decisions and studying how these interactions are affected by ICT use is another direction for further research. Finally, the current paper focuses on the activity-travel impacts of ICT use from an individual's perspective. Obviously, reductions in individual travel because of teleshopping will be associated with an increase in delivery travel. The estimation of the net travel impacts of ICT use will therefore require a broader systemwide perspective in analysis (Mokhtarian and Salomon, 2000).

REFERENCES

- Axhausen, K.W., Zimmerman, Z., Schönfelder, S., Rindsfuser, G. and T. Haupt (2000). Observing the rhythms of daily life: a six week travel diary. Forthcoming in *Transportation*.
- Bhat, C.R. (1996). A hazard-based duration model of shopping activity with nonparametric baseline specification and nonparametric control for unobserved heterogeneity. *Transportation Research B*, 30, 3, 189-207.
- Bhat, C.R. (2000). Duration modeling. In D.A. Hensher and K.J. Button (eds), *Handbook of Transport Modelling*, Elsevier Science, 91-111.
- Bhat, C.R. (2001). Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transportation Research B*, 35, 677-693.
- Boden, R.J. (1999). Flexible working hours, family responsibilities, and female self-employment: gender differences in self-employment selection. *American Journal of Econometrics and Sociology*, 58, 71-83.
- Chamberlain, G. (1980). Analysis of covariance with qualitative data. *Review of Economic Studies*, 47, 225-238.
- Diggle, P.J., Liang, K.-Y., Zeger, S.L. (1994). *Analysis of Longitudinal Data*. Clarendon Press, Oxford, U.K.
- Droege, P., ed. (1997). *Intelligent Environments*. Elsevier, Oxford.
- Forrester (2000). *B2B Insights: eMarketplaces*. Forrester Research, Cambridge MA, <http://www.forrester.com/>
- French, D., et al., eds. (1999). *Internet Based Learning: An Introduction and Framework for Higher Education and Business*. Stylus, sterling. VA.
- Gould, J. and T.F. Golob (1997). Shopping without travel or travel without shopping? An investigation of electronic home shopping. *Transport Reviews*, 17, 355-376.
- Graham, S. and S. Marvin (1996). *Telecommunications and the City: Electronic Spaces, Urban Places*. Routledge, London.
- Greene (2000). *Econometric Analysis*. Prentice Hall, New Jersey.
- Hajivassiliou, A., and Ruud, P.A. (1994). Classical estimation methods for LDV models using simulation. In R.F. Engle and D.L. McFadden (eds), *Handbook of Econometrics*, 4, North Holland, Amsterdam, 2383-2441.
- Handy, S. and T. Yantis (1997). The impacts of telecommunications technologies on nonwork travel behavior. Research Report SWUTC/97/721927-1F, Southwest Region University Transportation Center, Center for Transportation Research, The University of Texas at Austin, January.
- Harvey, A.S. and M.E. Taylor (2000). Activity settings and travel behaviour: a social contact perspective. *Transportation*, 27, 1, 53-73.
- Henderson, D.K. and P.L. Mokhtarian (1996). Impacts of center-based telecommuting on travel and emissions: analysis of the Puget Sound Demonstration Project. *Transportation Research D*, 1, 29-45.
- Hensher, D.A. (1999). The valuation of travel time savings for urban car drivers: evaluating alternative model specifications. Technical paper, Institute of Transport Studies, University of Sydney.
- Hensher, D.A. and F.L. Mannering (1994). Hazard-based duration models and their application to transport analysis. *Transport Reviews*, 14, 1, 63-82.

