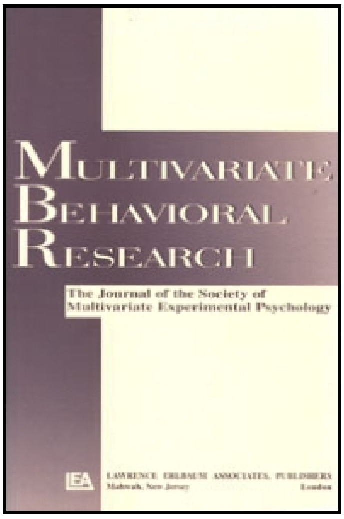

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American Time-Styles: A Finite-Mixture Allocation Model for Time-Use Analysis

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Time-use has already been the subject of numerous studies across multiple disciplines such as economics, marketing, sociology, transportation and urban planning. However, most of this research has focused on comparing demographic groups on a few broadly defined activities (e.g., work for pay, leisure, housework, etc.). In this study we take a holistic perspective, identifying a typology of latent "time-styles," that defines the different ways people allocate the 24 hr in a day across multiple competing daily activities. We propose a finite-mixture time-allocation model that accounts for differences in life priorities across individuals, taking into consideration the fact that we all have the same "budget" of 24 hr to spend every day and that this allocation leads to highly sparse, truncated data. This model is then applied to time-use data from the American Time Use Survey collected by the U.S. Bureau of Labor Statistics in 2006.

Time is the ultimate constraint on human activity (Joyce & Stewart, 1999). No matter how wealthy or powerful we are, we can't get more of it. In contrast to money, which can be traded among people and saved for the future, time can't be stored, borrowed, or lent. We are given 24 hr that must be spent each day, and how we distribute these 24 hr to our daily activities should tell something about how we live our lives. Therefore, it would be useful and informative to categorize daily schedules according to how the 24 hr are distributed across the activities that make up our daily lives. Having this purpose in mind, we propose a finite-

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mixture time-allocation model that addresses several methodological challenges in the study of how individuals allocate this valuable, perishable, and limited resource in their daily lives, creating a typology of "time-styles" that reflect the typical ways people spend a day.

Time-use analysis has been quite prevalent in the literature from a wide range of disciplines such as sociology (Andorka, 1987; Andorka & Falussy, 1982; As, 1979; Gershuny & Sullivan, 1998; Govaerts, 1969; Gronmo & Lavik, 1986; Javeau, 1970), economics (Blundell, Ham, & Meghir, 1987; Carlin & Flood, 1997; Hamermesh, Frazis, & Stewart, 2005; Juhn, 2003; Juster & Stafford, 1991; Landenfeld & McCulla, 2000), urban planning (Guttenschwager, 1973), health (Fisher, 2000; Pentland & McColl, 1999), marketing (Cotte, Ratneshwar, & Mick, 2004; Feldman & Hornik, 1981; Schary, 1971), and transportation (Bhat, 1996; Ettema, Borgers, & Timmermans, 1995; Golob & McNally, 1997; Goulias, 1999, 2002). Researchers in these disciplines have performed time-use analysis to study teenagers' use of time for employment and other activities (Porterfield & Winkler, 2007), the impact of increasing shopping hours on consumers' allocation of time (Jacobsen & Kooreman, 2005), demand for leisure time (Robinson, 1969), allocation of time to mass media (Feather & Shaw, 2000; Hornik & Schlinger, 1981), and many other topics.

Although this literature provides valuable insights into how people in different demographic groups and countries allocate their time, most of these studies have focused on only a small subset of the many activities engaged in by people throughout the day, usually combined into a few broad aggregates such as "work for pay," "housework," "shopping," and so on (Bhat, 1996; Ettema et al., 1995). This focus on a few aggregates avoids the fact that time allocations throughout a full day are highly sparse (except for sleep) and that, at some level, all these activities compete against each other for the same "budget" of 24 hr a day.

In order to understand how individuals differ in their usage of time on a full day, one must first acknowledge that we are quite diverse in our needs due to cultural differences, family life cycles, and many other factors, which should lead to unobserved heterogeneity in time priorities across people. Therefore, any attempt to understand how we spend our days must account for this heterogeneity in "tastes" or life priorities. This challenge is addressed in our proposed model by using a finite-mixtures formulation (Dolan, Jansen, & van der Maas, 2004; Everitt, 2005; McLachlan & Peel, 2000; Wolfe, 1970) that classifies individuals into relatively homogeneous groups in terms of their life priorities.

Life offers us many options and opportunities, and therefore we each engage in only a subset of the many possible daily activities, depending on our diverse needs. As a consequence, time-use reports are highly sparse, with a high percentage of zero-allocations to many of the available activities. Although there is already a rich literature on the analysis of truncated and sparse data (Baba, 1990), we propose a structural model where the data-censoring mechanism is embedded in the constrained time-allocation process faced by each individual, so that truncated data arise as a direct consequence of this decision process.

Moreover, we all live on a fixed daily budget of 24 hr so that any time we devote to one activity reduces the time available for other activities and consequently, all activities compete against each other for our precious time. Most of the past literature has focused on a few activities in isolation (e.g., leisure, housework, and child care) and therefore could ignore the binding constraint of 24 hr we face in our daily lives. In contrast, our main purpose is to understand how different segments in the population spend their 24 hr in a day, and for this reason, we must take into account the trade-offs different individuals make to allocate their fixed time budget across activities, which we accomplish with a constrained optimization model.

METHODOLOGICAL CHALLENGES POSED BY TIME-USE SURVEY DATA

Time-use data are most commonly collected through a diary in which each respondent is asked to report how he or she spent every minute across daily activities prespecified by the researcher on a single day also prespecified by the researcher. Therefore, the most commonly available data are for single individuals reporting their time-use in minutes on a single day on a standard set of daily activities common for all respondents. Readers interested in the methodological details of time-use data collection are referred to the Multinational Time Use Study (MTUS) at Oxford University (http://www.timeuse.org/mtus) or the American Time Use Survey (ATUS) collected by the U.S. Bureau of Labor Statistics (http://www.bls.gov/tus/). The MTUS is a repository of time-use data collected across multiple countries over multiple time periods. Care is taken to ensure that the definition of life activities is consistent across cultures and that respondent demographics are harmonized across countries (Gauthier, Gershuny, & Fisher, 2006), but data are collected from different respondents in each time period. The ATUS provides nationally representative estimates of how Americans spend their time based on information collected from over 70,000 interviews from 2003 to 2007.

Although extremely rich in the information they contain regarding lifestyles, data obtained through these time-use diaries also have some limitations in terms of the insights they might provide about these lifestyles. First, because each respondent typically provides data on a single day, these data do not provide any insights into the interrelationships of life activities throughout the week. Second, because data are collected from individuals, insights on how responsibilities for certain activities (child care, labor, house care, etc.) are shared among members of the household are limited to the fewer cases where data are collected from all members of the household on exactly the same day. Third, because each respondent reports only for a single day, these data can provide valuable insights into the relative value or "life priorities" across activities for groups of individuals but are limited in the insights they can provide regarding the sequencing of these activities within a day at the individual level.

Even though the data obtained from time-use diaries may seem relatively simple at first glance, they present several methodological challenges to the analyst:

- *Heterogeneity in life priorities*—As argued earlier, there are many reasons one should expect individuals to differ in the value they assign to the competing daily activities. Any analysis that ignores these unobservable individual differences is likely to produce a biased assessment of life priorities.
- *Data truncation*—Because each individual is unlikely to engage in all competing daily activities, time-use data are highly sparse and truncated, and therefore a comparison of averages that ignores the truncated nature of these data will provide a biased assessment of life priorities.
- *Time constraint*—Given that we all face an equality constraint on our daily allocation of time, any additional time we allocate to one activity must happen in detriment to one or more competing activity, and therefore, a study of life priorities must take this equality constraint into account.

We present next our finite-mixture time-allocation model, which deals with the issues discussed earlier while representing the decision process faced by individuals allocating their "time budget" of 1,440 min across the competing activities of daily life. We assume that individuals have an implicit value or "life priority" for each daily activity and allocate time to these activities to maximize the total value derived from them, subjected to the constraint that the total allocated time must be no more or less than 1,440 min (24 hr). This constrained optimization model makes it possible to study time-use over the entire day while accounting for the binding constraint on total time and allowing for zero-allocations, thereby explaining why individuals choose not to engage in many activities, leading to the highly truncated data commonly observed in time diaries. We also formulate our time-allocation model as a finite-mixture, thereby accounting for unobserved heterogeneity in life priorities while identifying groups of individuals with distinctive life priorities or "time-styles."

After developing and discussing the methodology for "time-style" segmentation, we apply the methodology to time-use data from the American Time Use Survey (ATUS) collected by the U.S. Bureau of Labor Statistics in 2006.

A FINITE-MIXTURE TIME-ALLOCATION MODEL

In developing our framework for time-use analysis, we consider the decision faced by an individual scheduling her day. This individual has a budget of 1,440 min and must decide how to make the best use of this limited resource. In other words, she must allocate this time budget to multiple daily activities in a way that maximizes the total return or value on the time "invested" in these activities.

