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ABSTRACT

Although individuals are all endowed with the same time budgets, time use patterns differ owing to heterogeneity in preferences and constraints. In today's health policy arena there is considerable discussion about how to improve health outcomes by increasing levels of physical activity. In this paper, we explore how individuals endowed with different levels of human capital allocate time to physically-demanding activities that we characterize as health-producing behaviors. Our data are drawn from multiple years of the American Time Use Survey (ATUS), which are based on daily time use diaries and include information on detailed physical activity time uses. Since ATUS time use categories are mutually exclusive and exhaustive -- i.e. "multitasking" is not accommodated -- we employ a novel econometric share equation techniques to enforce the adding-up requirement that time use is constrained to 1,440 minutes per day. We find that differential human capital endowments result in different manifestations of how time is used to produce health. While more-educated individuals, e.g., sleep much less than less-educated individuals, they utilize some of the time so liberated to exercise and work more. We find as well that various features of individuals' environments, broadly defined, play important roles in time allocation decisions.

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1. Background and Motivation

Physical Activity, Health, and Time Use

Despite evidence that regular physical activity is associated with decreased risk for obesity, chronic diseases, and premature mortality (USDHHS, 1996), fewer than half of the U.S. population engaged in recommended levels of physical activity in 2005 (MMWR, 2007). Moreover, there are significant disparities in physical activity by gender, race, and socioeconomic status such that women, racial/ethnic minorities, and people with lower education and income have significantly lower levels of physical activity (MMWR, 2007).

A burgeoning literature aims to understand the various barriers to physical activity in order to improve the health of the population and reduce health disparities. In making choices about how to allocate time to health-enhancing physical activities, individuals necessarily balance preferences for healthiness and (perhaps) the intrinsic utility of physical activity against the opportunity costs of the time spent engaged in such activities, recognizing that the magnitudes of such opportunity costs arise in part from factors that are exogenously fixed at the time such decisions are made. When individuals themselves are asked about their perceived barriers to exercise, they often cite lack of time due to work and other demands (Sallis and Owen, 1999; Wolin et al., 2008). However, very little is known about people's actual time use for physical activity, particularly how time allocations for physical activity are related to time allocations for other aspects of life (such as work, sleep, caring for others, and other non-exercise leisure activities), and how factors such as gender, education, and family structure affect allocation of time for physical activity.

Time use studies allow us not only to investigate how people allocate time for a particular health-producing activity (i.e., physical activity), but to examine the allocations that people make for this activity versus others, and factors that are systematically related to these time-use allocations (Russell et al., 2007). As described further below, human capital and its relationship to time use and health is part of the fundamental analytical tradition in health economics.

Research on time use demonstrates that there have been increases in overall leisure time in the U.S. in recent decades (Aguiar and Hurst, 2008) including an increase in leisure time allocated to physical activity (Berry, 2007). Aguiar and Hurst (2008) demonstrate that the increases in leisure time have been greater among individuals with less education than among those with more. Nevertheless, SES differences in physical activity remain. For example, estimates from the 2005 Behavioral Risk Factor Surveillance Survey (BRFSS) show that 54.6% of men and 53.3% of women who were college graduates engaged in regular physical activity, compared with 37.2% of men and 37.1% of women with less than a high school education (MMWR, 2007).

Our main task in this paper is to examine the structure of adults' time use patterns, with an emphasis on time allocated to physical activity. We examine whether individuals' economic endowments, human capital, demographic circumstances, and external environments influence time use choices in general and, specifically, with respect to time allocated to physical activity. We are particularly interested in whether human capital, in the form of educational attainment, influences the manner in which individuals allocate time towards or away from physical activity.

Since time is a fundamental input into the production of health, understanding how and why time use patterns emerge should be an important ingredient in thinking more creatively about how to improve individual and population health. We anticipate that this research will advance understanding of health-related time allocation decisions by providing a solid economic conceptualization of these phenomena, by utilizing extraordinarily interesting data that speaks to this conceptualization, and by deploying a novel econometric methodology within which these issues can be addressed straightforwardly and robustly.