- Hsiao, C. (1986). *Analysis of Panel Data*. Cambridge University Press, Cambridge, MA.
- Johnson and Kotz (1970). *Distributions in Statistics: Continuous Univariate Distributions*. New York, Wiley, Chapter 21.
- Jones, P. and M. Clark (1988). The significance and measurement of variability in travel behaviour. *Transportation*, 15, 65-87.
- Kiefer, N.M. (1988). Econometric duration data and hazard functions. *Journal of Econometric Literature*, 27, 646-679.
- Kilpala, H.K., Seneviratne, P.N., and S.M. Pekkarinen (2000). Electronic grocery shopping and its impact on transportation and logistic with special reference to Finland. Presented at 79th Annual Meeting of the Transportation Research Board, January 9-13, Washington DC.
- Koenig, B.E., Henderson, D.K., and P.L. Mokhtarian (1996). The travel and emissions impacts of telecommuting for the State of California Telecommuting Pilot Project. *Transportation Research C*, 4, 13-32.
- Koppelman, F., Salomon, I., and K. Prousaloglou (1991). Teleshopping or store shopping? A choice model for forecasting the use of new telecommunications-based services. *Environment and Planning B*, 18, 473-489.
- Lee, L.-F. (1992). On the efficiency of methods of simulated moments and maximum simulated likelihood estimation of discrete response models. *Econometric Theory*, 8, 518-552.
- Lund, J.R., and P.L. Mokhtarian (1994). Telecommuting and residential location: theory and implications for commute travel in the monocentric metropolis. *Transportation Research Record*, 1463, 10-14.
- Manski, C.F. and I. Salomon (1987). The demand for teleshopping: an application of discrete choice models. *Regional Science and Urban Economics*, 17, 109-121.
- Mannering, J.S. and P.L. Mokhtarian (1995). Modeling the choice of telecommuting frequency in California: an exploratory analysis. *Technological Forecasting and Social Change*, 49, 49-73.
- Martens, M.J. and W. Korver (2000). Forecasting the mobility effects of teleservices using a scenario approach. Presented at 79th Annual Meeting of the Transportation Research Board, January 9-13, Washington DC.
- Moberg, A. (1993). Satellitkontor: en studie av kommunikationsmönster vid arbete på distans (in Swedish), Thesis No. 406. Linköping Studies in Science and Technology, Department of Computer and Information Science, Linköping University, Sweden.
- Mokhtarian, P.L. (1997). The transportation impacts of telecommuting: recent empirical findings. In P. Stopher and M. Lee-Gosselin (eds), *Understanding Travel Behaviour in an Era of Change*, Elsevier, Oxford, 91-106.
- Mokhtarian, P.L., and R. Meenakshisundaram (1999). Beyond tele-substitution: disaggregate longitudinal structural equations modeling of communication impacts. *Transportation Research C*, 7, 33-52.
- Mokhtarian, P.L., and I. Salomon (1997). Modeling the desire to telecommute: the importance of attitudinal factors in behavioral models. *Transportation Research A*, 31, 1, 35-50.
- Mokhtarian, P.L., and I. Salomon (2000). Emerging travel patterns: do telecommunications make a difference? Prepared for the Eighth Meeting of the International Association for Travel Behavior Research and forthcoming in the IATBR Austin Conference book.

- Mokhtarian, P.L., and K.V. Varma (1998). The trade-off between trips and distance traveled in analyzing the emissions of center-based telecommuting. *Transportation Research D*, 3, 419-428.
- Pendyala, R.M., Goulias, K.G., and R. Kitamura (1991). Impact of telecommuting on spatial and temporal patterns of household travel. *Transportation*, 18, 383-409.
- Pioneer Consulting (1999). *Next Generation Broadband Satellite Networks: A Market and Technology Assessment Report*. Pioneer Consulting, Cambridge, MA.
- Salomon, I. (1996). Telecommunications, cities and technological opportunism. *Annals of Regional Science*, 30, 75-90.
- Spittje, H.D. (1994). Tele/homework and time use/travel behaviour. Paper for presentation at IATAR Conference, July 18-23, Bielefeld, Germany. Contact: H.D.Spittje@trc.rug.nl.
- Tacken, M. (1990). Effects of teleshopping on the use of time and space. *Transportation Research Record*, 1285, 89-91.
- Train, K. (1999). Halton sequences for mixed logit. Technical paper, Department of Economics, University of California, Berkeley.
- Viswanathan, K. and K.G. Goulias (2001). Travel behavior implications of information and communications technologies (ICT) in the Puget Sound region. Presented at 80th Annual Meeting of the Transportation Research Board, January 7-11, Washington DC.
- Yen, J-R and H.S. Mahmassani (1998). Telecommuting adoption: conceptual framework and model estimation. *Transportation Research Record 1606*, 95-102.
- Yim, Y. (2000). Telecommunications and travel behavior: would cellular communication generate more trips? Presented at 79th Annual Meeting of the Transportation Research Board, January 9-13, Washington DC.
- Zimmerman, C.A., Campbell, J.L., and C. Cluett (2001). Impact of new information and communication technologies on transportation agencies: a synthesis of highway practice. NCHRP Synthesis 296, National Cooperative Highway Research Program, Transportation Research Board.
- Zumkeller, D. (1996). Communication as an element of the overall transport context – an empirical study. In A.J. Richardson, E.S. Ampt and A.H. Meyburg (eds), *Proceedings of the Fourth International Conference on Survey Methods in Transport*, 66-83, Eucalyptus Press, Melbourne.