The main purpose of the model we propose here is to identify what we call "time-styles," the most common types of lifestyles or life priorities in the use of time, reflected in the time allocations observed in time-use surveys. Therefore, our main focus is on how different individuals allocate their budget of 1,440 min across the competing activities of daily life. This focus is quite distinctive from most past studies, which concentrate on only a few activities and therefore do not have to deal with the fact that these activities compete for the same time budget and that time allocations across all daily activities are highly truncated and sparse (e.g., Bhat, 1996; Ettema et al., 1995).

The Time-Allocation Decision

We assume that every minute spent on an activity produces some value, and the participant's problem therefore is to distribute the 1,440 min of a day across all competing activities to maximize the total value derived from the time spent in them. This is akin to the assumption commonly made in choice modeling, where individuals are assumed to choose the alternative that provides the highest value or "utility" for them (Luce, 1996, 1997). Although the goal in choice modeling is to infer the decision maker's value function or preferences from observed choices, our goal here is to infer the individual's life priorities from the choice of activities and the observed time allocated to them.

We also assume that as the individual spends more time in one activity, the marginal value of that activity tends to decrease, so that the incremental value associated with an extra minute spent on that activity decreases with the time already spent on it. For example, the value associated with the first minutes of physical exercise might be high, but as the participant spends more time in it, the marginal value for additional time spent exercising decreases and is eventually dominated by some other activity, leading the person to abandon physical exercise in favor of the new activity. In other words, we assume that there are diminishing returns or "satiation" to the time invested in any activity. This assumption that the incremental value of extra time spent on an activity decreases as more time is spent on it is necessary because otherwise a rational person would spend 24 hr on the single activity that produced the highest value to her.

If the marginal value of an additional minute spent on an activity decreases with the time already allocated to it, the solution to the seemingly complex constrained time-allocation problem is relatively simple. The total value derived from the allocated 1,440 min in a day is maximized by following a simple rule: allocate every remaining minute to the activity that produces the highest marginal value, given the time already allocated to it. As the marginal value of time allocated in any activity decreases with more time spent in it, eventually another activity will offer more value, and the decision maker will switch to that activity. If the individual follows this simple allocation rule, by the end of the day, all activities receiving some allocated time will offer the same marginal value, which is greater than the marginal values offered by any of the nonchosen activities. This has to happen because otherwise, the allocation would be suboptimal in terms of total value derived from the 24 hr spent in a day, and the individual could reallocate some of the time to whatever activity offers a higher marginal value until all activities offer a marginal value that is equal or lower than this activity.

The researcher's problem then is to infer the participant's value function or life priorities for all competing activities, based on the activities chosen by the individual and the time she decided to spend on them. This estimation problem is akin to estimating the value offered by competing choice alternatives in conjoint measurement or choice modeling (Luce & Tukey, 1964), except that here we obtain information not only from the choice of activities but also from the time allocated to each and must also ensure that the total allocated time meets the binding constraint.

To model this allocation decision, we assume that the value individual i assigns to the time spent on all activities is a continuously differentiable quasi-concave function $G(x_i)$ over the J time allocations $X_i = (x_{1i}, x_{2i}, \ldots, x_{Ji})$. Our goal is to estimate this function based on the observed time allocations. As we discussed earlier, in order to represent the decisions made by a rational individual, the function $G(x_i)$ must be such that the incremental value drawn from an extra minute spent on any activity should be lower than the incremental value drawn from the previous minute. In other words, the marginal value of the next minute spent on any activity must decrease with the time already spent in it because otherwise, a rational individual would spend all her time on the single activity producing the highest initial value.

One might argue that in reality, the marginal value of time spent on an activity could initially increase due to learning or other reasons; for example, the incremental value of time spent watching a thriller on TV might increase as the plot thickens (that's why commercial breaks are shorter at the beginning of a TV show than toward the cliff-hanging end). However, the marginal value of time spent on this activity must eventually decrease to become dominated by some competing activity to account for the fact that we do not spent all 24 hr in a day on a single activity.

In our work, we use the Stone-Geary function (Stone, 1954), which has the form

$$G(X_i) = \sum_{j=1}^{J} \alpha_{ij} \ln(x_{ij} - \beta_j), \tag{1}$$

where $\alpha_{ij} > 0$, $(x_{ij} - \beta_j) > 0$, and J is the number of all available life activities in a day.

This function shows diminishing returns to scale, with a gradient given by

$$\frac{\partial G(X_i)}{\partial x_{ij}} = \frac{\alpha_{ij}}{(x_{ij} - \beta_j)}, \tag{2}$$

which is also shown graphically in Figure 1. Although this function implies that the incremental value of time spent on any activity always decreases, thereby precluding the possibility of learning or other effects that might initially increase the marginal value of an activity, we chose this function for its parsimony as an approximation for the "true" value function because allowing for initially increasing incremental value would require at least one extra parameter for each of the J activities.

The gradient shown in Equation (2) and Figure 1 provides some intuition about the Stone-Geary function. The ratio $\frac{\alpha_j}{-\beta_j}$ represents the initial gradient, or

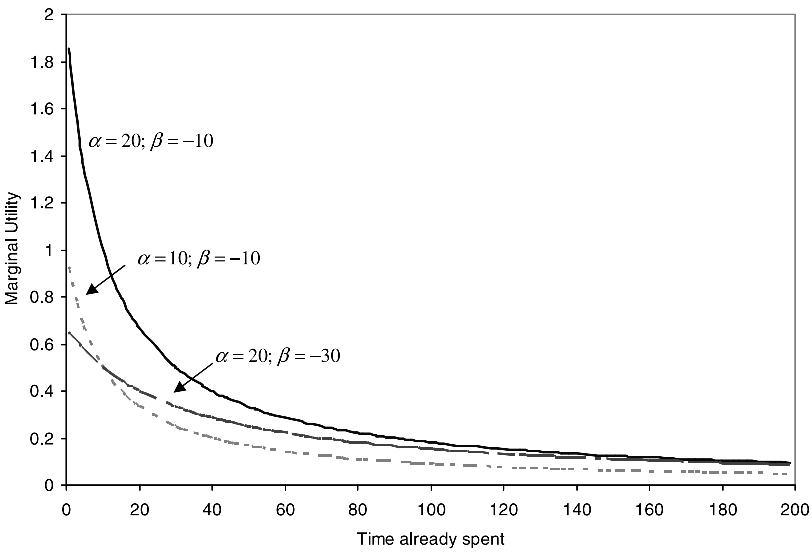

FIGURE 1 Stone-Geary marginal value function.

the value produced by the 1st s spent on the activity, so that activities with a high ratio are more likely to be selected by the individual. The parameter β_j determines the rate by which this marginal value will decrease as more time is spent on the activity; a value of β_j close to zero results into a rapidly declining marginal value, implying that individuals are likely to spend a short time in the activity, if any. A large negative value for β_j implies that those engaged in the activity are likely to spend a long time in it.

The marginal value or gradient is also positive, implying that additional time spent on any activity always produces value to the participant. In other words, we take the estimated life priorities for all life activities observed at one particular day as the net value accrued from the time invested in these activities. For example, an extra hour of work might be viewed negatively in terms of the effort put into it but produces a positive net present value to the individual in the form of income, which is what we attempt to measure with the Stone-Geary function in Equation (1).

Given the life priorities represented by the parameters α and β in Equation (1), the decision facing each individual is to allocate the 1,440 min in a day across the competing daily activities in a way that maximizes the total value drawn from the time invested in them. This constrained optimization problem implies that participant i will allocate the 1,440-min budget up to a point when the marginal values or gradients (Equation (2)) for all activities receiving some allocated time are equal to a certain value that is greater than the marginal values for the activities not receiving any allocation. Therefore, "at the end of the day," the observed time allocations are such that the gradients obtained from Equation (2) for all the engaged activities are equal to a constant ζ, which can be viewed as the value of an extra minute in the day if it were humanly possible to "buy time" beyond the 1,440 min of every day. The fact that the individual decided not to engage in some of the available daily activities also implies that these activities never offered a marginal value or gradient greater than ζ. These conditions are known as the first-order conditions for constrained optimization (Wales & Woodland, 1983) and are mathematically expressed as

$$\frac{\partial G(X_i)}{\partial x_{ij}} = \frac{\alpha_{ij}}{(x_{ij} - \beta_j)} = \zeta \qquad \text{for } x_{ij} \geq 0, \tag{3}$$

$$\frac{\partial G(X_i)}{\partial x_{ij}} = \frac{-\alpha_{ij}}{\beta_j} \leq \zeta \qquad \text{for } x_{ij} = 0, \tag{4}$$

$$\sum_{j=1}^{J} x_{ij} = 1440. \tag{5}$$

This time-allocation model implies that individuals allocate incremental minutes to the competing activities so that the one activity producing the highest marginal value or gradient at any stage of this allocation process receives the incremental minute, and the gradients are updated after each incremental allocation, until all 1,440 min are spent. When this binding time constraint is reached, all activities receiving some time effort produce the same marginal defined by the Lagrangean constant ζ. For those activities not receiving any allocation, we know only that they were dominated by those receiving some time allocation and therefore, their initial marginal utilities are lower than the constant ζ.