The remainder of the paper is organized as follows. Section 2 considers several conceptual or theoretical approaches to thinking about individuals' "demands" for health-enhancing time use. Section 3 describes the ATUS data, points out some important caveats about the ATUS data, and provides details about the construction of the subsamples we use to explore econometrically the observed time use patterns. Section 4 exposits our econometric strategy. Section 5 reports the empirical results, and section 6 closes with a discussion and some conclusions.

2. Time Allocation, Human Capital, and Health: Theory

The context of human capital and its relationship to time use and health is part of the fundamental analytical tradition in health economics dating back to Grossman's seminal work in 1972, and thus even further back to Becker's seminal work on the economics of time allocation in 1965. In the canonical Grossman model, time and goods are invested, via health production functions, in such a way as to influence the next period's health capital level which itself corresponds to how much healthy time and unhealthy time individuals enjoy in the subsequent period. In this context, human capital stocks (e.g. educational attainments) influence the efficiency by which time and goods translate into ultimate health outcomes. The role of time and time costs in health production has become quite prominent, for instance, in the conceptual and empirical economic analysis of obesity (Cutler et al., 2003; Philipson and Posner, 2008).

Our main premise is that individuals differentially endowed with human capital are likely to exhibit different patterns of time use when factors orthogonal to human capital endowments are held constant. Since one important feature of time use is how individuals allocate time budgets towards (or away from) time spent engaging in health-enhancing physical activities, one consequent prediction would be that the amount of human capital individuals bring to the Table will be related to the amount of human capital -- specifically, health capital -- that they take away from the Table.

However because some of the important determinants of time use patterns (e.g. shadow prices of different forms of time use, or wage rates) will typically not be orthogonal to human capital endowments -- e.g. higher educational attainment and higher wages -- the prediction of how human capital endowments influence health-enhancing time use patterns and, ultimately, health outcomes is theoretically ambiguous. The goal of this paper is to shed some empirical light on a set of such relationships in order to sharpen our understanding of time use determinants and, downstream, to understand how interventions might be designed to encourage healthier or discourage unhealthier uses of scarce time.

There are many potential pathways through which human capital stocks might be expected to influence time use patterns. First, and most obvious, is that differences in human capital stock levels (e.g. educational attainment) will translate into differences in labor market productivity that will in turn translate into differential marginal rewards (wage rates) for forms of time use like labor supply. At the margin, individuals will respond to such differential reward rates in making time allocation decisions, including how much time to dedicate (or not) to health enhancing activities. An important study in this genre is Biddle and Hamermesh, 1990, who demonstrate empirically how higher market opportunity costs of time (wage rates) translate into reduced demand for sleep time. To the extent that increased time over the typical margin in a population is health enhancing, the Biddle-Hamermesh results suggest that -- at least in a static context -- more human capital does not automatically translate into better health outcomes.

Alternatively, at a theoretical level, time constraints are equally binding for all individuals -- 1,440 minutes per day, 8,760 hours per year, etc. -- and within these bounds individuals are free to allocate their time budgets as they wish subject to constraints imposed by physical laws like gravity. At a practical level, however, choices -- including time use choices -- individuals have made in the past as well as the consequences of these choices are likely to imply varying degrees of quasi-fixity of current-period time use patterns, with the implication that departures from such patterns are likely to be costly either in a monetary or in a psychic sense.[1] (See Heckman, 1980, and Hamermesh, 2005, for two perspectives on how past time allocation choices might influence current patterns of time use.) The role of human capital stocks in such a setting is to dictate in part the extent to which the ostensible fixity of individuals' circumstances may be rendered more flexible by, e.g., the enhanced resources that can be commanded by individuals having higher levels of human capital (e.g. in the form of financial wealth).

Our guiding hypothesis is that many individuals are confronted with significant constraints on their allocation of time for physical activity, and these

[1] For instance, if my child attends regularly a formal day care setting and I elect to allocate my time in such a manner that I fail to pick her up by the 6PM closing time (e.g. by attending an after work event at a local tavern), then I am likely to pay both monetary costs (for staff overtime) as well as to suffer psychic costs (for being a lousy parent).

constraints differ importantly by level of human capital (e.g., educational attainment). However, the prediction of how human capital influences time allocated to physical activity is ambiguous because there are both substitution and wealth effects at work: since the shadow price of non-labor time use is relatively greater for high-wage individuals, they may spend less time engaged in health-promoting activities (as was documented in the Biddle-Hamermesh study for activities like sleep). Yet individuals who have amassed high levels of human capital are both more able to afford health-producing behaviors and more likely to prefer greater levels of produced health.