LIST OF FIGURES

Figure 1. Sample Hazard Function

Figure 2. Baseline Hazard Functions

LIST OF TABLES

Table 1. Inter-Shopping Duration and Sample Hazard

Table 2. Variable Definitions and Sample Statistics (Number of individuals = 255)

Table 3. Mobile Phone Use Propensity

Table 4. Computer Use Propensity

Table 5. Hazard Duration Model Results

Table 6. Effect of ICT Use on Intershopping Hazard

Table 7. Percentage of Intershopping Hazard Variation Explained by Observed and Unobserved Factors

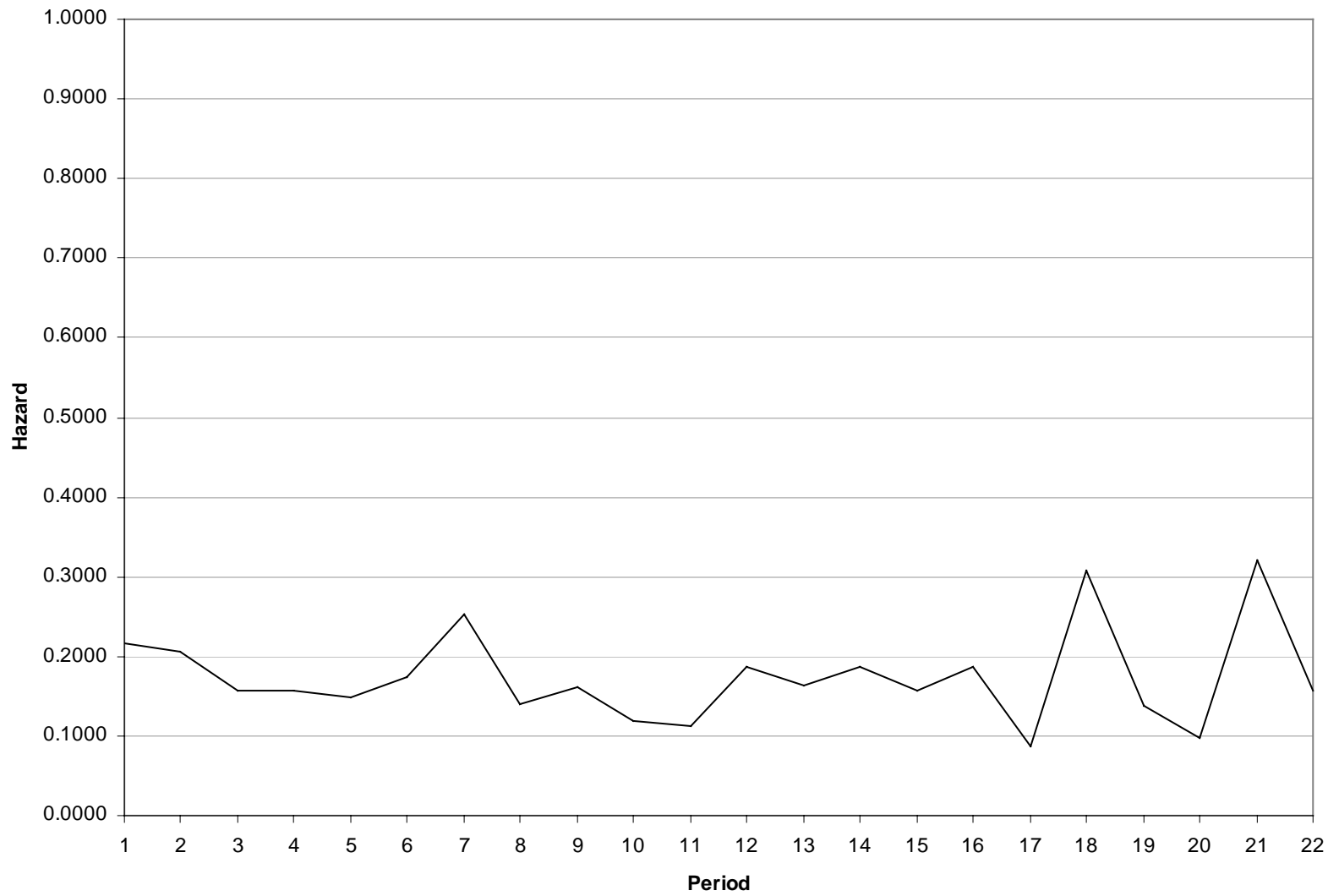


Figure 1. Sample Hazard Function

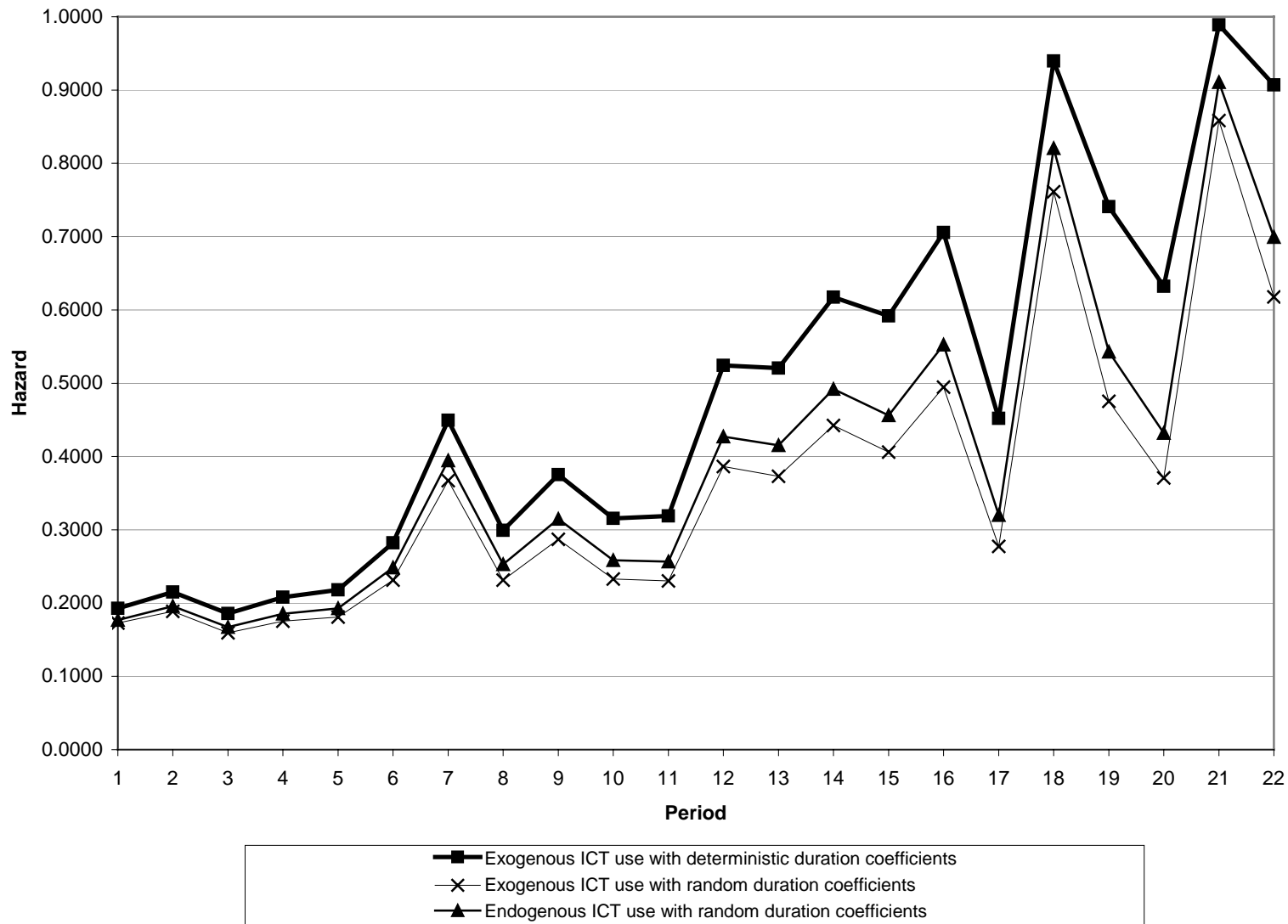


Figure 2. Baseline Hazard Functions

Table 1. Inter-Shopping Duration and Sample Hazard

Period	Risk Set	# Terminated	Hazard	t-stat
1	1144	248	0.2168	17.03
2	896	185	0.2065	14.91
3	711	111	0.1561	9.72
4	600	94	0.1567	10.33
5	506	75	0.1482	8.98
6	431	75	0.1740	8.39
7	356	90	0.2528	10.19
8	266	37	0.1391	6.00
9	229	37	0.1616	6.46
10	192	23	0.1198	4.76
11	169	19	0.1125	4.22
12	150	28	0.1867	5.32
13	122	20	0.1640	4.64
14	102	19	0.1863	4.04
15	83	13	0.1567	3.93
16	70	13	0.1858	3.73
17	57	5	0.0877	2.17
18	52	16	0.3078	4.53
19	36	5	0.1389	2.25
20	31	3	0.0968	1.74
21	28	9	0.3215	3.34
22	19	3	0.1579	1.72
23	16	16	1.0000	1.00

Table 2. Variable Definitions and Sample Statistics (Number of individuals = 255)