The solution to this constrained maximization problem is illustrated in Figure 2, which shows the marginal value functions for a simple allocation problem with four competing activities (A, B, C, and D) and a budget of 70 hr. This individual would first spend time in Activity C, which offers the highest initial marginal value. As more time is devoted to Activity C, its marginal value decreases up to a point where it is worth it to spend some time in Activity D and later in Activity B. Eventually, the budget of 70 hr is exhausted at $x_A = 0$, $x_B = 3$, $x_C = 19$ and $x_D = 48$. At this point, activities B, C, and D produce the same marginal value ζ, which is higher than the marginal value offered by Activity A, as shown in Figure 2. Notice that we observe only

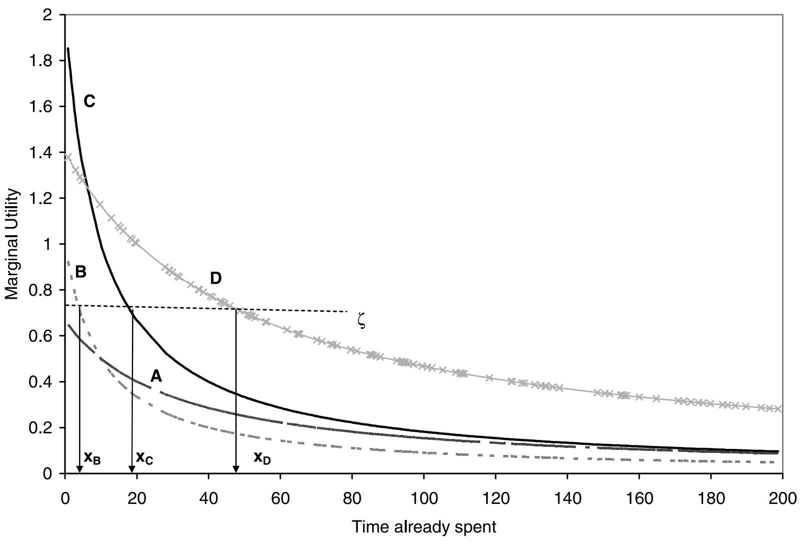

FIGURE 2 Illustration of the allocation model.

the final allocations (x) from each respondent but must recover the shape of the marginal functions (parameters α and β) from this limited information.

Solution of this optimization problem leads to the following time allocations:

$$x_{ij} = \beta_j + \theta^*_{ij}\left(1440 - \sum_{j=1}^{J^*}\beta_j\right), i = 1, 2, \ldots, J^*, \tag{6}$$

where $\theta^*_{ij} = \frac{\alpha_{ij}}{\sum_{j=1}^{J^*}\alpha_{ij}}$, and J^* is the set of life activities the individual is engaged in (i.e., with positive time allocation).

Accounting for Unobserved Heterogeneity in Preferences

Given the model described earlier, the researcher's problem is to infer the participant's life priorities (i.e., α_{ij} and β_j) given the observed daily time allocations. However, the model would not be identifiable if estimated at the individual level because we typically observe the time allocations only for a single day for each respondent. On the other hand, one must account for the fact that people differ on their life priorities or preferences for the competing activities. One possibility would be to account for observed differences by making the "taste" parameter α_{ij} a function of the individual's demographic profile. Instead, we chose to account for unobserved heterogeneity by assuming that individual i may be a member of a latent class $s = 1, 2, \ldots, S$ and, conditional on being a member of class s, define the individual's parameters as

$$\alpha_{ij} = \exp(\gamma_{js} + \varepsilon_{ij}) \text{ and} \tag{7}$$

$$\beta_j = \min(x_j) - \exp(\eta_j) \text{ to ensure that } x_{ij} - \beta_j > 0 \text{ for } \forall i, \tag{8}$$

where

$e^{\gamma_{js}}$ is the taste parameter for category j among members of latent class s;
ε_{ij} is a random disturbance normally distributed with mean zero and standard deviation σ_j.

Similar to other models for truncated or censored data (Muthen, 1990), our proposed model makes distributional assumptions about the latent variable generating the observed data rather than the actual data.

Implications of the Proposed Finite-Mixture Time-Allocation Model

With this finite-mixture formulation, we use the observed time allocations to directly identify "time-styles" or latent classes representing distinct preferences for the competing activities. The parameters γ_{js} and β_j provide insights into the average preference for activity j within each latent class. We only allow for individual differences in the "taste" or "life priority" parameter α_{ij}, assuming the same β_j across individuals, to ensure model identification.

As discussed earlier, the ratio $\frac{e^{\gamma_{jsa}}}{-\beta_j}$ shows the marginal value for activity j among members of class s before any time is devoted to that activity. Thus, a comparison of this ratio across activities and latent classes provides some empirical evidence of the daily life priorities within each latent class. Similarly, the ratio $\frac{-\beta_j}{30-\beta_j}$ shows how much the marginal value associated with activity j would drop after the first 30 min are spent on it, indicating the rate by which preferences or priorities are "satiated" as more time is spent in each activity.

Most important, the parameters from the proposed model provide insights into individual preferences for the competing activities of daily life, taking into account not only their propensity to engage in these activities but also the amount of time allocated to some of them, within the fixed schedule of 24 hr. In other words, the proposed finite-mixture allocation model translates highly truncated time data across multiple activities into direct measures of individual preferences for all activities while still taking into account the binding constraint of 24 hr.

Rather than imposing an arbitrary censoring mechanism such as the Tobit regression model the aforementioned model allows for zero time allocations as a corner solution of a constrained optimization problem, thereby allowing us to infer the participants' preferences for each of the competing activities based on their observed time allocations, representing their life priorities or time-styles. The proposed model also ensures that any predicted schedule will always be logically consistent (i.e., nonnegative time allocations that sum up to a day length of 1,440 min).

At first glance, our proposed framework would seem similar in purpose to *latent budget analysis* (Clogg, 1981), a variant of Goodman's (1974) *latent class analysis*. However, the two approaches differ in two important ways. First, latent budget analysis was developed for the decomposition of contingency tables, positing that each budget observed in the contingency table is composed of a combination of several latent ones. There, the goal is to decompose budgets observed at some level of aggregation into the unobservable budgets that composed each of the observed ones. In contrast, our focus is on individual budgets; our goal is to understand individual preferences, but for the sake of parsimony we combine individuals into relatively homogeneous latent classes. Because we focus on individual budgets, our data are highly sparse, requiring a corner-solution model such as the one described earlier, where structural zeros are direct and valid solutions of the time-allocation problem.

Second, we attempt to model the allocation decision faced by each individual following a constrained optimization paradigm, thereby providing insights into individual differences in preferences or life priorities. In contrast, latent budget analysis is a decomposition tool that attempts to infer latent budgets from observed contingency tables without any attempt to model the individual time-allocation process.

Model Estimation

Given our parameterization of $\alpha_{ij} = \exp(\gamma_{js} + \varepsilon_{ij})$ for members of latent class s in Equation (6), the first-order conditions (Equations (3) and (4) for the constrained optimization problem lead to, respectively,

$$\gamma_{js} + \varepsilon_{ij} - \ln(x_{ij} - \beta_j) \leq \ln\zeta \qquad \text{for } x_{ij} = 0 \text{ and} \tag{9}$$

$$\gamma_{js} + \varepsilon_{ij} - \ln(x_{ij} - \beta_j) = \ln\zeta \qquad \text{for } x_{ij} > 0. \tag{10}$$

The parameters to be estimated, given the observed time allocations x_{ij}, are γ_{js}, $\beta_j = \min(x_j) - \exp(\eta_j)$ and σ_j, which we collect in the vectors Γ_s, B and Σ, respectively. Without any loss of generality, we standardize all gradients around the Lagrangean constant (setting $\ln\zeta = 0$). We also assume that every panelist must sleep at least a minute (i.e., $x_{i1} > 0$ for $\forall i$), and for identification purposes, we set γ_{1s} and σ_1 to zero, which means that Equations (9) and (10) can be simplified as, respectively,

$$\varepsilon_{ijs} \leq \ln(x_{ij} - \beta_j) - \ln(x_{i1} - \beta_1) - \gamma_{js} \qquad \text{for } x_{ij} = 0 \text{ and} \tag{11}$$

$$\varepsilon_{ijs} = \ln(x_{ij} - \beta_j) - \ln(x_{i1} - \beta_1) - \gamma_{js} \qquad \text{for } x_{ij} > 0. \tag{12}$$