While our focus is ultimately on time use as an *input* into the production of health, it is useful to sketch a broader economic framework that encompasses considerations of the "demands" for various forms of time use but that also speaks to the broader issues of the role of human capital sketched above. Assume individuals are endowed with utility functions

$$u = u(h,\mathbf{z},\mathbf{t},\mathbf{v};\mathbf{e}),$$

where h is a measure of health, **z** is a vector of other commodities produced by combining goods and time, $\mathbf{t}=[t_1,...,t_M]$ is a vector of time use activities, **v** is a vector of other commodity-producing variable inputs that may also confer direct utility, and **e** is a vector of exogenously given environmental (social, natural, etc.) measures that may influence the marginal utilities of the other utility determinants (e.g. ceteris paribus, ice cream and time jogging may be more enjoyable at temperatures of 75F than of 15F).

Health outcomes are produced via the health production function

$$h = h(\mathbf{t},\mathbf{v},\mathbf{k},\mathbf{q},\mathbf{e})$$

in which **k** is a vector describing dimensions of non-health human capital, and **q** is a vector representing features of family or household structures. The other commodities, **z**, are produced using the same inputs as go into production of h; note that **z** may include outputs like the health or wellbeing of other family members. The full income (time and money) constraint is

$$\mathbf{pv} + w(\mathbf{k})\sum_{m=2}^{M} t_m = E + w(\mathbf{k})T,$$

where labor supply is t_1, total time endowment is T (e.g. 1,440 minutes per day, 8,760 hours per non-leap year, etc.), endowment income is E, and where market wages are written as an explicit function of human capital. The demand or choice functions that result from constrained utility maximization include the time demand functions

$$t_m = t_m(\mathbf{k}, \mathbf{q}, \mathbf{e}, E, \mathbf{p}), \qquad m=1,\ldots,M$$

or, in shorthand,

$$\mathbf{t} = \mathbf{t}(\mathbf{x}),$$

whose empirical counterparts, cast as the conditional expectations $E[\mathbf{t}|\mathbf{x}]$, are the main focus of the subsequent analysis. In this setting, we will be focusing particularly on the roles played by human capital (measured here most prominently by educational attainment), family structure (kids' age structure, marital arrangements), and environmental features of several kinds.[2]

3. ATUS Data and Sample Construction

ATUS Surveys

Empirical analysis of time use data is certainly not a new enterprise (see Juster and Stafford, 1991, and Hamermesh and Pfann, 2005). However, only recently have data been sufficiently rich that analysts can begin realistically

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[22] It should be noted that the empirical analysis we undertake below does not have information on any relevant goods' prices (**p**) and has at best rough proxy measures of endowment income (E).

thinking about how to deploy time use data to explore issues involving individuals' health (see Russell et al., 2007, for a discussion of health-related measures in the ATUS). While this paper does not tackle health issues *per se*, the ATUS data nonetheless provide a level of breadth and depth that permits us to explore how determinants of time use are likely to translate into health outcomes through the time use channel—particularly through time use for physical activity.

The data used in this study are from the 2005 and 2006 American Time Use Surveys administered by the U.S. Bureau of Labor Statistics. The ATUS universe is all residents living in households in the U.S. who are at least 15 years old, excluding active military personnel and persons residing in institutions (e.g., nursing homes and prisons). The ATUS sample is drawn from the Current Population Survey (CPS), using a three-stage process. In the first stage, CPS respondents are sampled to produce an ATUS sample that is distributed across the states in approximate proportion of the national population each state represents. In the second stage, households are oversampled if they have a Hispanic or non-Hispanic black householder. Households with children are over-sampled and households without children are under-sampled. In the third stage, a respondent from each household is randomly chosen among all eligible householders (civilian, non-institutionalized persons ages 15 or older). The ATUS response rate averaged 56.6% in 2005 and 55.1% in 2006.