Variable	Definition	Mean	Std. Dev.
Individual characteristics			
Employed	1 if individual is employed, 0 otherwise	0.60	0.49
High education	1 if individual has attended technical college or university, 0 otherwise	0.30	0.46
Age 16-20 years	1 if individual is between 16 and 20 years of age, 0 otherwise	0.09	0.29
Age 20-29 years	1 if individual is between 20 and 29 years of age, 0 otherwise	0.14	0.34
Age 30-49 years	1 if individual is between 30 and 49 years of age, 0 otherwise	0.40	0.49
Age >50 years	1 if individual is over 50 years of age, 0 otherwise	0.37	0.48
Male	1 if individual is male, 0 otherwise	0.48	0.50
Primary mode used is car	1 if car is the most frequently used mode for shopping, 0 otherwise	0.60	0.49
Fraction of shopping episodes chained	Fraction of total non-maintenance shopping episodes that are chained with other activities	0.51	0.35
Household characteristics			
Income (in thousands of DM)	Monthly household income	4.32	2.05
Number of adults	Number of adults in household	2.26	0.83
Nuclear family	1 if household is a nuclear family, 0 otherwise	0.44	0.50
Couple family	1 if household is a couple family, 0 otherwise	0.32	0.47
Residential location characteristics			
Karlsruhe	1 if home is in Karlsruhe, 0 if home is in Halle	0.58	0.49
Urban-suburban residence	1 if home is in an urban-suburban area, 0 otherwise	0.42	0.49
