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Sarah M. Flood
University of Minnesota, Floo0017@umn.edu

Rachelle Hill
Minnesota Federal Statistical Research Data Center

Katie R. Genadek
University of Minnesota

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Sarah M. Flood[1] · Rachelle Hill[2] · Katie R. Genadek[1]

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Abstract Research on daily time and how it is allocated has generally considered the time spent in specific activities. However, social theory suggests that time use is socially patterned whether by social organization, heterogeneity, and/or stratification. Drawing on four broad types of time (contracted, committed, necessary, and free), we use Multinomial Logit Latent Class Analysis to discuss eight daily temporal pathways and associations with individual characteristics. Our analysis highlights the variations and similarities across pathways, the impact of paid work in structuring daily life, the social patterning of sleep and leisure, and socio-demographic profiles of the pathways of working-age Americans.

Keywords Daily life · Latent class analysis · Pathways · Time use

1 Introduction

The way people spend their time on a daily basis is a means for understanding a variety of social phenomena from a sociological perspective, including the value of children or gendered dynamics in the home (Bianchi et al. 2000, 2006; Brines 1994; Craig 2006; Presser 1989; Raley et al. 2012). Since the 1960s, social scientists have collected and used

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✉ Sarah M. Flood
Floo0017@umn.edu

[1] Minnesota Population Center, University of Minnesota, Twin Cities, 50 Willey Hall, 225 19th Avenue South, Minneapolis, MN 55455, USA

[2] Minnesota Federal Statistical Research Data Center, U.S. Census Bureau, 50 Willey Hall, 225 19th Avenue South, Minneapolis, MN 55455, USA

time diary data to examine the social organization of time. In the early twenty-first century, large-scale nationally representative time diary data are being collected around the world, yielding knowledge about how time is used by subpopulations within nations, cross-country and cross-time patterns in time allocation, and the use of technology. Scholars have used diary data to investigate a range of activities from housework negotiations to labor market participation to time invested in children (Bianchi et al. 2006; Bittman et al. 2003; Craig 2006; Ekert-Jaffé 2011; Gershuny 2011), focusing primarily on the sum total time spent in a given activity. However, the data are extremely rich and many opportunities remain for answering new questions with these data. This paper uses Latent Class Analysis to examine patterns in sequences of daily events derived from time diary data. We show that common structures underlie the patterns of daily life, and we analyze how demographic characteristics are associated with these structures.

In this paper, we extend the common discrete-time approach to using time diary data by leveraging activity-level data from the 2006 and 2007 American Time Use Survey. We ask two research questions. First, what are the common structures that underlie daily temporal pathways? Second, how are daily temporal pathways related to individual demographic characteristics? We answer these questions by applying Latent Class Analysis to time diary data to reveal the timing and sequencing of activities across weekdays. We find evidence of eight unique configurations of work, home, leisure, and sleep/personal care activities, which are more or less typical for individuals with different demographic characteristics.

2 Background

2.1 Social Time

Concerns about the social aspects of time—as opposed to other types of time—have a long history in philosophical and social thought (for reviews see Cipriani 2013 and Nowotny 1992). Rhythms of daily life—that is, the ways humans organize and divide time—are the basis of social time (Durkheim 1912). Two specific characteristics of social time as opposed to other types of time are its collective nature and heterogeneity. Social time is collective in that meanings are derived from social life and social life reinforces the meanings (Durkheim 1912). Activities are understood collectively to have different meanings—work is different than leisure (Stein 2012)—and how much time to allocate to activities is also governed by social norms (for the case of work see Epstein and Kalleberg 2001). Social time is also heterogeneous as evidenced by terminology to describe differences between days (weekend versus weekday, holidays versus non-holidays) despite the days consisting of the equal amounts of time (Sorokin and Merton 1937). Heterogeneity in social time is also present to the extent that different groups have different "time systems" (Sorokin and Merton 1937). Based on this theorizing, we expect that common ways of organizing daily life will exist—what we call daily temporal pathways—and that there will be heterogeneity in the rhythms of daily life based on demographic characteristics.

Daily temporal pathways can be thought of as typologies of time. One such pathway may be organized around working the standard workday. A worker may wake at 7:00 a.m., shower, and eat breakfast. She is at work by 9:00 a.m. and works until 5:30 p.m., having lunch around 1:00 p.m. She eats dinner around 7:00 p.m., washes dishes, watches television or engages in some other leisure activity, and then goes to bed around 11:00 p.m. Of course, this example is highly generalized and few people follow this schedule exactly.

Yet, even with significant variation in when one activity ends and another begins, this general pattern is likely identifiable over and over again in time diary data. Similarly, we may find general patterns for those individuals whose time is oriented around caring for themselves or others, attending educational institutions, or engaging in leisure. While one can easily imagine how time is socially patterned, this paper identifies the dominant pathways of weekday life among working-age Americans in 2006 and 2007.

Time is also stratified, with institutional-organizational time—that is, the time schedules of organizations, such as schools, workplaces, etc.—taking priority over interaction with others, which in turn takes priority over time for oneself (Lewis and Weigert 1981). Organizational time may, for example, delineate the times in which interactions with others and self time are possible or allowed (Anttila et al. 2015; Lewis and Weigert 1981). These different strata of social time may be evident in the quantity of time spent working and/or caregiving. To the extent that paid work takes precedence over interaction with others and self time, we should see a large part of the working-age population working for pay during "standard" U.S. work hours (typically between the hours of 9:00 a.m. and 5:00 p.m.). For example, parent–child interaction may be constrained by organizational structures such as if and when the parent must work as well as if and when the child is expected to attend school. Time allocation may also be influenced by time structures imposed by others. Infants, for example, require physical care and nourishment and parents' self time is often subordinate to the demands of the child (Lewis and Weigert 1981).

Because social actions are embedded in time structures, synchronicity is another characteristic of social time. Synchronicity in this context "involves the ordering of actions and expectations as a means for the achievement of future goals" (Lewis and Weigert 1981, 451). Individuals synchronize their time by "choosing" when to engage in particular activities such as working for pay or eating dinner together (Brannen et al. 2013). Such choices account for the embeddedness of social actions in larger dimensions of time and recognize humans' ability to be planful about their days, weeks, and years ahead. Synchronicity can happen at many different levels including families where dual-income couples manage interaction time along with work and school/daycare schedules (Lesnard 2004; Presser 1988, 1994) as well as within organizations where companies require core business hours (Epstein and Kalleberg 2001). Based on individuals' knowledge of their time demands, it becomes clear that time spent at any point of the day is related to past, present, and future time use choices that reflect both the agency of the individual and the constraints imposed by social time.

2.2 Time and the Life Course

A life course approach highlights the ways in which individual lives unfold over several years. It emphasizes the temporal aspects of human behavior and helps conceptualize how social time is both an opportunity for agency as well as constrained by social roles and demographic characteristics. Trajectory, transition, and duration are key life course concepts (Elder 1985). Transitions between states (such as from married to divorced or unemployed to employed) as well as the duration of states (such as how long one has been married) are the building blocks of sequences or trajectories, and the interlock of trajectories represent pathways through the life course (Macmillan and Eliason 2003). While pathways are structured by cultural models of behavior, individuals are purposeful actors, making choices that shape their lives even if constrained by cultural ideas and structural conditions. While these life course concepts are generally used to understand change and stability over longer spans of time, they can also be applied to smaller blocks of time like days and hours. There are many transitions between what people do during the course of a single day as they manage work and family demands—two common focal points in the life course literature—that influence small units of time allocation as well as patterns across months and years.

Within the life course literature, a great deal of focus has been aimed at work and parenting because of the way these roles often dominate individual lives. Work, for example, is one of the primary markers of adulthood (Macmillan and Copher 2005; Macmillan and Eliason 2003), and work and employment play a powerful role in the organization of time and energy (Coser 1974; Williams 2000, 2010). Employment patterns, including the duration of employment and the timing of exits, are frequently investigated in the social sciences (Blair-Loy 1999; Han and Moen 1999). Children can also influence the duration and sequence of parents' activities because young children must have care throughout the day and older children require coordination and supervision (Kingston and Nock 1987). Research has supported this as parents have been found to adjust schedules in order to care for children (Hamermesh 2000; Klaveren and Brink 2007; Presser 1987, 1994), even if in gendered ways (Galvez-Muñoz et al. 2013).