Over 2,000 respondents participated per month in the ATUS during each of 2005 and 2006, for approximate annual sample sizes of 26,000 for each of these years. The monthly sample was divided into four randomly selected panels for each week of the month. The sample was then further split evenly between weekdays and weekend days, with 10% of the sample assigned to each weekday and 25% assigned to each of the two weekend days. The designated respondent was randomly assigned a day of the week to report on. The phone interviews with respondents (in English or Spanish) included a combination of structured questions and conversational interviewing, focusing particularly on a time-use diary.

Time Use Data

The time-use diary collects a detailed account of the respondent's sequential activities "yesterday" starting at 4:00 a.m. the previous day and ending at 4:00 a.m. on the interview day. For each activity reported, the interviewer also collected information about how long the activity lasted, and for most activities, data were collected about who was present and where the activity took place. If respondents listed multiple activities at one time, they were asked to choose which one was the primary activity. Activities were then coded in minutes and add up to a total of 1,044 minutes, with only one primary activity coded for any given minute. The only secondary or simultaneous activity that was coded was care of children under age 13. These secondary childcare estimates are made by summing the duration of activities during which respondents had a child under age 13 in their care while doing a primary activity. While we do not undertake an analysis of these data in the current version of this paper, we expect to incorporate considerations of these issues in a future version.

One of the strengths of this study is that we examine several types of time use categories simultaneously. We break the allocation of time into six categories: sleep, household and personal activities, care for others, work, non-exercise leisure activities, and physical activities. (This categorization of the time use measures is primarily based on aggregating the 18 two-digit classifications used in the ATUS, with exceptions noted).

Since sleep time has been of considerable interest in the health literature, and has been shown to vary by SES in particular (Biddle and Hamermesh, 1990), we include a separate time use category for "sleep" (*tsleep*). For our purposes, the total amount of time sleeping includes an estimate of actual sleep time but does not include time listed as "sleepless" (which is combined under other household and personal care activities).

"Household and personal activities" (*thhpers*) includes a number of activities viewed as part of daily life such as household chores, using services (professional, personal, or household), consumer purchases, eating and drinking, and personal care (other than sleeping). In addition, all time spent in travel between activities (except for walking listed for the purpose of exercise) are coded here.

"Caring for others" (*tcare*) includes providing care for and helping both household and nonhousehold members of any age. This class of coding has fairly conservative coding criteria as it requires that the care or help be not only the primary activity, but also that it not be easily counted as something else. For example, "watching television with my child" is coded as a leisure activity rather than care, and "helping my spouse cook dinner" is considered a household activity rather than care. Care provided through an organization is coded as a volunteer activity rather than as care for a nonhousehold member.

"Work" (*twork*) refers to all working and work-related activities (except travel to and from work), including activities like work-related socializing and job search activities. While the term "market work" is not used in the ATUS lexicon, it is appropriate to think of this work category as such.

For leisure time, we distinguish between time spent on "physical activity/exercise, not work-related" (*texerc1*), which we refer to as “physical activity”, and "non-exercise leisure activities" (*tnonexc1*). We consider physical activity/exercise to include all the ATUS codes under "Sports and Exercise" (e.g., playing sports, running, lifting weights) with the exception of some subcodes that we decided might not count as exercise as they, on average, are less active: billiards, boating, bowling, fishing, hunting, and vehicle touring/racing. The latter activities were allocated to non-exercise leisure activities, which puts them with other recreational activities such as watching sports, watching television, relaxing, listening to music, and attending arts, cultural, and entertainment events; we also put religious and volunteer activities in this category, as well as education activities (note that we restrict our analyses to respondents ages 25 and older). However, in a sensitivity analysis described later, we create a second set of measures in which billiards, boating, bowling, fishing, hunting, and vehicle touring/racing are allocated to the physical activity category (*texerc2*) and away from the non-exercise leisure category (*tnonexc2*).

Explanatory Variables

Because ATUS respondents were chosen from among CPS respondents, CPS data are merged with ATUS data. The CPS interview takes place approximately five months before the ATUS diary date. As a consequence, the range of measures available for defining explanatory variables is extended significantly since both the

ATUS interview component as well as the CPS information can be utilized.