Suburban residence	1 if home is in a suburban area, 0 otherwise	0.23	0.42
ICT use			
Mobile phone use	1 if individual has a mobile phone available for use, 0 otherwise	0.36	0.48
Home computer use	1 if individual has a private email address, 0 otherwise	0.22	0.41

Table 3. Mobile Phone Use Propensity

Variable	Exogenous ICT use with deterministic coefficients hazard		Exogenous ICT use with random coefficients hazard		Endogenous ICT use with random coefficients hazard	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Constant	-0.2312	-0.445	-0.2279	-0.438	-0.2796	-0.510
Individual characteristics						
Employed	0.5234	2.680	0.5236	2.680	0.6210	2.873
High education	0.5110	2.174	0.5118	2.177	0.5294	2.098
Age (Base is 16-19 years)						
20-29 years	-1.3773	-2.938	-1.3804	-2.944	-1.4574	-2.972
30-49 years	-0.5484	-1.469	-0.5510	-1.476	-0.6326	-1.605
> 50 years	-0.8627	-2.319	-0.8655	-2.326	-0.9603	-2.448
Household characteristics						
Income	0.0695	1.360	0.0694	1.359	0.0760	1.405
Number of adults	-0.2783	-1.852	-0.2785	-1.853	-0.3030	-1.875
Nuclear family	1.2180	4.188	1.2175	4.186	1.3181	4.169
Residential location characteristics						
Karlsruhe	0.2698	1.279	0.2700	1.280	0.2970	1.318
Urban-suburban residence	0.4485	1.948	0.4484	1.948	0.5080	2.081
Suburban residence	0.4032	1.702	0.4030	1.702	0.4583	1.789