Yet, working and parenting are not isolated roles in individuals' lives. Rather, working and parenting often overlap with one another and with other roles that also shape how people spend their time. For example, research on work/family conflict focuses on how demanding workplaces and work roles (Greenhaus and Beutell 1985; Moen and Roehling 2005; Williams 2000) conflict with expectations for one's personal life, particularly as it relates to parenting (Hays 1996; Townsend 2002). Such research implicitly focuses on how this set of demands—work and family—intersect and interact (Bianchi et al. 2000; Hochschild and Machung 1990; Milkie et al. 2004). Research also considers relationships between demographic characteristics and types of time use, such as housework (Bianchi et al. 2000; Sullivan 2011), caregiving (Bianchi et al. 2006; Sayer et al. 2004), and multitasking (Offer and Schneider 2011).

2.3 Daily Temporal Pathways

Much of the theory and research using time diary data focuses on time availability or time budgets (Bianchi et al. 2000; Blood and Wolfe 1960; Lesnard 2004; Nomaguchi and Bianchi 2004). The theory assumes that those individuals who have the least time committed will spend the most time engaged in other activities. Time is viewed as a resource similar to money that can be spent; individuals prioritize activities (either due to outside constraints such as the need to work or internal preferences such as the enjoyment derived from reading) and spend their time accordingly. Similarly, much of the empirical research using time diary data examines the individual factors associated with the amount of time spent in particular activities such as paid work, childcare, housework, and leisure. Regardless of what is included in a particular type of time use, activities are considered as discrete entities. That is, the amount of time spent in particular activities for different subgroups is documented. Furthermore, comparisons may be made between two or more discrete activities such as paid work and housework (Bianchi et al. 2000; Hook 2010) or childcare (Kalil et al. 2012; Raley et al. 2012).

Two characteristics of time are problematic for the time availability approach: (1) the "synchronicity" or interdependence of activities and (2) the structuring and stratification of time, which limits when certain activities can be performed. First, because there is an unbreakable 24-h ceiling on time each day, time available for one activity is inherently related to time spent in another activity, particularly for activities that are more time consuming. For example, on average, time spent working is inversely related to time spent sleeping (Burgard and Ailshire 2009; Hale 2005). Secondly, individuals are not completely free to choose when to perform activities. There are both individual and organizational time constraints regarding when particular activities can be completed. For example, even if an individual would like to exercise at a community gym, it is not possible if the facility is not open when an individual's schedule allows.

A limited amount of research using time diary data has gone beyond the discrete-time approach. We briefly highlight two approaches that offer more than a quantification of time. The first considers the "quality" of time while the second considers the timing and sequencing of activities.

Some scholars argue that total leisure time masks the fragmentation or contamination that women experience during leisure (Bianchi et al. 2006; Bittman and Wajcman 2000; Mattingly and Bianchi 2003; see also Sevilla et al. 2012 for education differences). Men have slightly more "free" (i.e. non-housework and non-paid work) time than women, and it is of higher quality than women's leisure time (e.g. Bianchi et al. 2006). Though women have more leisure episodes than men, the leisure episode of the longest duration for women is shorter, on average, than men's longest leisure episode; women's leisure episodes are also more likely to be accompanied by unpaid work (Bittman and Wajcman 2000). The timing and sequence approach considers the overlap/non-overlap between work schedules (Lesnard 2004, 2008), typical work patterns (Glorieux et al. 2008; Hellgren 2014; Lesnard and de Saint Pol 2009; Lesnard and Kan 2011; Minnen et al. 2015), and leisure patterns (Glorieux et al. 2010) to understand what and for whom different sequencing patterns exist.

Our research is most similar to the work of researchers using sequence analysis (Glorieux et al. 2008, 2010; Hellgren 2014; Lesnard 2004, 2008; Lesnard and de Saint Pol 2009; Lesnard and Kan 2011; Minnen et al. 2015). Like these scholars, we use the detailed activity data available from time diaries to analyze sequences of activities. Whereas most previous research using sequence analysis has examined patterns in paid work, however, our goal is broader, seeking to identify patterns among four broader types of time meant to identify similarities across types of activity as opposed to focusing one type of time that renders the other types of activities invisible. Glorieux et al. (2010) take the most similar approach using Flemish time diary data from 1999 and 2004 and identifying sequences of activities that cluster together to show similar patterns of time use throughout the day. Their focus is on how individuals spend their time with an emphasis on leisure and, as such, they compare the respondents whose activities belong to two leisure classes. Our focus is on empirically uncovering the temporal structures of daily life on weekdays in the U.S. more broadly as well as to further examine associations between these structures and individual socio-demographic characteristics, which we expect will influence patterns of time use. Though our methodologies are different—we use Latent Class Analysis while Glorieux et al. (2010) use optimal matching and cluster analysis—there is evidence that the two methods produce largely similar results (Barban and Billari 2012); both have been applied to the study of life course trajectories (Amato et al. 2008; Blair-Loy 1999; Macmillan and Copher 2005) as well as other areas of inquiry. However, what is unclear from this prior research is how all types of activities (e.g. paid and unpaid work, leisure, and self care) hang together to produce complete days that meet the needs and demands of individuals with social time constraints.

3 Data and Methods

In the sections that follow, we describe the data and methods used in this research. Then we apply Multinomial Logit Latent Class Analysis to weekday diaries from the 2006 and 2007 American Time Use Survey to show the eight daily pathways resulting from our analysis and the associations between pathways and selected individual-level characteristics. We also compare and contrast the results with the typical discrete-time approach used to analyze time diary data and the purely descriptive tempograms that researchers have used to examine the timing of activities over the course of the day. Finally, we discuss the insights this approach offers in comparison to traditional analytic techniques for time diary data, the limitations of this approach, and directions for future research.

3.1 Data

We use integrated American Time Use Survey (ATUS) data for our analyses (Hofferth et al. 2013). The ATUS is the first large scale, federally funded, nationally representative time dairy study of Americans. Data are collected throughout the calendar year using a computer assisted telephone interview (CATI). ATUS sample members are invited to complete the survey following their exit from the Current Population Survey (CPS), which is a household survey of the civilian, non-institutionalized U.S. population. One individual aged 15 or older per former CPS participating household is randomly selected to respond to the ATUS two to five months following their exit from the CPS. Partly due to this prior survey participation, response rates tend to be lower for the ATUS than other national surveys. The response rate for 2006 and 2007 is 55.1 and 52.5 % respectively (U.S. Bureau of Labor Statistics 2015).

ATUS respondents report the activities they engaged in over a 24-h period from 4:00 a.m. of yesterday until 4:00 a.m. of the reporting day, as well as where, when, and with whom activities were done. Respondents may report activities in as little as one-min intervals. Over 400 detailed activity codes are represented in the three-tier six-digit activity coding scheme. Limited information about secondary activities is available in the ATUS; in 2006 and 2007, detail about secondary activities is only collected for childcare, eating, and drinking. Data are collected on all days of the week, and weekends are oversampled. Though the data may not typify respondents' daily activities, aggregations of the data are representative of the American population.

During 2006 and 2007, a nationally representative sample of 25,191 civilians age 15 and older participated in the ATUS. We restrict our sample to respondents who responded on a weekday (N = 12,566) and who were age 25 to 64 (N = 8894). Our focus on weekdays is appropriate in this case because weekends and weekdays are substantively different in the U.S. and because we are interested in analyzing Americans' daily routines during the typical workweek.

3.2 Measures

Recognizing the complexity of daily life while also attempting to focus on the commonalities across individuals, we employ a broad classification and divide activities into "four kinds of time" (Aas 1978): (1) necessary time, (2) contracted time, (3) commited time, and (4) free time (see Table 1).