The main covariates from the ATUS and ATUS-CPS data used in the analysis are: gender (*female*); age in years (*age*); race/ethnicity (*blacknh* (non-Hispanic black), *Hispanic*, *otherre* (other race), and non-Hispanic white (omitted)); educational attainment (*hsgrad*, *somecoll*, *collgrad*, *advdeg* (less than high school graduate omitted); or a pseudo-continuous years of education measure, *educ*); marital status (*widowed*, *divsep*, *nevmarr* (currently married omitted)); presence of a spouse in the household (*sppreshh*); household size (*hhsize*); season (*autumn*, *winter*, *spring* (summer omitted)); and day of week (*sun* (Saturday omitted); or *tue,...,fri* (Monday omitted)).

Additionally, we anticipate that intra-household demographic structures will play an important role in the way adult household members allocate time. As such, we define and include in our econometric specifications various sets of measures that indicate the age categories of the youngest child in the household (*yghh0005* (5 or younger), *yghh0611* (6-11)), a variable indicating the presence of an own non-household child under the age of 18 (*pknhlt18*), a variable indicating the number of household children under the age of 18 (*nkhhlt18*). Finally, in some specifications we consider the inclusion of family income measures despite the legitimate concern about their endogeneity in a model of time use (*fi2550*, *fi5075*, *fi75100*, *fi100150*, *fi150up* (family income $0-$24,999 omitted)).

These ATUS and ATUS-CPS measures are supplemented by merging at the state- and diary-month-level information on several factors that may reasonably be hypothesized to influence time use choices. First, state-level data on average monthly temperature (*temperature*) and total precipitation (*precip*) from the National Oceanic and Atmospheric Administration (NOAA) are linked (data are not available for Alaska and Hawaii). Obviously these are coarse measures, particularly so for states having large latitude ranges.[3] Second, state-level monthly data on unemployment rates from the Bureau of Labor Statistics (BLS) are merged; contemporaneous and one-month lagged measures are considered (*uerate*,

[3] In future work we plan to obtain and merge more geographically- and temporally-specific climate data. See Connolly, 2008, for discussion.

ueratelg). Finally annual state-level data (estimates, more accurately) on the prevalence of overweight/obese or obese adults (*stobover*, *stobese*) from the Centers for Disease Control and Prevention (CDC) Behavioral Risk Factors Surveillance System (BRFSS) are merged. Based on the individual's diary month, a weighted average of the current and prior years' data is computed, with weights (month-1)/12) and ((13-month)/12), respectively.

Sample Characteristics

In the combined 2005 and 2006 ATUS, there are 18,484 observations on individuals ages 25-64. We focus on this age group in our analysis based on the notion that individuals of these ages are (largely) post-schooling and (largely) pre-retirement. In this age window, 16,217 observations have fully intact time use data and thus constitute the main estimation sample.[4] Of these, 8,265 are observations on individuals whose time diaries were completed on weekends or holidays and 7,952 are on observations whose time diaries were completed on non-holiday weekdays (recall that the sampling structure is designed to accomplish an approximately 50% split between weekends and weekdays). Since we expect time use patterns to be different on weekends and weekdays, we will estimate separate models for these subsamples (controlling via dummy variables in both instances for the particular day of week on which the sample is taken). Due to the missing climate data for Alaska and Hawaii, the main estimation samples will be based on samples comprising 8,216 weekend observations and 7,907 weekday observations.

The unweighted summary statistics for the time use measures and the covariates are presented in Tables 1 and 2. Table 3 demonstrates the differences in summaries of the time use measures between the unweighted and weighted

[4] Fully intact time use data correspond to observations having zero values for all of the ATUS two-digit "50" subcategories. Insofar as selection on observables within the 25-64 sample is concerned, a simple logit regression of time use data missingness on basic demographic variables suggests that older individuals, females, individuals with larger household sizes, and college graduates and advanced degree holders are relatively more likely to have missing or otherwise unusable time use data than their respective counterparts.

samples.[5] Figure 1 displays pie graphs of the time use measures by gender and time of week, while Figure 2 depicts time use patterns by educational attainment and time of week. Even at this level of evidence, gender, education, and time-of-week differences are evident and prominent. Figure 3 displays the detailed sample distributions of each time use measure.