Table 4. Computer Use Propensity

Variable	Exogenous ICT use with deterministic coefficients hazard		Exogenous ICT use with random coefficients hazard		Endogenous ICT use with random coefficients hazard	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Constant	0.2901	0.534	0.2868	0.528	0.2931	0.540
Individual characteristics						
High education	0.6829	2.671	0.6829	2.671	0.6853	2.686
Household characteristics						
Income	0.1236	2.385	0.1236	2.385	0.1238	2.387
Number of adults	-0.8502	-3.711	-0.8486	-3.708	-0.8523	-3.722
Nuclear family	0.7099	2.075	0.7084	2.071	0.7143	2.088
Single person household	-0.8449	-2.205	-0.8428	-2.200	-0.8423	-2.201
Residential location characteristics						
Karlsruhe	0.5584	2.708	0.5583	2.707	0.5580	2.709
Unobserved correlation between mobile phone and computer use propensities	0.3394	2.587	0.3395	2.588	0.3569	2.480

Table 5. Hazard Duration Model Results

Variable	Exogenous ICT use with deterministic coefficients hazard		Exogenous ICT use with random coefficients hazard		Endogenous ICT use with random coefficients hazard	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Individual characteristics						
Male	0.2600	2.028	0.2400	2.031	0.2385	1.974
Primary mode used is car	0.2847	2.352	0.2764	2.339	0.2752	2.358
% of shopping episodes chained	-0.4676	-2.362	-0.4264	-2.550	-0.4670	-2.638
Household characteristics						
Income	-0.0421	-1.182	-0.0250	-0.851	-0.0335	-1.091
Couple family	-0.2794	-2.258	-0.2428	-2.114	-0.2155	-1.802
ICT use variables						
Mobile phone use						
Constant	0.3937	2.047	0.3898	2.037	0.6321	2.855
High education	-0.2903	-1.270	-0.2714	-1.296	-0.2606	-1.213
Karlsruhe	-0.2894	-1.299	-0.3002	-1.382	-0.3289	-1.438
Computer use						
Constant	0.2932	1.853	0.2577	1.492	0.2465	1.297
Standard deviation	-	-	0.3358	1.507	0.3898	1.670
Sample selection and heterogeneity terms						
Common unobserved error component between mobile phone use propensity and duration hazard	-	-	-	-	0.4174	4.468
Unobserved heterogeneity						
Across individuals	-	-	0.4040	6.394	0.0900	0.561
Across spells	0.8078	3.510	0.6224	2.765	0.6602	3.037

Table 6. Effect of ICT Use on Intershoppping Hazard

ICT use	Mean percentage change in hazard in...		
	Exogenous ICT use with deterministic coefficients	Exogenous ICT use with random coefficients	Endogenous ICT use with random coefficients
Mobile telephone use			
Low education, Halle residence	-33	-32	-47
High education, Halle residence	-10	-11	-31
Low education, Karlsruhe residence	-10	-8	-26
High education, Karlsruhe residence	+20	+20	-4
Computer use	-25	-23	-19

Table 7. Percentage of Intershopping Hazard Variation Explained by Observed and Unobserved Factors

Heterogeneity source	Percentage of total intershopping hazard variation explained by each heterogeneity source in...		
	Exogenous ICT use with deterministic coefficients model	Exogenous ICT use with random coefficients model	Endogenous ICT use with random coefficients model
Observed heterogeneity	11	32	32
Unobserved heterogeneity	89	68	68
<i>Intra-individual</i>	-	73	72
<i>Inter-individual</i>	-	27	28
<u>Response to home computer use</u>	-	9	11
<u>Intrinsic heterogeneity related to mobile phone use</u>	-	-	85
<u>Intrinsic heterogeneity unrelated to ICT use</u>	-	91	4