Table 1 American Time Use Survey activity code mapping onto four types of time (% of 1 h episodes in each type of time)

ATUS-X category labels (2 and 4 digit, where applicable)	Analytic categories	Distribution of non-missing category codes (%)
Personal care	Necessary time	39.98
Sleep		
Eating and drinking		
Related travel		
Paid work and paid work-related activities	Contracted time	24.74
Education		
Related travel		
Household activities	Committed time	13.48
Caring for and helping household members		
Caring for and helping non-household members		
Consumer purchases		
Professional and personal care services		
Household services		
Related travel		
Socializing, relaxing, and leisure	Free time	17.67
Sports, exercise, and recreation		
Government services and civic obligations		
Religious and spiritual activities		
Volunteer activities		
Telephone calls		
Data codes		
Related travel		
	Missing	4.13
	N	2,13,456

Necessary time is required by all humans to fulfill basic physiological needs such as sleep, eating, and other personal care. There is some freedom in the timing, frequency, and duration of these activities but not in whether an individual performs them. Research on sleep has focused on gendered dynamics of sleep interruptions and quality (Burgard 2011; Maume and Sebastian 2009) while research on eating has primarily argued that people who spend more time in food preparation and eating are more advantaged and healthier (Hamermesh 2010; Reifschneider et al. 2011).

Acknowledging the dominating impact work has in how Americans organize their days (Coser 1974; Moen and Roehling 2005), *contracted* time is a single category of time consisting of paid work and education activities as well as related travel. While individuals may choose to engage in these activities, such choices are typically made during a time span that exceeds the one day diary. Furthermore, these activities “structure and influence” (Aas 1978: 134) other daily activities. We can look, for example, to research on non-standard work hours to understand how paid work at different times of the day is related to time with family (Mills and Täht 2010; Wight et al. 2008) and time in unpaid labor (Craig and Powell 2011; Hewitt et al. 2012).

In line with the importance of parenting and household responsibilities for individuals' time (Hays 1996; Hochschild and Machung 1990), we next consider committed time. *Committed* time, like contracted time, is also largely a consequence of prior decisions. Homeowners and parents, for example, typically enter these statuses prior to the diary day, yet they have consequences for how people spend their time on subsequent days. Activities included in this category include housework and care work. The unpaid work encapsulated under committed time is distinguished from other activities because it could be outsourced and done by others. For example, one could hire someone to clean house but not to sleep or earn a wage for oneself. Research on unpaid labor abounds, with particular interests in gender differences in who performs what kinds of unpaid labor (Bittman et al. 2003; Hook 2006).

Finally, *free* time is the remainder of the 24 h period that is left after necessary, contracted, and committed time have been allotted. Free time is essentially leisure, which may include activities such as watching television, socializing, or exercising. Current research on how leisure time is allocated has examined two areas of study, disparities in health behaviors (Nomaguchi and Bianchi 2004; Ruhm 2005) and gender differences in engaging in leisure time (Mattingly and Sayer 2006; Milkie et al. 2009; Sevilla et al. 2012). Free time is likely the most contested categorization of time because it includes a wide variety of activities that could be classified elsewhere (see Aguiar and Hurst 2007 for analysis of four leisure definitions). For example, playing a board game with children could be categorized as committed or free time under our four-category classification depending on how the respondent reported the activity during the ATUS interview. Rather than reclassify activities that could be considered in two categories, we follow Aas (1978) and simply code all activities as free time that have not been elsewhere classified.

In the ATUS, travel activities are coded to correspond to the activity that follows the travel. For example, if a respondent reported riding the bus and then performing paid work activities at work, the travel by bus episode would be coded as "travel related to paid work." The exceptions are travel episodes that are followed by activities performed at the respondent's home or an unspecified place; in these cases, travel is coded to match the previous activity. We combine travel with the associated activity based on the ATUS coding specifications.

The ways in which people spend time throughout the day are not independent of their demographic characteristics. To understand how time use varies across the population, we consider relationships between daily temporal pathways and a set of demographic characteristics (gender, parental status, age, education, and urban area of residence). *Woman* distinguishes between male and female respondents, where man is the reference category. *Parental status* distinguishes those respondents who have an own child under 18 living in the household (reference is no own co-resident child). *Age* is coded into eight dichotomous variables, each of which represents one five-year age group between 25 and 64 (reference is 25 to 29 year olds). *Some college* identifies those respondents who have attended some college, even if they do not have a degree (reference is no college attendance). *Urban* identifies individuals who live in metropolitan and surrounding areas.

3.3 Data Structure

For this analysis, we use activity (or episode) level data. Table 1 shows how we mapped the 17 two-digit activity categories onto our four broader activity categories, differentiating between the four kinds of time. Table 1 also shows the percentage of 1-h activity blocks for which each kind of time is the modal activity. Necessary time, which is composed primarily of sleep (60 %) and also includes eating and drinking (33 %) and related travel, is the primary activity in 39.98 % of the hourly intervals. Contracted time is the second most common type of modal activity (24.74 %); paid work and related travel account for the vast majority of contracted time (94 %). Free time (17.67 % of one-hour intervals) is comprised of television watching (29 %) and socializing (12 %) as well as other leisure and related travel, though the category also includes activities such as volunteering, making phone calls, attending church or other spiritual events. Committed—unpaid work such as household cleaning and maintenance and caregiving—is the modal activity in 13.48 % of 1-h intervals.

We coded the modal activity during each 1 h interval from 4:00 a.m. to 4:00 a.m.; modal activities are our primary units of analysis. To illustrate, consider a 1-h interval containing the following activities:

Episode (start–stop)	Original activity	New activity
12:00–12:05	Walking	Free
12:05–12:35	Eating	Necessary
12:35–12:40	Traveling	Free
12:40–1:00	Work	Committed

The modal "new activity" is "necessary," which occurs for 30 min of the 1 h interval. In cases where there were two modal activities of equivalent duration (e.g. 30 min in committed and 30 min in necessary time), we coded the activity as missing; 4.13 % of intervals do not have a modal activity assigned.

Our choice of 1-h intervals and modal activities is well supported in the data. The average number of activities per 1-h time interval is 1.7, with 64 % of intervals containing only one activity and over 95 % containing three or fewer activities. In only 4 % of intervals is a choice made about how to code the interval—that is, given our broad coding scheme, most of the time individuals are doing a similar type of activity (i.e. contracted, committed, necessary, free) during a 1-h interval. The modal activity occurs for an average of 40 min per 1-h interval when the modal activity is not performed for the entire interval. This suggests that the patterns we observe in the data are likely robust to differing lengths of time intervals.

3.4 Method

To better understand the collective nature of social time, we use the ATUS to examine *daily temporal pathways*, which are empirically derived graphical representations of the temporal organization of single days. Our goal is to capture the dynamics of continuity and change—both the sequencing and timing of transitions between types of time use over the course of a day. With billions of possible combinations of activities over the course of the day (4 modal activities at 24 time points) and 8676 unique sequences (out of over 40,000 possible) in the data, only the most common patterns can be discerned through direct observation. Latent Class Analysis is used to assess the underlying relationships in the data. Classes are considered latent in the data because they are unable to be clearly seen by simply examining the cross-classification of statuses over time. The results of the analyses—latent classes—represent the predominant temporal patterns of daily life. The number of latent classes and individual cluster membership are neither observed nor pre-specified. Maximum likelihood methods determine both the size and shape of latent classes based on the observed data.

We use a three step approach (Bakk et al. 2013; Vermunt 2010) to identify *daily temporal pathways* and relationships between the latent classes and individual-level demographic characteristics. All analyses are weighted, include cases with missing data, and are conducted using Latent GOLD 5.1. The first step is to estimate the latent class model. The specific goal of a Latent Class Analysis is to identify parsimonious clusters (i.e. latent classes) of relationships between observed states over time such that differences between classes exceed differences within classes. Latent class probabilities indicate the estimated population probability of each latent class. Within each latent class, conditional probabilities for the observed states at each time point reveal the interlock between activities over the course of a day. Each individual is assigned a probability of membership in each latent class, with the sum of the individual's probability of membership in each class equal to one. In the second step, individuals are assigned to the latent class for which they have the highest membership probability. The third step in the analysis is to estimate the relationship between demographic characteristics of individuals and latent class membership using a multinomial logistic regression model. The advantage of this three-step approach is that it corrects for errors associated with assigning an individual to a specific latent class in the second step.