4. Econometric Strategy

Limited Dependent Variable Estimation

The available time use data from the ATUS comprise M mutually exclusive and exhaustive-of-1440-hours information on respondents' time use patterns for one randomly selected weekday or one randomly selected weekend day. Because these data necessarily satisfy the adding up condition $\sum_{j=1}^{M} t_j = T$, the nature of the time demand functions is formally that of economic share equations found, for example, in the analysis of household expenditure patterns or portfolio allocation decisions (Poterba and Samwick, 2002; Woodland, 1979). Normalizing the total amount of time available to T=1 formalizes the comparison to the share equation context. Various econometric methods have been used in the literature to analyze time use (Kooreman and Kapteyn, 1987, and Wales and Woodland, 1977, as well as related literature analyzing budget share models, e.g. McElroy, 1987, and Woodland, 1979). Many of these approaches are built on a multivariate Tobit or on a Dirichlet probability structure.

Multivariate Fractional Regression (MFREG, MFLOGIT)

As an alternative, this paper uses a generalization of the fractional regression models proposed by Papke and Wooldridge, 1996, in their study of voluntary individual contributions to retirement accounts in which the main dependent variable was the fraction of allowable contributions made by each individual. The key result in the Papke-Wooldridge paper is that even when the outcome variables take on values at the extremes of the bounded range they occupy -- i.e. y=0 or

[5] The analysis relies henceforth exclusively on the unweighted samples. The most prominent differences would appear to be with the *tcare* variable.

y=1 -- the fractional regression (FREG) or fractional logit (FLOGIT) method provides consistent estimates of the parameters of a univariate conditional mean function $\mu(\mathbf{x};\boldsymbol{\beta})$ so long as $\mu(\mathbf{x};\boldsymbol{\beta})$ is specified with the correct functional form.

In the ATUS time use data, there are many observations of $t_{ij}=0$ on particular time use categories. Multivariate Tobit-type estimators can handle such data structures, albeit at the costs of computational complexity and possible non-robustness to non-homoskedastic-Gaussian or non-Gaussian probability structures. Dirichlet distributions may also be non-robust to distributional departures, and also may not accommodate well the y=0 phenomenon. The proposed extension of the Papke-Wooldridge strategy to multivariate outcomes usefully steers clear of these econometric potholes (additional details are provided in Mullahy, 2006).

To this end, let $y_{im}=t_{im}/T$, m=1,...,M, be the marginal outcomes of interest such that $y_{im}\in[0,1]$ and $\sum_{m=1}^{M} y_{im} = 1$. Then it is natural to want the estimation strategy to enforce two restrictions that are likely to be important in applications. First is that $E[y_{im}|\mathbf{x}_i]\in(0,1)$ for all i; second is that $\sum_{m=1}^{M} E[y_{im} \mid \mathbf{x}_i]=1$ for all i; in this notation, $\mathbf{x}_i$ summarizes all relevant exogenous determinants of the specified conditional means.

One functional form that embeds both these considerations is the multinomial logit functional form

$$
\begin{aligned}
E[y_{im}|\mathbf{x}_i] &= \frac{\exp(\mathbf{x}_i\boldsymbol{\beta}_m)}{\sum_{k=1}^{M}\exp(\mathbf{x}_i\boldsymbol{\beta}_k)}, \qquad m=1,\ldots,M \\
&= \frac{\exp(\mathbf{x}_i\boldsymbol{\beta}_m)}{1+\sum_{k=2}^{M}\exp(\mathbf{x}_i\boldsymbol{\beta}_k)} \\
&= \mu_{im}(\mathbf{x}),
\end{aligned}
$$

using the normalization $\boldsymbol{\beta}_1=\mathbf{0}$. In keeping with the Papke-Wooldridge terminology, this model might be termed a multivariate fractional regression (MFREG) or multivariate fractional logit (MFLOGIT) mode. This model can be estimated straightforwardly using modifications of standard multinomial logit estimation algorithms (see the Appendix for further details on estimation and inference).[6]