To simplify the likelihood function, we use a variable transformation $\varepsilon^*_{ijs}(x_i) = \ln(x_{ij} - \beta_j) - \ln(x_{i1} - \beta_1) - \gamma_{js}$. With this variable transformation, and with the assumption that the random errors ε_{ij} are independently normally distributed, the likelihood contribution of participant i, conditional on the fact that the person belongs to class s, can be written as (see Kao, Lee, & Pitt, 2001, for details)

$$L_i(X_i|\Gamma_s, \mathrm{B}, \Sigma) = \prod_{j=1}^{l_i} \frac{1}{\sigma_j} \phi\{\varepsilon^*_{ijs}(x_i)/\sigma_j\} \times \left| \frac{\partial \varepsilon^*_{2,\ldots,l_i,is}}{\partial x_{2,\ldots,l_i,i}} \right| \times \prod_{l_i+1}^{J} \Phi\{\varepsilon^*_{ijs}(x_i)/\sigma)j\}, \tag{13}$$

where

$$x_{ij} > 0 \text{ for } \forall i \in (1, \ldots, l_i),$$

$$x_{ij} = 0 \text{ for } \forall i \in (l_i + 1, \ldots, J),$$

ϕ and Φ are the density and cumulative normal functions, and $\left| \frac{\partial \varepsilon^*_{2,\ldots,l_i,is}}{\partial x_{2,\ldots,l_i,i}} \right|$ is the determinant of the $(l_i - 1) \times (l_i - 1)$ Jacobian of the transformation from the observed data $x_{2,\ldots,l_i,i}$ to the random variables $\varepsilon^*_{2,\ldots,l_i,is}$, which is a continuous one-to-one mapping because $x_{ij} = 1440 - \sum_{j' \neq j} x_{ij'}$.

After replacing the Jacobian in Equation (13), the conditional likelihood can be written as

$$L_i(X_i|\Gamma_s, \mathrm{B}, \Sigma) = \prod_{j=1}^{l_i} \frac{1}{\sigma_j} \phi\{\varepsilon^*_{ijs}(x_i)/\sigma_j\} \times \frac{\sum_{j=1_{i+1}}^{J} (x_{ij} - \beta_j)}{\prod_{j=l_i+1}^{J} (x_{ij} - \beta_j)} \times \prod_{j=l_i+1}^{J} \Phi\{\varepsilon^*_{ijs}(x_i)/\sigma_j\}. \tag{14}$$

One can see some similarities between the conditional likelihood shown here and what one would specify for a multivariate Tobit model (Kamakura & Wedel, 2001) for the same data. The main distinctions are the definition of $\varepsilon^*_{ijs}(x_i)$ and the variable transformations implemented through the Jacobian, which account for the binding constraints in our constrained optimization problem.

The unconditional likelihood for participant i is then computed across all S latent classes as

$$L_i(X_i|\Gamma, \mathrm{B}, \Sigma, \Pi) = \sum_{s=1}^{S} \pi_s L_i(X_i|\Gamma_s, \mathrm{B}, \Sigma), \tag{15}$$

or more completely, as

$$L_i(X_i|\Gamma, \mathrm{B}, \Sigma, \Pi) = \sum_{s=1}^{S} \pi_s \left(\prod_{j=1}^{l_i} \frac{1}{\sigma_j} \phi\{(\ln(x_{ij} - \beta_j) - \ln(x_{i1} - \beta_1) - \gamma_{is})/\sigma_j\} \times \frac{\sum_{j=l_{i+1}}^{J} (x_{ij} - \beta_j)}{\prod_{j=l_i+1}^{J} (x_{ij} - \beta_j)} \times \prod_{l_i+1}^{J} \Phi\{(\ln(x_{ij} - \beta_j) - \ln(x_{i1} - \beta_1) - \gamma_{is})/\sigma_j\} \right). \tag{16}$$

Maximum-likelihood estimates of the model are obtained via a gradient search on the likelihood function in Equation (16). The likelihood equations necessary to obtain the parameter estimates with a gradient search are

$$\frac{\partial \ell}{\partial \gamma_{js}} = \sum_{i=1}^{N} \tau_{is} \left[I_{ij} \frac{A_{ijs}}{\sigma_j} - (1 - I_{ij}) \frac{H\{A_{ijs}\}}{\sigma_j} \right] = 0, \tag{17}$$

$$\frac{\partial \ell}{\partial \sigma_j} = \sum_{i=1}^{N} \sum_{s=1}^{S} \tau_{is} [I_{ij} A_{ijs}(A_{ijs} - 1) - (1 - I_{ij}) H\{A_{ijs}\} A_{ijs}] = 0, \tag{18}$$

$$\frac{\partial \ell}{\partial \eta_j} = \sum_{i=1}^{N} \sum_{s=1}^{S} \tau_{is} \left[-I_{ij} e^{\eta_j} \left(\frac{1}{x_{i1} - \beta_1} - \frac{1}{\sum_{j=1}^{J} I_{ij}(x_{ij} - \beta_j)} + \frac{A_{ijs}}{\sigma_j} \right) + (1 - I_{ij}) \frac{e^{\eta_j} H\{A_{ijs}\}}{\sigma_j (x_{i1} - \beta_1)} \right] = 0, \tag{19}$$

and

$$\frac{\partial \ell}{\partial \theta_s} = \sum_{i=1}^{N} (\pi_s - \tau_{is}) = 0, \tag{20}$$

where

$$\tau_{is} = \frac{\pi_s L_i(X_i | \Gamma_s, \mathrm{B}, \Sigma, \Pi)}{\sum_{s'=1}^{S} \pi_{s'} L_i(X_i | \Gamma_{s'}, \mathrm{B}, \Sigma)},$$

$$A_{ijs} = \frac{\ln(x_{ij} - \beta_j) - \ln(x_{i1} - \beta_1) - \gamma_{is}}{\sigma_j},$$

$$I_{ij} = \begin{matrix} 1 & \text{if } x_{ij} > 0 \\ 0 & \text{otherwise'} \end{matrix}$$

$$H\{a\} = \phi\{a\} / \Phi\{a\},$$

$$\pi_s = \frac{e^{\theta_s}}{\sum_{s'=1}^{S} e^{\theta_{s'}}}, \theta_1 = 0, \text{ and}$$

$$\beta_j = \min(x_j) - e^{\eta_j}.$$

The gradients in Equations (17)–(20) can also be used to test the local identifiability of the proposed finite-mixtures model, which is confirmed when the Jacobian formed by these gradients is of full rank.

Predicting Time Allocations Using the Estimated Model

Once the model parameters are estimated, time allocations for each segment can be predicted by simulating the decision process assumed for each individual belong to the segment in the formulation of the proposed model. First, each individual has the same budget of 1,440 min to allocate. Then we proceed to simulate the time allocations for a "synthetic" member of latent class s as follows:

1. Draw a value z_{sj} from the standardized normal distribution for members of class s and every activity $j = 1, 2, \ldots, J$.

2. Compute the current marginal value for each activity given the cumulative time x_{sj} currently assigned to activity j.

$$G'(x_{sj}) = \frac{\partial G(X_s)}{\partial x_{sj}} = \frac{\exp(\gamma_{js} + z_{sj}\sigma_j)}{(x_{sj} - \beta_j)}.$$

3. Assign a minute to the activity j^* with the highest marginal value $G'(x_{sj^*})$ and update the budget and cumulative allocations accordingly.
4. Repeat Steps 2 and 3 until the budget is depleted.

TIME STYLES IN AMERICA

In order to illustrate our time-allocation model, we apply it to data from the American Time Use Survey (ATUS) collected by the U.S. Bureau of Labor Statistics in 2006. In this survey, one individual from each selected household is interviewed only once about his or her time use during one preassigned day. For the preassigned day, an interviewer collects a detailed account of the respondent's activities, starting at 4 a.m. of the previous day and ending at 4 a.m. on the interview day. Details about the data collection process and of this rich database can be found at http://www.bls.gov/tus/atususersguide.pdf As discussed earlier, a clear limitation of these data is that only one diary is collected from each respondent for one prespecified day, which prevents any longitudinal study at the individual level and also limits the analyses to *diaries* (interactions of an individual and a day of the week), rather than *people*.

The data collected from the ATUS are available at different levels of details organized in a hierarchical data structure. For our analyses, we extracted data aggregated into 18 general activities summarized in Tables 1 through 3 by day of the week across a sample of 12,687 participants.

Table 1 clearly illustrates the challenges in studying how people spend the 24 hr in a day. First, this table shows the average number of minutes devoted to each activity across the sample, indicating that on average people spend 13 min on *religious/spiritual activities* per day and 40 min on Sundays. However, Table 1 also shows that incidence rates vary considerably across activities and days, making it clear that simple averages can be misleading. Once incidence is taken into consideration, one learns that those involved in *religious/spiritual activities* spend 74 min per weekday on average, and 140 min on Sundays, which is much more than the average spent by all respondents (3 and 40 min, respectively). Similar misleading conclusions are drawn for *education*, which shows 29 min per weekday, due to the low incidence of this activity across the sample, when in reality, respondents engaged in *education* spend more than 300 min per weekday, as shown in Table 1.