4 Results

4.1 Descriptive Results

Table 2 contains the means for each individual-level characteristic in this analysis. The sample is about equally divided among men (49.2 %) and women (50.8 %) and by 5-year age groups between 25 and 64, with a slightly smaller percentage of 60–64 year olds (8.8 %) compared to other age groups (about 13 % each). Just over half (59 %) of respondents have attended some college or more; 42 % are parents with co-resident children under 18; and 82.5 % live in urban areas.

Table 2 also shows the mean number of minutes spent in each of four kinds of time. Necessary time fills about 10 h of the day (600 min) followed by contracted time, which is about 6 h per day (363 min). Individuals with some college work about an hour more per day, on average, than those with less education (390 vs 325 min), and men spend more time in contracted activities than women (425 vs 303 min, respectively). Individuals living in urban areas also spend slightly more time in contracted activities (367 vs 345 min). There are also large differences in committed time based on gender and parental status. Committed time is higher among parents (257 min) and women (266 min). While non-parents enjoy more free time, women (259 min) and those with some college (250 min) spend less time in leisure activities than men (282 min) and less educated individuals (300 min).

In contrast to average amounts of time spent in a given set of activities, tempograms are often employed to view patterns of time use over the course of the day. A tempogram is a purely descriptive graph to show for some given duration of time the percentage of people engaged in each of a specified set of activities. It illustrates the ways in which kinds of time are allocated across hours of the day, both how a particular activity is more or less

Table 2 Percentages of covariates and mean minutes spent in activities per day, American Time Use Survey respondents ages 25–64 in 2006 and 2007 (N = 8894)

	%	Average minutes per day			
		Necessary	Contracted	Committed	Free
Gender					
Female	50.8	610.69	303.41	266.21	259.68
Male	49.2	590.19	425.31	141.85	282.65
Age categories					
25–29	12.93	610.56	398.06	183.50	247.88
30–34	12.18	602.39	369.52	224.92	243.17
35–39	13.16	593.45	390.59	220.03	235.93
40–44	13.91	593.86	368.51	215.26	262.38
45–49	14.38	591.40	382.96	196.60	269.04
50–54	13.11	597.73	389.03	179.23	274.00
55–59	11.5	603.35	320.70	202.66	313.29
60–64	8.82	620.57	241.07	225.71	352.65
Some college or more					
Yes	58.61	596.53	390.42	202.63	250.42
No	41.39	606.38	325.12	208.41	300.09
Parent					
Yes	42.19	589.48	361.06	257.78	231.68
No	57.81	608.73	365.09	166.52	299.66
Urban					
Yes	82.5	601.33	367.22	202.30	269.15
No	17.5	597.20	345.33	217.86	279.61
Full sample	–	600.61	363.39	205.02	270.98

Percentages and means are weighted

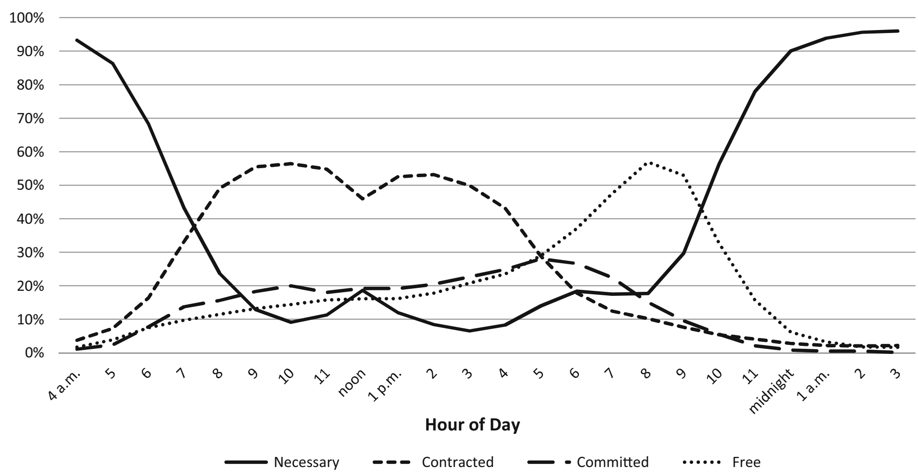

Fig. 1 Percent of respondents engaged in specified activities during 1 h time intervals

prevalent at different times of the day and the ways in which a decline in one activity is coupled with an increase in another activity. Figure 1 is a tempogram showing the percent of respondents engaged in each of four kinds of time during every hour of the day beginning with the 4:00–5:00 a.m. interval on the diary day and ending with the 3:00–4:00 a.m. interval on the following day. Ninety-three percent of the sample is engaged in necessary time (primarily sleeping) at 4:00 a.m. The percent of respondents reporting necessary time as the modal activity during and after the 5:00 a.m. hour (86 %) declines steadily until about 10:00 a.m.; increases by the noon hour when people are eating (18 %); drops off again to less than 10 % of respondents during the afternoon hours; and rapidly increases to over 90 % during the midnight to 3:00 a.m. intervals when 93 % of people are sleeping. When necessary time is lowest, between 8:00 a.m. and 3:00 p.m., nearly half of respondents engage in contracted time. Committed time is steady with about 20 % of respondents reporting this activity between 7:00 a.m. and 2:00 p.m. The majority of committed time during this time interval is housework (51 %), caregiving (21 %), and shopping (9 %). Free time is concentrated primarily during the afternoon and evening hours, reaching 20 % at 3:00 p.m. During the 8:00 p.m. and 10:00 p.m. intervals when free time peaks with over 50 % of respondents spending their time this way, 63 % of the respondents report watching television. Socializing with others and reading are the next most common free time activities during this time interval.

One can easily imagine types of people who might be doing particular activities at specific times of the day. One can also make tempograms for various subgroups. While tempograms offer an opportunity to consider the timing and sequencing of activities, it quickly becomes unwieldy as variation on several individual-level characteristics produces many unique combinations. For example, if we were to make tempograms for our all combinations of our covariates of interest, we would have hundreds of tempograms and interpretation of similarities and differences would be difficult if not impossible. Instead, we apply Latent Class Analysis to show the *underlying patterns* of daily life.

4.2 Multivariate Analyses

The first step in the Multinomial Logit Latent Class Analysis is to determine the models that best represent the underlying daily patterns of time use in the sample. Parsimonious models that use the fewest latent classes to best represent the data are preferred. Traditionally, models are selected based on model fit statistics, likelihood ratio statistics, and entropy. Information criteria statistics (e.g. BIC, AIC) are used to evaluate a series of models with different numbers of latent classes, where smaller BIC values indicate a more parsimonious model fit to the data than larger values (Raftery 1995; Schwarz 1978). Entropy-based measures indicate the uncertainty of classification. Unfortunately, however, there is no agreed upon gold standard for choosing the correct number of latent classes (e.g., Nylund et al. 2007; Tein et al. 2013). We estimated a range of models, specifying one to fifteen latent classes and including cases with missing data. As a robustness check, we excluded the cases that had any missing data during the 1-h time intervals; because our findings were similar when we include and exclude missing data, we retain the cases with missing data.