Average Partial Effects

Owing to the necessary parameter normalization that arises from the adding-up restriction, the interpretation of the parameter point estimates in multinomial logit-type models can be vexing (Crawford et al., 1998). More interesting are the average partial effects (APEs) of the x_{ik} on the conditional means $E[y_{im}|\mathbf{x}_i]$. To this end, in the case where x_k is a dummy variable, we compute APE_{mk} as the sample average, evaluated at $\boldsymbol{\beta} = \hat{\boldsymbol{\beta}}$, of the difference:

$$\frac{\Delta E\left[y_{im}|\mathbf{x}_i\right]}{\Delta x_{ik}} = \frac{\exp\left(\mathbf{x}_{-k,i}\boldsymbol{\beta}_{m,-k} + \beta_{mk}\right)}{1 + \sum_{j=2}^{M} \exp\left(\mathbf{x}_{-k,i}\boldsymbol{\beta}_{j,-k} + \beta_{jk}\right)} - \frac{\exp\left(\mathbf{x}_{-k,i}\boldsymbol{\beta}_{m,-k}\right)}{1 + \sum_{j=2}^{M} \exp\left(\mathbf{x}_{-k,i}\boldsymbol{\beta}_{j,-k}\right)},$$

where $\mathbf{x}_{-k,i}$ is the vector $\mathbf{x}_i$ for the i-th observation with the k-th element excluded. When dummy variables are included in $\mathbf{x}$ as mutually exclusive and exhaustive (save an "omitted" category) members of sets of indicators -- e.g. race/ethnicity groups, educational attainment indicators -- setting up the discrete APE to capture the proper counterfactual is accomplished by zeroing out *all* of the group's dummy

[6] Given the large number of parameters estimated by MFLOGIT, a concern arises regarding multiple comparisons in hypothesis testing. One could use a Bonferroni-type criterion to reduce the probability of type-1 errors across the family of t-tests or p-values that arise, but Bonferroni criteria are notoriously conservative, i.e. intolerant of type-1 errors. An alternative, more powerful, approach is to appeal to the false discovery rate (FDR) control strategies developed by Benjamini and Hochberg, 1995, and Benjamini and Yekutieli, 2001, which are based on the individual tests' p-values but accommodate some degree of tolerance of type-1 errors on the analyst's part, thus enhancing test power.

Since the p-values associated with the elements of $\hat{\boldsymbol{\beta}}$ will not be mutually independent, the conservative criterion suggested in Benjamini and Yekutieli, 2001, offers a sensible middle ground between the perhaps overly liberal approach of ignoring altogether the multiple comparisons issue (i.e. making inferences based only on individual parameters' p-values) and the perhaps overly conservative Bonferroni strategy. Supplementing the standard p-values, the tables of MFLOGIT results presented below provide the FDR hypothesis rejection (FDR=1) or non-rejection (FDR=0) recommendations at FDR rate .05.

variables at baseline (i.e. setting all group dummies for all observations equal to the omitted category) and then setting the x_{ik} the variable in question equal to one for all observations.[7]

For "continuous" x_k, APE_{mk} is computed as the sample average, evaluated at $\boldsymbol{\beta} = \hat{\boldsymbol{\beta}}$, of the partial derivative

$$\frac{\partial E\left[y_{im} \,|\, \mathbf{x}_i\right]}{\partial x_{ik}} = \exp\left(\mathbf{x}_i\boldsymbol{\beta}_m\right) \times \frac{\left(1+\sum_{j=2}^{M}\exp\left(\mathbf{x}_i\boldsymbol{\beta}_j\right)\right)\times\beta_{mk} - \sum_{j=2}^{M}\exp\left(\mathbf{x}_i\boldsymbol{\beta}_j\right)\times\beta_{jk}}{\left(1+\sum_{j=2}^{M}\exp\left(\mathbf{x}_i\boldsymbol{\beta}_j\right)\right)^2}.$$

As in a standard multinomial logit probability model, it is noteworthy that the sign of β_{mk} does not necessarily correspond to the sign of APE_{mk}. We compute and report 95% bootstrap confidence intervals[8] around the APEs so estimated using the C_2 method suggested by Hansen, 2008.[9]

In the empirical analysis that follows we elect to normalize the MFLOGIT coefficients by setting $\boldsymbol{\beta}_{tnonexc} = \mathbf{0}$; consequently the other categories' parameters should be interpreted as $\boldsymbol{\beta}_k - \boldsymbol{\beta}_{tnonexc}$. The interpretation of the APEs' estimates does not depend on the normalization, however, and as indicated above these and their sampling variation are likely to be more interesting for most purposes.