TABLE 1
Summary Statistics

	Sample Average			*Incidence Rate*			*Average Time Spent* [a]		
Activity	*Weekday*	*Saturday*	*Sunday*	*Weekday*	*Saturday*	*Sunday*	*Weekday*	*Saturday*	*Sunday*
Sleeping	497	536	575	100	100	100	497	536	575
Work and work-related activities	255	88	56	55	27	20	465	326	279
Education	29	7	12	9	4	9	326	179	134
Work and education-related travel	23	8	4	52	19	14	44	41	31
Personal care	47	44	49	85	74	77	56	60	63
Childcare	51	46	40	41	38	37	125	121	108
Housework	78	108	94	65	70	66	119	154	142
Food and drink preparation and cleanup	34	34	40	57	53	57	58	64	71
Eating and drinking	70	81	80	96	95	96	73	85	83
Shopping	35	64	44	41	54	40	85	118	109
Using professional and government services	13	8	2	14	10	3	90	78	84
Leisure and entertainment	208	256	269	91	92	93	228	279	290
Socializing	44	85	72	43	54	51	102	157	141
Sports, exercise, & recreation	18	28	23	18	18	17	100	157	139
Religious/spiritual activities	3	7	40	4	7	29	74	99	140
Volunteer activities	9	12	12	7	6	9	131	188	134
Telephone calls	8	7	9	19	16	17	44	42	51
Other	18	22	19	24	25	24	74	86	79

[a] Average time spent only among those engaged in the activity.

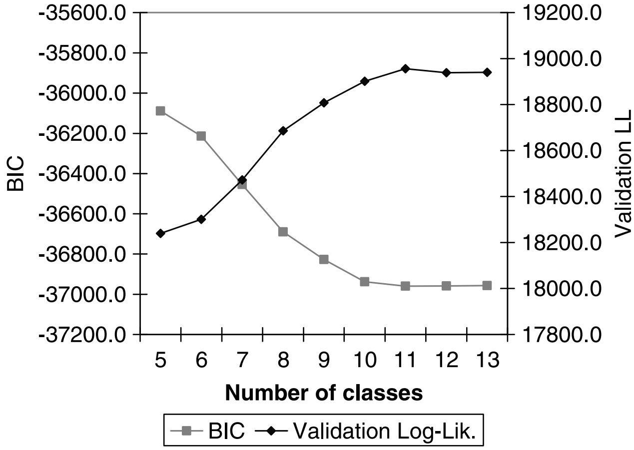

FIGURE 3 Criteria for model selection.

To determine the appropriate number of classes or "time-styles" in our data, we applied the model to a random sample of one third (4,226 cases) of the total sample, for 5 to 13 classes, and evaluated its predictive fit on another random hold-out sample of same size. We chose to determine the number of classes using only two thirds of the sample due to the large sample size (close to 13,000 cases), which made estimation of the model time consuming. Figure 3 displays the Bayesian Information Criterion from the estimation sample and Validation Log-Likelihood from the hold-out sample, suggesting an 11-class solution. We attempted to avoid potential problems with local optima by estimating each model starting from 10 different random values for the parameters. Local identifiability was established using the rank test described earlier.

To further test the robustness of the 11-class solution, we estimated the model using three separate random samples of 4,226 cases.[1] As a measure of consistency in the parameter estimates, we computed a correlation coefficient around the 45° line across all estimates. The correlation coefficients we obtained for the three pairs of estimates were $R_{12} = 0.93$, $R_{13} = 0.97$, and $R_{23} = 0.94$, showing reasonable consistency in the parameter estimates across the three random samples.

Once we decided on the 11-class solution, the model was reestimated using the entire sample of 12,687 participants. Instead of reporting the parameter

[1] To avoid the well-known label-switching problem with latent-class models, the classes were ranked by size so that parameter estimates were comparable across solutions.

estimates, we first transform them into more meaningful statistics, which are reported in Table 2. As discussed earlier, the $\frac{-\beta_j}{30-\beta_j}$ column shows the percentage reduction in marginal value after 30 min are spent in each activity, which is assumed constant across classes. From this column of Table 2, one can see that the marginal values decrease quite substantially after the first 30 min are spent on an activity. For example, the marginal value for *food and drink preparation and cleanup* drop to only 0.2% of the initial marginal value after only 30 min, suggesting that anyone engaged in this activity is likely to spend a short time in it. This decay in marginal value is less severe for activities such as *education* (3.8%), *sleeping* (2.6%), and *work and work-related activities* (2.2%), suggesting that people engaged in these activities will spend more time in them.

The results in Table 2 show that three classes (A, B, and E) account for over 57% of the sample and that one particular class (K) contains only 0.8% of the sample, suggesting that this last class might represent a small group of outliers.

The columns for each latent class show the initial marginal values for each activity $\left(\frac{e^{\gamma_{jsa}}}{-\beta_j}\right)$, which define life priorities for that latent class and are directly related to the incidence rates for each activity within a latent class. As one would expect from their high incidence rates, personal care activities (*sleeping*, *eating & drinking*, and *other personal care*) show the highest priorities across all latent classes. The same is true for *leisure and entertainment,* leading to high incidence rates for these activities across all classes. Classes A and B also show high initial marginal values for *work and work-related activities* and *work and education-related travel,* whereas Class C shows relatively high initial marginal values for *work and education-related travel* and *education*, suggesting that the diaries contained in these two classes might be reported on weekdays rather than weekends.

A better intuitive sense of the time-styles represented in each of the latent classes can be gained from the average times reported by individuals belonging to each class, which are shown in Table 3 as deviations from the overall sample average. These results confirm that Classes A and B represent time-styles reported on a working day, as they contain between 4 to 5 more hr of *work or work-related activities* than the average reported in the sample. Classes A and B also represent the most sleep-deprived time-styles, as they contain 81 and 42 min less of *sleep* than average, respectively.

Table 3 also shows that Class C represents the time-style of students, as it contains 4.5 hr more of *education* than the average daily report. Latent Classes D, E, and F, on the other hand, seem to reflect the time-style of homemakers, showing higher than average time spent on committed work (*housework*, *food and drink preparation*, *childcare*, *shopping*).

The last five classes (G, H, I, J, and K) are more focused on personal care (particularly *sleeping*) and free time than the other classes. Class G spends

TABLE 2
Parameter Estimates for the 11-Class Solution

			$\exp(\gamma_{js})/-\beta_j$										
Activity	*Sigma*	$\frac{-\beta}{(30-\beta)}$	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*
Work and work-related activities	0.161	2.2%	1.288	1.339	0.732	0.701	0.691	0.273	0.642	0.530	0.251	0.286	0.283
Work and education-related travel	0.615	0.1%	1.772	2.451	1.528	0.057	0.139	0.046	0.076	0.196	0.055	0.059	0.109
Housework	0.414	0.4%	1.043	0.736	0.886	1.363	2.213	1.322	0.807	0.602	1.164	0.753	0.731
Food and drink preparation and cleanup	0.451	0.2%	0.979	0.716	0.762	1.239	1.027	1.110	0.541	0.467	1.065	0.774	0.718
Childcare	0.377	0.7%	0.876	0.648	0.690	0.997	0.571	0.882	0.698	0.506	0.160	0.521	0.564
Shopping	0.293	0.9%	0.854	0.675	0.744	0.946	0.715	0.854	0.847	0.543	0.797	0.686	0.605
Sleeping	0.000	2.6%	1.234	1.234	1.234	1.234	1.234	1.234	1.234	1.234	1.234	1.234	1.234
Personal care	0.357	0.2%	1.504	1.343	1.448	1.413	0.935	0.144	1.397	0.887	1.554	0.799	7.118
Eating and drinking	0.469	0.1%	2.148	1.995	2.019	2.254	2.053	2.010	2.928	1.192	2.229	1.651	1.624
Using professional and government services	0.402	0.9%	0.577	0.348	0.463	0.569	0.425	0.376	0.454	0.437	0.554	0.430	0.537
Education	0.203	3.8%	0.617	0.615	0.979	0.565	0.286	0.540	0.614	0.468	0.561	0.508	0.310
Religious/spiritual activities	0.256	2.1%	0.597	0.509	0.687	0.652	0.480	0.196	0.703	0.492	0.684	0.536	0.562
Volunteer activities	0.387	1.8%	0.508	0.427	0.529	0.540	0.388	0.342	0.537	0.342	0.470	0.151	0.340
Socializing	0.491	0.5%	0.831	0.648	0.859	0.969	0.558	0.867	1.127	0.878	0.833	0.608	0.638
Sports, exercise, & recreation	0.425	1.1%	0.584	0.525	0.645	0.595	0.470	0.531	0.688	0.520	0.567	0.490	0.457
Telephone calls	0.616	0.2%	0.525	0.284	0.539	0.579	0.422	0.330	0.396	0.303	0.633	0.356	0.300
Leisure and entertainment	0.188	1.5%	1.052	1.036	1.048	1.097	1.121	1.105	1.084	0.874	1.367	1.562	0.966
Other	1.056	0.1%	0.456	0.206	0.472	0.626	0.193	0.460	0.543	0.233	0.233	0.261	0.219
Class sizes			20.7%	13.5%	5.0%	23.6%	5.8%	5.1%	8.1%	2.2%	8.4%	6.9%	0.8%