We present a number of information criteria statistics associated with the models we estimated (see Table 3). Information criteria statistics gauge model fit and account for the complexity of the model. Lower values on information criteria statistics indicate better fit of the model to the data. We find that the information criteria statistic values (BIC, AIC, SABIC) decline with the inclusion of each additional latent class in the model. When data are sparse, as in our case, these traditional statistics for assessing model fit may be problematic; therefore, we also consider the Integrated Classification Likelihood (ICL-BIC) and the Approximate Weight of Evidence (AWE) statistics, which consider how well

Table 3 Information statistics and classification errors when adding classes to the model

Number of classes	Number of parameters	df	Information statistics					Classification errors
			BIC	AIC	SABIC	ICL-BIC	AWE	
1	72	8822	384,100	383590	383,871	384,100	384,971	0.000
2	145	8749	325,431	324,403	324,970	325,597	327,350	0.004
3	218	8676	311,341	309,795	310,649	311,785	314,421	0.010
4	291	8603	305,216	303,152	304,291	306,422	309,941	0.028
5	364	8530	299,262	296,680	298,105	302,034	306,436	0.066
6	437	8457	296,297	293,198	294,909	299,157	304,441	0.067
7	510	8384	294,478	290,860	292,857	297,833	304,000	0.075
8	583	8311	292,037	287,902	290,185	295,356	*302,406*	0.075
9	656	8238	290,634	285,981	288,550	294,479	302,412	0.086
10	729	8165	289,513	284,342	287,197	293,856	302,672	0.097
11	802	8092	288,776	283,088	286,228	293,805	303,503	0.111
12	875	8019	288,208	282,001	285,427	293,097	303,678	0.108
13	948	7946	287,373	280,648	284,360	292,311	303,776	0.108
14	1021	7873	286,952	279,710	283,707	*292,044*	304,391	0.113
15	1094	7800	*286,455*	*278,696*	*282,979*	292,139	305,369	0.126

Lowest values for each information statistic are italicized

the model classifies the data in addition to their fit and parsimony (Banfield and Raftery 1993; McLachlan and Peel 2000). For the ICL-BIC we observe a reversal of the values and identify a minimum ICL-BIC value for fourteen latent classes. Based on the AWE statistic, the eight class model fits our data the best.

Classification errors closer to zero are also preferred. The classification error indicates the proportion of cases that would be misclassified if each case were assigned to the class to which it has the highest probability of belonging. Classification errors (Table 3) are higher in models with five to eight latent classes compared to models with fewer classes, though still relatively low with <8 % of cases misclassified.

The preferred number of latent classes in our model is not straightforward as is often the case for these types of models. Using all of this information together and reviewing the latent classes, we narrow down our choice of latent classes to four through eight. Our information statistic values continue to decline and never reverse direction (see Fig. 2). Nonetheless, based on the drop in and leveling off of fit statistics, four seems to be the minimum number of latent classes that represent the data and around eight is the maximum number of classes. Review of models with four through eight latent classes confirms this. The six-class model introduces a small proportion of night-time contracted activities that are not independently represented in the four and five class models; the seven-class model identifies a part-time work class; finally, the eight-class model shows three pathways predominated by contracted time, but varying in the start and end of that type of time as well as two shorter-hour contracted time pathways. Because all of the pathways are sensible and distinct, we selected the eight-class model, which shows nuanced differences in daily paid work participation. The chosen LCA models—depicted and discussed next—provide good fit to the data and offer a set of empirically based classifications of the temporal patterns of daily life.

Figure 3a shows one of two latent classes in which contracted time is *not* the predominant activity during the day. Nineteen percent of the sample respondents' daily

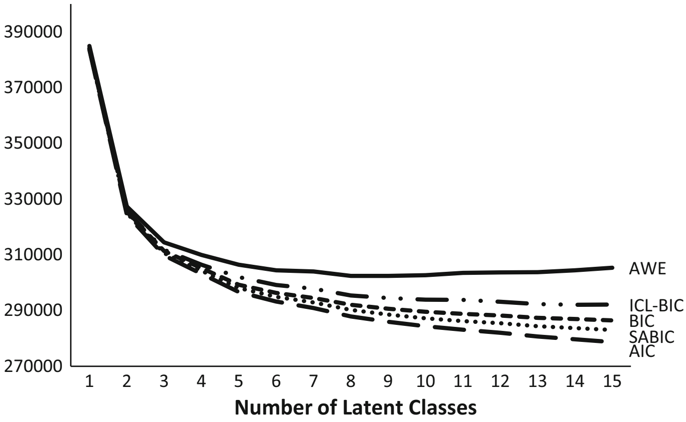

Fig. 2 Model fit statistics when adding classes to the model

patterns are best represented by this latent class—*committed time*—in which respondents engage in committed, but unpaid activities at modest to high levels (probability >0.5) between 8:00 a.m. and 6:00 p.m. The primary committed activities done by respondents in this latent class are cleaning, childcare, preparing meals, and shopping. Patterns of necessary time, characterized by sleep at the beginning and end of the day, with probabilities declining sharply after the 5:00 a.m. hour, remaining extremely low throughout the day with a slight uptick between noon and 2:00 p.m. and again between 5:00 p.m. and 8:00 p.m. for primarily eating-related activities, then rising very quickly between 9:00 p.m. and midnight to a 0.95 probability (predominately sleep). The probability of engaging in free time activities is quite low (<0.25) throughout the day until about 5:00–10:00 p.m., where it increases to a high of 0.56 during the 9:00–10:00 p.m. hour before declining again.

The class depicted in Fig. 3b is characterized by moderate to high levels of free time when not engaged in necessary activities like sleep or eating. This *free time* class represents approximately 16 % of the sample. Leisure activities reach a 0.57 probability by 10:00 a.m. and increase to a maximum of 0.77 at 8:00 p.m. after which leisure activities decline and are replaced by necessary activities, which primarily include sleep. Wake times and bed times are less standardized compared to the *committed time* pathway as indicated by the more gradual exit from and entry into sleep activities. There is a consistently low probability of time in committed activities throughout the day (0.22 or lower), which falls off into the late afternoon and evening hours when the probability of free time increases.

The remaining six latent classes characterize different daily rhythms around contracted time, which is largely comprised of paid work. The most prevalent latent class (depicted in Fig. 3c) includes 27 % of the sample respondents. This class is characterized by the high probability (approximately 0.8) of engaging in contracted activities, which consist of paid work and education, during the standard work and school hours of 8:00 a.m. and 4:00 p.m. We refer to this latent class hereafter as representing *standard hour contracted time*. The probability of necessary time (primarily sleep) is the highest during the day (0.95) at 4:00 a.m. and 5:00 a.m. and declines dramatically until 8:00 a.m. when the probability is <0.10. The probability of necessary time remains low until noon (probability = 0.21), falls off again until 6:00 p.m. (probability = 0.19), both of which represent eating, and increases rapidly after 9:00 p.m. when most respondents in this class are again engaging in necessary activities, in this case sleep, by midnight (probability >0.96). Free time is modest in the

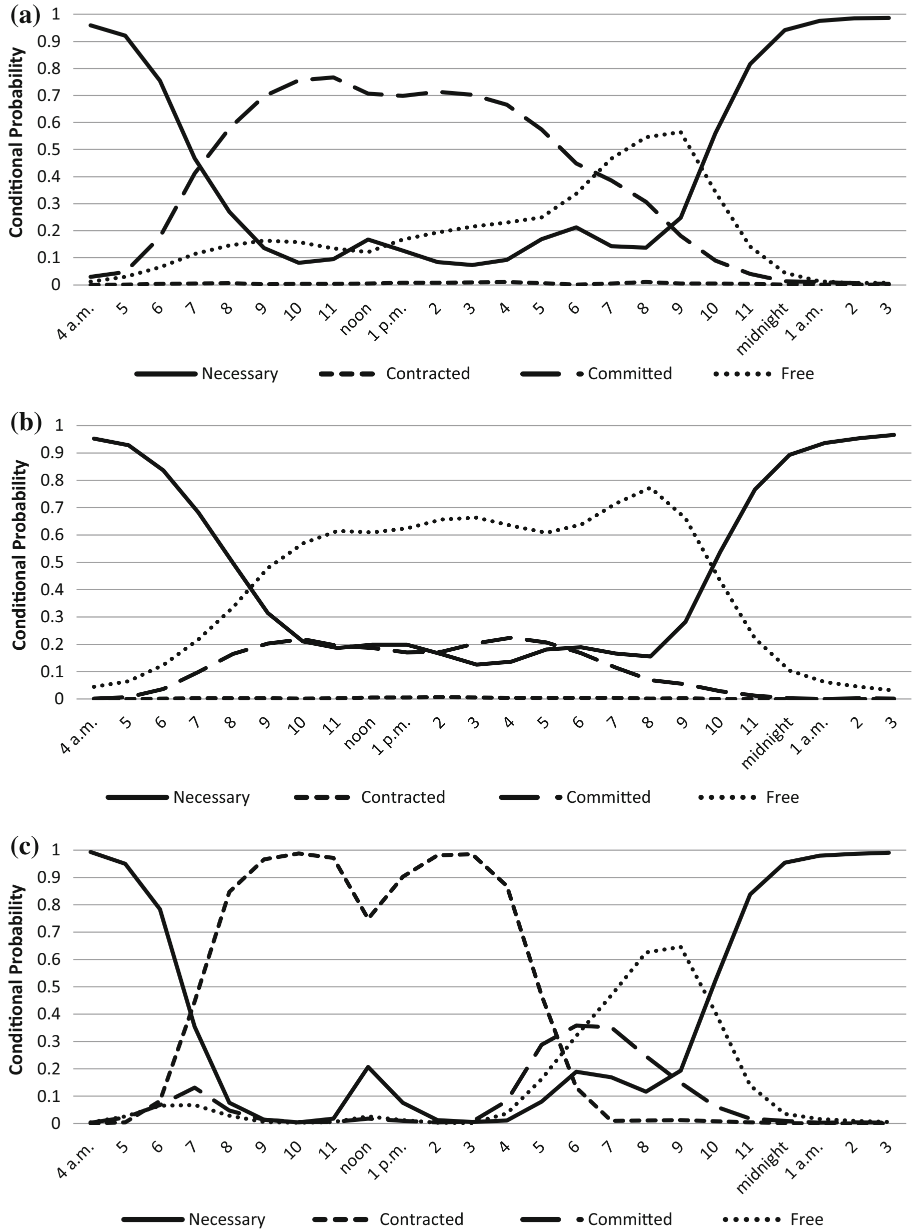

Fig. 3 **a** Committed time (estimated population probability = 0.19), **b** free time (estimated population probability = 0.16), **c** "standard" hour contracted time (estimated population probability = 0.27), **d** "early" contracted time (estimated population probability = 0.15), **e** long hour contracted time (estimated population probability = 0.09), **f** early day short hour contracted time (estimated population probability = 0.07), **g** late day short hour contracted time (estimated population probability = 0.05), **h** night hours contracted time (estimated population probability = 0.02)

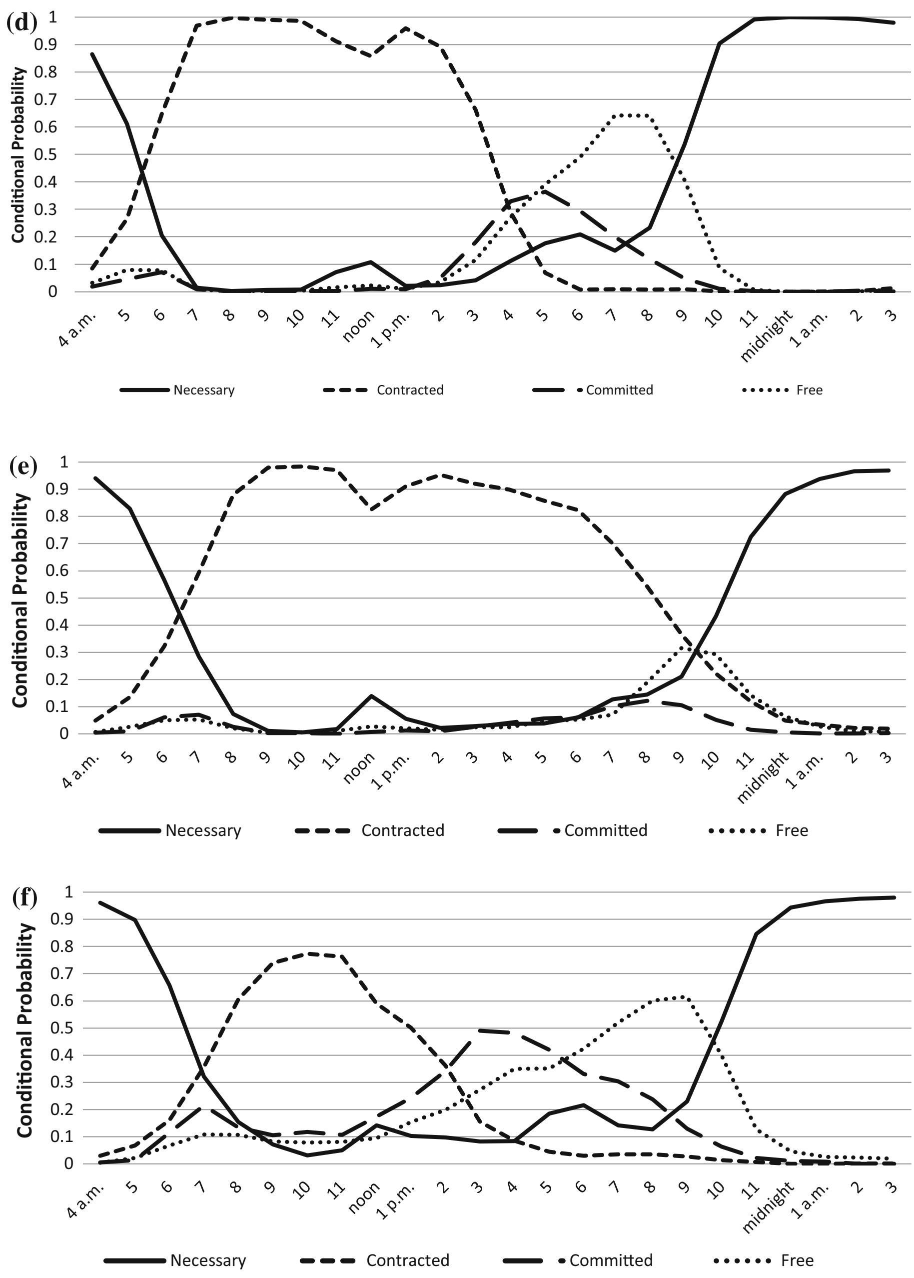

Fig. 3 continued

evening reaching a conditional probability of 0.63 at 8:00 p.m. and declining to <0.15 by 11:00 p.m. Finally, committed activities also reach modest levels before and especially after work; these consist primarily of preparing meals, pet care, and childcare in the

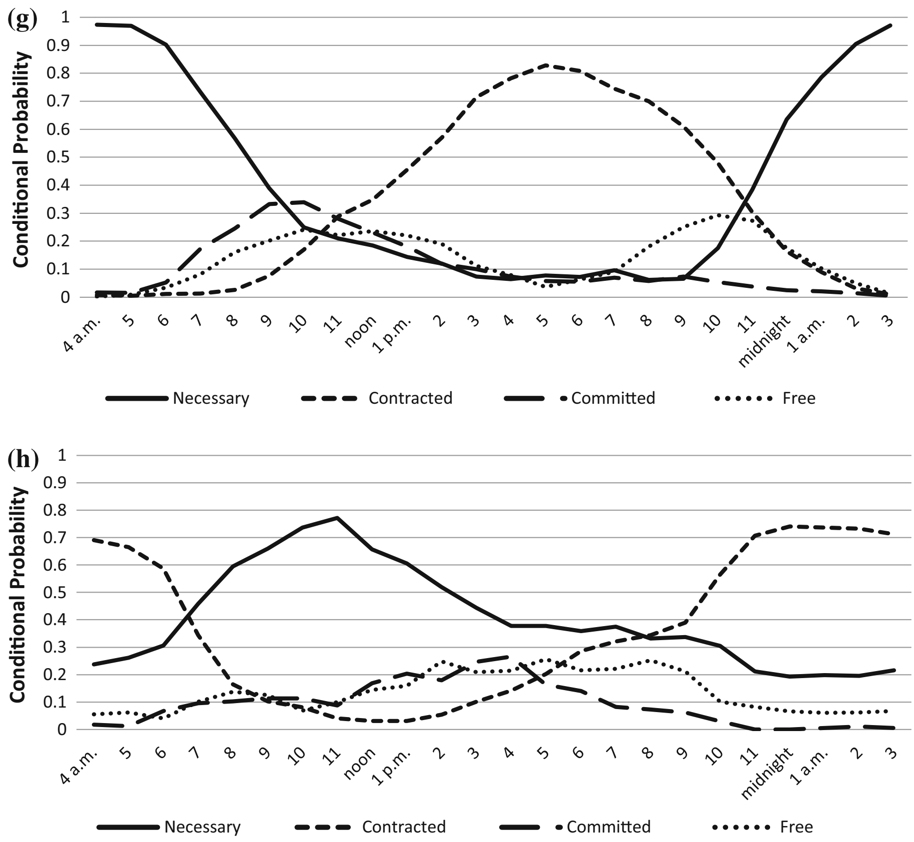

Fig. 3 continued

morning before work and cleaning, preparing meals, childcare, and shopping in the evening after contracted activities.