TABLE 3
Average Time Spent on Each Activity by Each Latent Class

Class Size	*20.7%*	*13.5%*	*5.0%*	*23.6%*	*5.8%*	*5.1%*	*8.1%*	*2.2%*	*8.4%*	*6.9%*	*0.8%*	
	Deviations From the Sample Average											
Activity	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*Avg.*
Work and work-related activities	**253**	**375**	**−150**	**−156**	**−148**	**−164**	**−157**	**−164**	**−164**	**−164**	**−164**	164
Work and education-related travel	12	**42**	13	−15	−15	−15	−15	−15	−15	−15	−15	15
Housework	−27	**−73**	**−46**	**42**	**283**	**57**	**−68**	**−61**	21	**−55**	**−62**	90
Food and drink preparation and cleanup	−5	−24	−18	26	0	**45**	**−35**	**−32**	13	−11	−20	35
Childcare	8	**−31**	−22	**52**	**−44**	**85**	−25	−29	**−47**	**−39**	**−35**	47
Shopping	−8	**−35**	−20	**37**	−15	27	18	−10	−7	−23	−20	44
Sleeping	**−82**	**−41**	1	−6	**70**	**65**	**38**	**286**	3	**68**	25	526
Personal care	3	−5	7	2	**−31**	**−47**	1	−12	22	**−36**	**478**	47
Eating and drinking	−7	−10	−10	5	−3	−3	**75**	**−42**	9	−22	−24	75
Using professional and government services	3	**−9**	−5	5	0	−8	−4	4	5	−3	11	9
Education	−15	−8	**286**	−16	−19	−13	−6	−11	−15	−18	−19	19
Religious/spiritual activities	−8	−12	14	6	−13	−13	26	8	17	−9	−2	13
Volunteer activities	−1	−7	1	8	−10	−11	18	−5	1	−11	−10	11
Socializing	−17	**−39**	−5	29	**−39**	8	**58**	**117**	−8	−29	−28	62
Sports, exercise, & recreation	−7	−10	9	−1	−7	−7	**58**	28	−1	−13	−12	22
Telephone calls	1	−7	3	4	−4	−5	−4	−1	11	−4	−5	8
Leisure and entertainment	**−102**	**−90**	**−65**	−41	9	−17	13	**−67**	**172**	**391**	**−87**	235
Other	−2	−17	5	17	−15	16	9	6	−17	−7	−10	19

Note. Boldface values show deviations greater than half hour from sample averages.

the most time in *sports, exercise, & recreation* and is among the highest on *socializing* and *eating & drinking*, reflecting an active leisure-oriented time-style. Classes H, J, and K are quite peculiar as they spend much more time on *sleeping* (286 min more than average), *leisure and entertainment* (391 min more than average), and *personal care* (478 min more than average), respectively.

As demonstrated earlier (Table 1), average time allocations computed across individuals are potentially misleading because not all participants engage in all activities during a day. For this reason, we report the incidence rate for each activity within each latent class in Table 4 along with the average time spent by those engaged in each activity in Table 5. These two tables show that the latent classes clearly captured individual differences in the propensity to engage in all daily activities, and therefore sample averages within each class (Table 3) lead to similar conclusions as the average times among those engaged in each activity (Table 5), in contrast to what we earlier reported for the whole sample (Table 1).

Notice that each participant reported his or her daily activities for one pre-assigned day of the week. Therefore, the 11 classes described in Tables 2–5 represent prototypical time-styles observed from different people in different days rather than segments or groupings of individuals. In other words, we identified latent classes of time-use rather than people, which provides an opportunity to study how time-styles vary not only across people but also over time.

Robinson and Godbey (2000) identify five main factors affecting the way individuals use their time: biological (age, gender, race), social status (education, income, occupation), role (work hours, marital status, parenthood) temporal (day of the week, month), and environmental (urbanization, region). Robinson and Godbey also show that the first four factors have the most impact across all daily activities within the United States. Table 6 shows the profile of the 11 latent classes along some of these factors known to affect time-use.

As we speculated, based on their time allocations, the first three classes represent time-styles observed mostly on weekdays, which account for more than 75% of all cases in these first three classes, compared with 50% in the whole sample. The demographic profiles in Table 6 also show that the first two time-styles (A and B) are reported by participants in their 20s to 50s, in upper income brackets, who are active in the labor force. The main difference between these two time-styles is that the first one (the more sleep-deprived Class A) has a higher percentage of females than the second (B), which in turn shows more time spent at *work* but less time spent in committed work (*housework, childcare, shopping*). These first two time-styles clearly illustrate the "poverty of time" discussed in the literature (Hochschild, 1989; Schor, 1991), with less time available for *sleep* and *leisure* compared with other time-styles due to more time spent at work (Time-style B) and committed work (Time-style A).

TABLE 4
Incidence Rates Within Each Latent Class

	Deviations From the Sample Incidence Rate											
Activity	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*Total*
Work and work-related activities	**61%**	**61%**	−21%	−27%	−24%	−39%	−32%	−39%	−39%	−39%	−39%	39%
Work and education-related travel	**50%**	**61%**	**55%**	−35%	−34%	−35%	−35%	−35%	−35%	−35%	−35%	35%
Housework	7%	**−35%**	−14%	**23%**	**32%**	19%	**−33%**	**−32%**	16%	−22%	**−30%**	67%
Food and drink preparation and cleanup	8%	−24%	−17%	**23%**	−4%	23%	**−53%**	**−43%**	17%	−7%	−18%	56%
Childcare	15%	−20%	−9%	**32%**	**−32%**	**31%**	−10%	−19%	**−39%**	**−28%**	−23%	39%
Shopping	8%	**−25%**	−10%	**22%**	−17%	8%	3%	−14%	−3%	−18%	**−29%**	44%
Sleeping	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	−3%	100%
Personal care	12%	7%	11%	12%	**−34%**	**−80%**	5%	−10%	17%	**−39%**	**20%**	80%
Eating and drinking	1%	−2%	1%	1%	0%	0%	4%	−13%	3%	−3%	−7%	96%
Using professional and government services	6%	−10%	−4%	6%	−5%	−9%	−5%	−2%	3%	−4%	4%	10%
Education	−4%	−2%	**85%**	−5%	−7%	−4%	2%	−2%	−4%	−7%	−7%	7%
Religious/spiritual activities	−4%	**−9%**	**10%**	5%	−11%	**−11%**	**14%**	−1%	**14%**	−7%	−4%	11%
Volunteer activities	1%	−5%	4%	6%	−6%	−7%	5%	−5%	1%	−7%	−6%	7%
Socializing	1%	**−21%**	6%	15%	**−26%**	−2%	**22%**	**17%**	−1%	**−18%**	**−20%**	48%
Sports, exercise, & recreation	−1%	−5%	8%	2%	−7%	−6%	**21%**	2%	3%	−10%	−9%	18%
Telephone calls	4%	−15%	4%	9%	−9%	−11%	−9%	−4%	**16%**	−8%	−11%	18%
Leisure and entertainment	−3%	−4%	−3%	1%	2%	2%	1%	−12%	8%	8%	**−24%**	92%
Other	8%	−20%	5%	**19%**	−19%	5%	5%	−6%	−20%	−10%	−12%	24%

Note. Boldface values show substantial deviations from sample proportions.

TABLE 5
Average Time Spent in Each Activity Among Those Engaged in the Activity

	Deviations From the Sample Average											
Activity	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*Total*
Work and work-related activities	0	**121**	**−340**	**−350**	**−312**	**−418**	**−321**	**−418**	**−418**	**−418**	**−418**	418
Work and education-related travel	−11	17	−12	**−43**	**−31**	**−43**	**−43**	**−43**	**−43**	**−43**	**−43**	43
Housework	**−50**	**−81**	**−52**	14	**242**	**38**	**−72**	**−50**	0	**−58**	**−59**	134
Food and drink preparation and cleanup	−16	−29	−17	15	4	**39**	**−45**	**−33**	3	−13	−22	63
Childcare	−19	**−40**	**−36**	19	**−77**	**69**	**−45**	−28	**−120**	**−50**	**−46**	120
Shopping	**−30**	**−49**	**−30**	22	8	**36**	**31**	12	−10	−16	**59**	101
Sleeping	**−82**	**−41**	1	−6	**70**	**64**	**37**	**285**	3	**68**	**40**	526
Personal care	−4	−10	0	−5	−24	**−59**	−2	−9	13	**−31**	**467**	59
Eating and drinking	−8	−9	−11	4	−3	−4	**72**	**−38**	7	−21	−21	78
Using professional and government services	−14	−26	−25	−5	**69**	−14	3	**63**	19	15	**53**	87
Education	**−124**	**−35**	**77**	**−129**	**−253**	**−71**	**−114**	**−96**	**−152**	**−157**	**−253**	253
Religious/spiritual activities	**−48**	**−46**	7	−4	**−121**	**−121**	**39**	**84**	1	−21	42	121
Volunteer activities	**−31**	−3	−36	1	**−88**	**−144**	**91**	**74**	−4	**−144**	**−114**	144
Socializing	**−38**	**−45**	−23	15	−27	23	**43**	**147**	−14	−19	−7	128
Sports, exercise, & recreation	**−32**	**−30**	−3	−15	17	3	**81**	**125**	−24	−7	−19	123
Telephone calls	−7	−15	6	−1	4	1	−3	5	11	−5	1	45
Leisure and entertainment	**−106**	**−90**	**−63**	**−46**	4	−23	11	**−46**	**152**	**370**	**−39**	256
Other	−25	**−36**	4	6	5	**41**	18	**54**	**−30**	10	−3	79

Note. Boldface values show deviations greater than half hour from sample averages.