The second most common contracted time pathway is represented in Fig. 3d. Compared to the *standard hour contracted time*, the *early contracted time* pathway characterizes days in which paid work starts and ends earlier (probability = 0.15). The probability of engaging in contracted activities is 0.65 during the 6 a.m. hour, is 0.85 or higher between 7:00 a.m. and 2:00 p.m. By 5:00 p.m. the probability of engaging in contracted activities is <0.10. Contracted time gives way to committed and free time between 4:00 p.m. and 8:00 p.m. and necessary time increases rapidly after 9:00 p.m.

Figure 3e represents *long hour contracted time* and about 9 % of respondents. The probability of engaging in contracted work is 0.59 at 7:00 a.m. and remains high until 7:00 p.m. (probability = 0.70). Committed time is less pronounced for this pathway compared to the *standard hour contracted time* and the *early contracted time* pathways as is free time, reaching a maximum probability of 0.32 at 9:00 p.m. By 11:00 p.m. more than half of individuals in this pathway are sleeping (probability >0.72).

Figures 3f (*early day short hour contracted time*) and 3 g (*late day short hour contracted time*) characterize relatively short bursts of contracted and committed time.

Table 4 Multinomial logistic regression coefficients and relative risk ratios of membership in daily pathways relative to standard hour contracted time pathway, American Time Use Survey respondents ages 25–64 in 2006 and 2007 (N = 8894)

	Committed time		Free time		"Early" contracted time		Long hour contracted time		Early day short hour contracted time		Late day short hour contracted time		Night hours contracted time	
	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)
Female	−0.12	0.89	−0.48*	0.62	1.20*	3.30	−0.67*	0.51	0.88*	2.41	−0.04	0.96	−0.32	0.73
	(0.09)		(0.1)		(0.1)		(0.12)		(0.14)		(0.14)		(0.19)	
Parent	−0.33*	0.72	0.26	1.30	1.04*	2.82	−0.01	0.99	0.25	1.28	−0.20	0.82	−0.40	0.67
	(0.11)		(0.11)		(0.11)		(0.13)		(0.15)		(0.16)		(0.21)	
Age														
30–34	0.13	1.13	0.42	1.52	0.40	1.50	−0.13	0.88	0.71	2.03	−0.21	0.81	0.48	1.61
	(0.23)		(0.2)		(0.16)		(0.23)		(0.28)		(0.27)		(0.38)	
35–39	0.05	1.05	0.30	1.35	0.09	1.09	0.01	1.01	0.64	1.89	−0.82*	0.44	0.24	1.27
	(0.21)		(0.2)		(0.15)		(0.21)		(0.27)		(0.26)		(0.36)	
40–44	0.60	1.82	0.56	1.75	0.25	1.28	0.02	1.03	0.76	2.13	−0.15	0.86	0.13	1.13
	(0.21)		(0.19)		(0.16)		(0.21)		(0.28)		(0.26)		(0.37)	
45–49	0.41	1.51	0.73*	2.07	0.24	1.28	−0.06	0.94	0.81	2.25	−0.39	0.68	−0.33	0.72
	(0.2)		(0.19)		(0.17)		(0.21)		(0.29)		(0.25)		(0.4)	
50–54	0.37	1.45	0.72*	2.06	0.43	1.53	0.00	1.00	0.53	1.70	−0.57	0.57	0.17	1.19
	(0.21)		(0.21)		(0.18)		(0.23)		(0.31)		(0.27)		(0.36)	
55–59	0.95*	2.59	0.74*	2.10	0.99*	2.69	−0.14	0.87	0.96*	2.62	−0.49	0.61	−0.25	0.78
	(0.21)		(0.23)		(0.19)		(0.25)		(0.32)		(0.3)		(0.45)	
60–64	1.34*	3.81	0.66	1.94	1.55*	4.70	−0.59	0.56	1.07*	2.91	−0.60	0.55	−0.41	0.67
	(0.22)		(0.25)		(0.2)		(0.32)		(0.34)		(0.35)		(0.48)	
Some college	−1.14*	0.32	−1.24*	0.29	−0.85*	0.43	−0.01	0.99	−0.41	0.67	−0.71*	0.49	−1.09*	0.34
	(0.1)		(0.1)		(0.09)		(0.13)		(0.14)		(0.15)		(0.19)	
Urban	−0.18	0.84	−0.24	0.79	−0.15	0.87	0.03	1.03	−0.17	0.84	0.00	1.00	−0.40	0.67
	(0.12)		(0.13)		(0.11)		(0.16)		(0.16)		(0.18)		(0.25)	

Table 4 continued

	Committed time		Free time		"Early" contracted time		Long hour contracted time		Early day short hour contracted time		Late day short hour contracted time		Night hours contracted time	
	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)	beta/se	exp(b)
Year														
2007	−0.01	0.99	0.11	1.12	0.05	1.05	−0.34*	0.71	−0.07	0.94	0.29	1.34	−0.32	0.73
	(0.09)		(0.1)		(0.08)		(0.11)		(0.12)		(0.14)		(0.19)	
Constant	0.03	1.03	−0.06	0.94	−1.49	0.23	−0.61	0.55	−2.28	0.10	−0.86	0.42	−1.17	0.31
	(0.21)		(0.22)		(0.19)		(0.25)		(0.32)		(0.28)		(0.36)	

Reference categories for independent variables are male, year = 2006, not a parent, age = 25–29, HS degree or less, not living in an urban area

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Figure 3f (probability = 0.07) represents individuals for whom contracted time has a probability >0.5 (between 8:00 a.m. and 1:00 p.m.) that then gives way to committed time in the afternoon (probability >0.4 between 3:00 and 5:00 p.m.) and free time in the evening (probability >0.4 between 6:00 p.m. and 10:00 p.m.). By contrast, contracted time predominates Fig. 3g (probability = 0.05) between the hours of 1:00 p.m. and 10:00 p.m., when probabilities exceed 0.40. The Fig. 3g morning hours are characterized by committed and free time commitments.

Finally, Fig. 3h represents about 2 % of the sample with *night hour contracted time*. Necessary time is highest among those in this class between 7:00 a.m. and 3:00 p.m. Contracted time is high (probability >0.5) between 4:00 a.m. and 6:00 a.m. as well as 10:00 p.m. and 3:00 a.m.

The results of the third step of our analysis, based on a multinomial logit model, show how selected individual-level characteristics are associated with our estimated daily pathways. The results in Table 4 show logit coefficients and odds ratios for the multinomial regression estimation where membership in the estimated latent classes is our outcome variable. The reference category is the *standard hour contracted time* class (Fig. 3c). We find that parents are 0.72 times as likely as non-parents to have daily pathways dominated by *committed time* (Fig. 3a) compared to *standard hour contracted time* (Fig. 3c). Individuals in their mid-50 s to mid-60 s have more than twice the risk of individuals 25–29 to be in the *committed time* pathway versus the *standard hour contracted time* pathway, which makes sense since labor market participation begins to decline in the mid-50 s (e.g., Warner et al. 2010). The *free time* pathway is also more common than the *standard hour contracted time* pathway among older respondents, with the risk of participation in this pathway twice as high for 45–60 year olds as for 25–29 year olds. *Early contracted time* versus *standard hour contracted time* is more common among women (RRR = 3.3) and parents (RRR = 2.82) than men and non-parents; older workers (55–64) also tend to begin their work days earlier than 25–29 year olds. Women compared to men are at the lowest risk of *long hour contracted time* (RRR = 0.51) versus *standard hour contracted time*. Women compared to men (RRR = 2.41) and older workers (55-59 RRR = 2.62 and 60-64 RRR = 2.91) compared to 25–29 year olds are more prone to *early day short hour contracted time* versus *standard hour contracted time*. Individuals with some college have lower risks of being in the *late day short hour contracted time* and *night hours contracted time* pathways compared to the *standard hour contracted time* pathway.

5 Discussion

Most research using time diary data takes a discrete-time approach and sums time spent in a given activity during the course of a day and predicts the total amount of time spent in that activity based on individual and family characteristics. This approach has yielded an important body of work but has inadequately leveraged the richness of time diary data. Time diary data have the capacity to give us insight into issues such as the timing, sequence, and interdependence of activities. These features of the data have only begun to be analyzed by researchers (Glorieux et al. 2008, 2010; Hellgren 2014; Lesnard 2004, 2008; Lesnard and de Saint Pol 2009; Lesnard and Kan 2011; Minnen et al. 2015). Our research as well as this recent line of inquiry takes a more holistic approach and considers the composition of days, recognizing that individuals are purposeful actors even if they are operating within structures that limit or constrain their abilities to be agentic.

Our results illustrate the rhythm of daily life in the U.S. population. We also empirically demonstrate some of the theoretical ideas we presented earlier, such as social organization, heterogeneity, and stratification. In terms of the social organization of time, we find eight *daily temporal pathways* for Americans ages 25 to 64 using the 2006 and 2007 ATUS data. If time were not socially organized, the Latent Class Analysis of the over 8000 unique sequences of time use in the data would not produce a parsimonious set of time use pathways that are more similar to one another than they are different. The eight pathways we find are as follows. The *committed time* pathway is organized around activities such as childcare and housework. The *free time* pathway is characterized by a day primarily organized around leisure—specifically watching television. The remaining six pathways are organized around contracted time—largely paid work—but to differing degrees. *Standard hour contracted time* is the most common pathway and represents the typical work day largely between the hours of 8:00 a.m. and 5:00 p.m. *Early contracted time* shows a very similar pattern to *standard hour contracted time* but begins and ends earlier. *Long hour contracted time* extends longer into the evening than does *standard hour paid work* with less pronounced participation in committed and free activities. *Early day short hour contracted time* and *late day short hour contracted time* pathways have concentrated periods of paid work early and late in the day, respectively. They differ from the *standard hour*, *early*, or *long hour contracted time* pathways because contracted time fills less of the day. The final pathway, *night hours contracted time*, shows necessary time during the early part of the day and contracted time during the hours when most people are sleeping.

The eight pathways we identify are also heterogeneous and show evidence of stratification. Stratification in terms of the prioritization of organizational time (Lewis and Weigert 1981) is certainly evident for the *standard hour committed time*, *early contracted time*, and *long hour contracted time* pathways. The conditional probabilities of paid work during standard work hours for individuals in these pathways suggests the prioritization of organizational time—that is, rules about when paid work happens. Combined these pathways—and contracted time as an organizing feature of social time—represent over half of the working-age adult population. Work structures definitely contribute to the patterning of daily time allocation among paid workers, which is in line with Lewis and Weigert (1981) as well as work/family scholars who have theorized about the powerful role of the organization and workplace in orienting modern time use (Coser 1974; Moen and Roehling 2005; Williams 2000).

There is also heterogeneity in social time, as Sorokin and Merton (1937) theorized, regarding the social-demographic profiles of individuals following different pathways. It is more common, for example, for women as opposed to men to begin their days early (*early contracted time* pathway) and to work standard rather than long hour work days (*long hour contracted time* pathway). The moderate levels of largely housework and childcare in the *committed time* pathway compared to the high levels of paid work in the *standard hour paid work* pathway suggests greater flexibility with committed time than contracted time and reinforces the relevance and salience of organizational time on individual time use patterns. Finally, even within this subsample of working-age Americans (25–65), we find that older individuals compared to 25–29 year olds are more likely to have days that are dominated by committed but not contracted time, engagement in leisure, and early and short day contracted time.

The Latent Class Analysis not only highlights the presence of time structures and the ways in which individual-level characteristics are associated with membership in each pathway, it also gives us insight into the timing or synchronicity of activities (Lewis and Weigert 1981). Work as a time structure is evident in multiple pathways; there is a high probability of working for pay between the "standard" work hours of 8:00 a.m. and 4:00 p.m. Similarly, the peak free time period is generally between 7:00 p.m. and 9:00 p.m., even if it is not equally pronounced across pathways.

As social theorists have previously argued (e.g., Durkheim 1912; Lewis and Weigert 1981; Sorokin and Merton 1937), time is social and there is similarity across individuals in the ways in which they organize their days that are socially patterned. Like the previous research applying sequence analysis techniques to time diary data (e.g., Glorieux et al. 2010), we find that common structures of daily life exist. The role of paid work in organizing daily lives and the consistent pattern of evening leisure we see in our analysis of the U.S. working-age population are consistent with work by Glorieux et al. (2010) on the Flemish population as are the general daily patterns observed. Our work goes beyond previous research, however, in analyzing heterogeneity in the pathways across activity types and by considering the results in a broader theoretical framework.

Our research is not without limitations. Our portrait of American daily temporal pathways on weekdays may be reflective of this particular place and point in time. Future analyses should consider how American weekdays have changed over time, since the data exist to conduct such analyses, and whether there is something distinctly American about the social organization of time and prevalence of particular patterns. Our focus is on weekdays; an important extension would be to examine patterns on weekend days. Similarly, it would be interesting to examine the relationship between weekend and weekday time use, which is unfortunately not possible with the ATUS data since individuals are only interviewed on one randomly selected day. Seasonality may also affect time use, especially in climates with considerable variation in weather, which may affect time spent outdoors or time in different types of leisure.

In this analysis, we did not consider secondary activities. Using the the 2006 and 2007 ATUS, we cannot fully address the overlap between primary and secondary activities because secondary activities are limited to childcare, eating, and drinking. Childcare is a substantial share of parents' activities, but is very small for non-parents. For all individuals in our sample, a focus on childcare as a secondary activity misses the myriad other types of committed time that may be done at the same time as other activities, and secondary childcare may only be reported during non-paid work and non-personal care activities, so the inclusion of secondary childcare would only allow us to differentiate between committed and free time activities while performing (or not) secondary childcare. Similarly, eating and drinking represent a small share of secondary activities possible for individuals to partake in and a small share of total necessary time.

While they are outside the scope of this analysis, overlapping or concurrent activities are important to consider in future analyses of daily pathways. Using the ATUS, more targeted analyses of daily pathways and how they relate to family demands or health could draw on secondary childcare or secondary eating and drinking activities to add nuance to these literatures. More generally, drawing on data that collects information on detailed secondary activities has the possibility to contribute to an ongoing discussion regarding the fragmentation of time. For example, there is evidence that daily contributions to non-market work are underestimated by excluding the analysis of secondary activities and that the quality of leisure time is of substantial interest (e.g., Floro and Miles 2003; Glorieux et al. 2010; Offer and Schneider 2011; Sevilla et al. 2012). With the availability of detailed secondary activities, research could examine the timing of performing single activities versus multitasking and the characteristics of individuals whose days are characterized, for example, by multitasking at various times of day. If detailed secondary data were available, using the current approach would require coding each combination of four primary and secondary activities for 16 categories total (four primary activities only and 12 primary-secondary combined activities) as opposed to four in the current analysis.

Despite the limitations of this research, we extend prior theory on social time and the life course by depicting eight temporal pathways that summarize how time is allocated in the U.S. and how daily temporal pathways relate to individual demographic characteristics, including work and family. In addition to finding evidence in support of prior research, our findings illuminate the structural similarities in the timing of Americans' time use choices. Recognizing the existence and shape of temporal pathways may help us to further explore other social phenomenon by recognizing the ways in which time is socially constructed.

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