TABLE 6
Demographic Profile for Each Time-Style

		Time-Style Segment											
Variable	*Levels*	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*Total*
Day of week	Sunday	9	8	24	**31**	**31**	**30**	**42**	**38**	**35**	**31**	**31**	24
	Monday	**14**	**14**	**13**	7	7	7	4	5	8	7	11	10
	Tuesday	**15**	**17**	**15**	7	6	6	4	6	7	8	2	10
	Wednesday	**14**	**16**	**14**	8	6	6	5	6	7	8	9	10
	Thursday	**16**	**15**	**11**	8	7	6	4	5	7	8	7	10
	Friday	**16**	**14**	**13**	7	8	8	6	7	8	6	9	10
	Saturday	16	15	10	**32**	**35**	**37**	**35**	**34**	28	**32**	**31**	26
	Total	100	100	100	100	100	100	100	100	100	100	100	100
Age group in decades	10s	3	5	**53**	3	4	2	**17**	**27**	5	7	3	8
	20s	12	**17**	11	10	7	**18**	**14**	**14**	4	8	5	11
	30s	**25**	**25**	11	**26**	16	**32**	15	14	5	10	8	20
	40s	**30**	**27**	10	23	21	22	13	18	12	13	21	22
	50s	**20**	18	5	15	**21**	10	15	11	15	15	**20**	16
	60s	7	6	5	10	**16**	9	11	5	**20**	**19**	**19**	11
	70s or older	2	1	6	12	**15**	7	**15**	10	**39**	**29**	**25**	12
	Total	100	100	100	100	100	100	100	100	100	100	100	100
Spouse present	No spouse	44	49	**79**	39	52	37	56	**72**	**64**	**65**	63	50
	Spouse	56	51	21	**61**	48	**63**	44	28	36	35	37	50
	Total	100	100	100	100	100	100	100	100	100	100	100	100
Respondent is female	Male	40	**64**	41	28	49	34	**56**	**51**	32	**56**	32	43
	Female	60	36	59	**72**	51	**66**	44	49	**68**	44	**68**	57
	Total	100	100	100	100	100	100	100	100	100	100	100	100
Working status	Working	**97**	**99**	39	48	54	48	51	44	26	28	20	61
	Unemployed, absent	2	1	**13**	9	9	**13**	9	**13**	6	8	**12**	7
	Not in labor force	1	0	49	42	37	39	40	43	**68**	**64**	**68**	32
	Total	100	100	100	100	100	100	100	100	100	100	100	100
Child younger than 12	None	57	65	69	50	**77**	38	**73**	**71**	**91**	**85**	**82**	64
	At least one	**43**	35	31	**50**	23	**62**	27	29	9	15	18	36
	Total	100	100	100	100	100	100	100	100	100	100	100	100
White	Non-White	17	20	22	15	12	16	16	**30**	19	24	**30**	18
	White	83	80	78	85	**88**	84	84	70	81	76	70	82
	Total	100	100	100	100	100	100	100	100	100	100	100	100
Family income group	< $20K	12	13	19	17	21	21	14	**32**	**35**	**37**	**42**	19
	$20–$35K	18	18	17	17	21	**24**	19	21	21	**24**	**25**	19
	$35–$60K	25	24	23	22	**28**	**26**	24	22	22	20	13	23
	$60–$100K	**27**	**26**	24	25	20	18	22	17	13	14	15	22
	$100K+	**19**	**19**	17	**19**	11	12	**22**	8	9	5	6	16
	Total	100	100	100	100	100	100	100	100	100	100	100	100

Note. Boldface values show substantial deviations from sample proportions.

The third time-style (C) also is reported mostly on weekdays by single (79%) young (64% under age 30) participants, which is consistent with the fact that this time-style shows the highest time spent in education.

The remaining time-styles are reported mainly (but not exclusively) on weekends, which account for more than 62% of the cases in these classes. Time-styles D and F, which emphasize committed work, have higher representations of married females with at least one child under 12, as one would expect for this time-style. Time-style E, which shows more than 6 hr of housework in a day, is comprised of older, childless, middle-income participants. Time-style H, which shows almost 14 hr of sleep in a day and focuses its free time on socialization, has higher than average proportions of young, single, nonworking, childless, non-White, lower income, and males. The most *leisure and entertainment*-oriented time-style (J), which spends over 10 hr in this particular activity, has a higher than average proportion of older, single, nonworking, childless, low-income males.

DISCUSSION AND DIRECTIONS FOR FUTURE RESEARCH

In this study we have proposed a segmentation tool that provides a broader perspective on how different individuals spend their time on different days than the common approach taken in the literature to focus on a few activities or to analyze each activity independently. Because each of us has exactly the same time "budget" to spend every day and given that time can't be stored, borrowed, or lent, we believe this form of segmentation provides unique insights into the distinct lifestyles or "time-styles" within a society.

When developing our time-allocation model at the individual level, we assumed that the values individuals accrue from the time spent on daily activities were additive-separable across activities, as shown in Equation (1). In other words, we assumed that time spent on one category only affects the value the individual will derive from another activity through the depletion of the time available for competing activities. This simplifying assumption was made for obvious reasons, as incorporating the impact of all other activities on the value for each activity would increase the number of parameters within each latent class by the square of the number of activities. However, one must be aware of the potential caveats associated with this simplifying assumption. Additive-separability implies that activities cannot be complementary. For example, one could argue that the value of *work and education-related travel* increases with time spent in *education* or *work*. There are two issues to be considered here. First, is obvious that only people who work or attend school would find any value in *work and education-related travel*. This association or correlation in values between these activities across individuals is already taken into account by our latent classes so that groups of individuals who work or attend school also have a higher than average value for *work and education-related travel*. However, whether the amount of time spent working or attending school in a day should affect the value attached to the time spent commuting is open to debate as it is not clear that a marginal increase in time spent at work or school should increase the marginal value of commuting time. This form of complementarity between activities cannot be accommodated by our model. If the analyst believes certain activities are indeed complementary in this particular way (time spent on one activity increases the marginal value of time spent on another activity), the simplest solution would be to avoid the problem by collapsing the complementary categories into a single one.

Another assumption implicit in the Stone-Geary utility function we used to formulate our model is that the marginal utility of any activity cannot increase as more time is allocated to that activity. The assumption that the marginal utility for time allocated to any activity will eventually decrease is necessary because otherwise participants would have an incentive to always spend more time on that single activity. However, one might argue that the marginal utility might initially increase as more time is spent on it. This might happen, for example, due to learning, as we discussed earlier. A more flexible formulation allowing for learning would require at least one additional parameter in the marginal utility function for each activity. We leave this extension and empirical tests comparing it to our more parsimonious formulation for future research.

Our focus when developing our proposed finite-mixture time-allocation model was on identifying "time-styles" defined in terms of the life priorities different individuals assign to the competing daily activities. Our main goal was to identify the life priorities behind the most typical time-styles rather than understanding how these life priorities are formed. Obviously, one should expect these individual life priorities to be a function of the respondents' roles within a household and of their time allocations over multiple days, which would require data from multiple members of the same households over more than a single day and therefore is left for future research.

Time-use surveys are becoming more prevalent across the world, leading to comprehensive cross-national and longitudinal databases, such as the Multinational Time Use Survey (MTUS; Gauthier et al., 2006) and the American Time Use Survey (ATUS) made available by the U.S. Bureau of Labor Statistics. This wealth of time-use data creates new opportunities for comprehensive time-style analyses utilizing extensions of our proposed time-allocation model. For example, the MTUS surveys provide a golden opportunity for creating a cross-cultural typology of time-styles and comparing time-styles across countries. Application of the proposed finite-mixture time-allocation model to cross-national time-use data would show whether some of the identified time-styles are unique to certain cultures, or shared across cultures, and also how biological, sociological, chronological, and environmental factors affect these time-styles across countries.

The longitudinal data in the ATUS database and for some countries in the MTUS database also create an opportunity for dynamic segmentation. Here, the approach will depend on the nature of the data available. If longitudinal data are available for a rotating panel over time, an extension of the proposed model with a Latent or Hidden Markov formulation (Du & Kamakura, 2006) might be necessary to account for the dynamic movement of individuals among the latent classes over time. On the other hand, if the samples are independent over time (as it seems to happen in most time surveys), our proposed model can be applied across the multiple surveys over time to detect possible structural changes in the time-styles and in their relative sizes over time.

When developing our time-allocation model we chose a finite-mixture framework to account for unobserved heterogeneity in the value assigned to the competing activities, which led to the identification of the most common "time-styles" reflected in the reported time allocations. In other applications, researchers might be interested in measuring the direct impact of biological, sociological, chronological, and environmental factors on time-use. For example, some researchers might want to know how the opening of retail shops during the weekend in one community affects the time spent shopping and all other daily activities. Others might want to understand how the time saved from commuting to work affects the time-styles of "telecommuters." These direct effects of explanatory variables on time allocations can be estimated through a simple extension of the proposed model, replacing γ_{ij} in Equation (7) with a linear function of these explanatory variables.

Finally, the proposed framework for time-use analysis is not restricted to daily activities such as those reported in time-use surveys (ATUS and MTUS) and used in our empirical illustration. To the contrary, the framework can be applied to any other situation where participants allocate time across multiple activities competing for the same time budget. For example, organizational researchers may apply the proposed methodology to time-use data gathered from managers, lawyers, physicians, and other professionals through their appointment calendars, phone, and e-mail logs, uncovering different "working-styles," which can then be related to observable characteristics of these individuals and their working environment.

REFERENCES

Andorka, R. (1987). Time budgets and their uses. *Annual Review of Sociology, 13,* 149–164.

Andorka, R., & Falussy, B. (1982). The way of life of the Hungarian society on the basis of the time budget survey of 1976–1977. *Social Indicators Research, 11,* 31–74.

As, D. (1979). Studies of time-use: Problems and prospects. *Acta Sociologica, 21*, 125–141.

Baba, V. V. (1990). Methodological issues in modeling absence: A comparison of least squares and tobit analyses. *Journal of Applied Psychology, 75*, 428–432.

Bhat, C. R. (1996). A hazard-based duration model of shopping activity with nonparametric baseline specifications and nonparametric control for unobserved heterogeneity. *Transportation Research, 30B*, 189–207.

Blundell, R. W., Ham, J., & Meghir, C. (1987). Unemployment and female labour supply. *Economic Journal, 97,* 44–64.

Carlin, P. S., & Flood, L. R. (1997). Do children affect the labor supply of Swedish men? *Journal of Labour Economics, 4*, 167–183.

Clogg, C. C. (1981). Latent structure models of mobility. *American Journal of Sociology, 86,* 836–68.

Cotte, J., Ratneshwar, S., & Mick, D. (2004). The times of their lives: Phenomenological and metaphorical characteristics of timestyles. *Journal of Consumer Research, 31*, 333–345.

Dolan, C. V., Jansen, B. R. J., & van der Maas, H. L. J. (2004). Constrained and unconstrained multivariate normal finite mixture modeling of Piagetian data. *Multivariate Behavioral Research, 39*, 69–98.

Du, R., & Kamakura, W. A. (2006). Household lifecycles and life styles in America. *Journal of Marketing Research, 43,* 121–132.

Ettema, D., Borgers, A., & Timmermans, H. (1995). Competing risk hazard model of activity choice, timing, sequencing, and duration. *Transportation Research Record, 1493,* 101–109.

Everitt, B. S. (2005). *Finite mixture distributions*. Hoboken, NJ: Wiley.

Feather, P., & Shaw, W. D. (2000). Estimating the cost of leisure time for recreation demand models. Available from SSRN: http://ssrn.com/abstract=187411

Feldman, L. P., & Hornik, J. (1981). The use of time: An integrated conceptual model. *The Journal of Consumer Research, 7*, 407–419.

Fisher, K. (2000, October). The role of time diaries in measuring the outcomes of treatments for multiple sclerosis. *Multiple Sclerosis, S36*.

Gauthier, A. H., Gershuny, J., & Fisher, K. (2006). *Multinational time use study: User's guide and documentation, Version 2.* Available from http://www.timeuse.org/mtus/documentation/docs/OnLineDocumentation.pdf

Gershuny, J., & Sullivan, O. (1998). The sociological uses of time-use diary analysis. *European Sociological Review, 14*, 69–85.

Golob, T. F., & McNally, M. G. (1997). A model of activity participation and travel interaction between household heads. *Transportation Research, 31B,* 177–194.

Goodman, L. A. (1974). The analysis of qualitative variables when some of the variables are unobservable. *American Journal of Sociology, 79,* 1179–1259.

Goulias, K. G. (1999). Longitudinal analysis of activity and travel pattern dynamics using generalized mixed markov latent class models. *Transportation Research, 33B*, 535–557.

Goulias, K. G. (2002). Multilevel analysis of daily time use and time allocation to activity types accounting for complex covariance structures using correlated random effects. *Transportation, 29,* 31–48.

Govaerts, F. (1969). *Loisiers des femmes et temps libre* [Women leisure and free time]. Brussells: Universite Libre de Bruxelles.

Gronmo, S., & Lavik, R. (1986, August). *Consumer behavior and social interactions: An analysis of Norwegian time budget data.* Presented at the 10th World Congress of Sociology, Mexico City, Mexico.

Gutenschager, G. (1973). The time-budget activity systems perspective in urban research and planning. *Journal of the American Institute of Planners, 39,* 378–87.

Hamermesh, D. S., Frazis, H., & Stewart, J. (2005). Data watch: The American time use survey. *The Journal of Economic Perspectives, 19,* 221–232.

Hochschild, A. (1989). *The second shift: Working parents and the revolution at home*, New York: Viking.

Hornik, J., & Schlinger, M. J. (1981). Allocation of time to the mass media. *The Journal of Consumer Research, 7*, 343–355.

Javeau, C. (1970). *Les vingt quatre heures du Belge* [Twenty four hours of the Belgians]. Brussells: Universite Libre de Bruxelles.

Joyce, M., & Stewart, J. (1999, August). What can we learn from time-use data? *Monthly Labor Review,* pp. 3–6.

Juhn, C. (2003). Labor market dropouts and trends in the Wahes of black and white men. *Industrial and Labor Relations Review, 56*, 643–662.

Juster, F. T., & Stafford, F. P. (1991). The allocation of time: Empirical findings, behavioral models, and problems of measurement. *Journal of Economic Literature, 29*, 471–522.

Kamakura, W. A., & Wedel, M. (2001). Exploratory tobit factor analysis for multivariate censored data. *Multivariate Behavioral Research, 36,* 53–82.

Kao, C., Lee, L., & Pitt, M. M. (2001). Simulated maximum likelihood estimation of the linear expenditure system with binding non-negativity constraints. *Annals of Economics and Finance, 2,* 215–235.

Landenfeld, J. S., & McCulla, S. H. (2000). Accounting for nonmarket household production within a national accounts framework. *Review of Income and Wealth, 46*, 289–307.

Luce, R. D. (1996). When four distinct ways to measure utility are the same. *Journal of Mathematical Psychology, 40*, 297–317.

Luce, R. D. (1997). Several unresolved conceptual problems of mathematical psychology. *Journal of Mathematical Psychology, 41*, 79–87.

Luce, R. D., and Tukey, J. W. (1964). Simultaneous conjoint measurement: A new type of fundamental measurement. *Journal of Mathematical Psychology, 1*, 1–27.

McLachlan, G. J., & Peel, D. (2000). *Finite mixture models*. New York: Wiley.

Muthen, B. (1990). Moments of the censored and truncated bivariate normal distribution. *British Journal of Mathematical and Statistical Psychology, 43*, 131–143.

Pentland, W. E., & McColl, M. A. (1999). Application of time use research to the study of life with a disability. In W. E. Pentland, A. S. Harvey, M. Powell Lawton, & M. A. McColl (Eds.), *Time use research in the social sciences* (pp. 169–188). New York: Kluwer Academic/Plenum Publishers.

Porterfield, S. L., & Winkler, A. E. (2007, May). Teen time use and parental education: Evidence from the CPS, MTF, and ATUS. *Monthly Labor Review,* pp. 37–56.

Robinson, J. P. (1969). Television and leisure time: Yesterday, today and maybe tomorrow. *Public Opinion Quarterly, 33,* 210–222.

Robinson, J. P., & Godbey, G. (2000). *Time for life: The surprising ways Americans use their time* (2nd ed.). University Park: The Pennsylvania State University Press.

Schary, P. B. (1971). Consumption and the problem of time. *Journal of Marketing, 35*, 50–55.

Schor, J. (1991). *The overworked American.* New York: Basic Books.

Stone, R. (1954). Linear expenditure systems and demand analysis: An application to the pattern of British demand. *Economic Journal, 64,* 511–527.

Wales, T. J., & Woodland, A. D. (1983). Estimation of consumer demand systems with binding non-negativity constraints. *Journal of Econometrics, 21,* 263–285.

Wolfe, J. H. (1970). Pattern clustering by multivariate mixture analysis. *Multivariate Behavioral Research, 5,* 329–350.