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[7] We have estimated a set of specifications that include interactions involving gender, schooling attainment, and other covariates. Calculation of the relevant interaction-related APEs is somewhat computationally complicated, however. The next version of this paper will include a presentation of these results.

[8] Multiple comparisons issues may arise as well in the computation of multiple CIs (Benjamini and Yekutieli, 2005). We do not address these considerations in the present version of the paper.

[9] Given the size of the parameter vectors being estimated and corresponding size of the APE vector, the bootstrap exercise is somewhat time intensive (approximately four bootstrap iterations per minute). As such, the present version of this paper estimates the APE CIs using 500 bootstrap iterations for the baseline specifications and 100 bootstrap iterations for the comparison specifications.

5. Results

Baseline Specifications

The parameter estimates for our baseline specifications are presented in Tables 4 (weekends & holidays) and 5 (weekdays). These Tables present the point estimates (recall the $\boldsymbol{\beta}_{tnonexc} = \mathbf{0}$ normalization), robust t-statistics[10], and conservative FDR rejection (=1) or non-rejection (=0) recommendation. These are followed by Table 6, which reports the corresponding APE and .95 CI estimates. Note that the magnitudes of the parameter estimates are based on scaling the time use outcomes to the [0,1] or share intervals (i.e. dividing each time use measure for each individual by 1,440), whereas the APEs are defined on the natural units of measurement, minutes per day.

In Tables 4 and 5, neither the signs nor magnitudes of the **x**'s roles as determinants of the **t**'s are informative (owing to the parameter normalization). However, the statistical significance of many of the individual point estimates (most usefully indicated by FDR=1), the magnitude of differences *across* categories for given x_k, and the joint significance of the category-specific parameters (as indicated by the Wald χ^2 statistics) are all suggestive that the conditional time use patterns $E\left[t_k \middle| \mathbf{x}\right]$ are likely to vary nontrivially with at least some of the **x**'s. The magnitude of effects for each parameter can then be assessed most straightforwardly by consideration of the estimated APEs in Table 6.

Table 6 demonstrates the APE and .95 CI estimates. Looking at age, we see that age has a statistically significant association with all categories of time use on weekends/holidays. Each greater year of age is associated with almost two minutes more per day spent in personal and household tasks (1.883 minutes) and in non-exercise leisure time (1.965 minutes), and about one minute less spent in

[10] In this version of the paper, the parameter estimates' robust covariance matrix estimator does not consider possible clustering at the state level. The usual cluster parameter covariance estimator turns out to yield standard error estimates on the state-level variables that are actually *smaller* than their non-clustered counterparts. We have not yet developed the software to generate the clustered bootstrap confidence intervals (Field and Welsh, 2007); we expect to present these results in the next version of the paper.

sleep (-1.178 minutes), caring for others (-1.797), working (-.742), and exercising (-.131 minutes). For weekdays, there is no statistically significant relationship between age and time for sleep and physical activity, but age has a positive association with time spent for household and personal care and leisure activities, and a negative association with time caring for others and time working.

As demonstrated earlier in Figure 1, gender is significantly related to adult time use. Looking across all categories of time use on weekends/holidays and on weekdays, gender has a statistically significant relationship with all forms of time use except one—time spent in physical activity on weekdays. On a weekend/holiday day, women spend almost 7 minutes more time sleeping than do men, net of all other covariates. On weekdays, they spend about 15 more minutes sleeping than do men. Women also spend about 83 and 92 more minutes taking care of household and personal care activities on a weekend/holiday and weekday, respectively. Women spend more time caring for others on a given day (about 12 more minutes on weekend/holiday days and 39 minutes on weekdays). Women spend less time than men working and participating in non-exercise leisure activities on both weekends/holidays and weekdays. On weekends and holidays, women spend about ten minutes less in physical activity than do men, though there is no statistically significant relationship between gender and physical activity on weekdays.

When it comes to looking at race/ethnicity and time use, our results demonstrated that there are clear differences between racial/ethnic groups, and that the patterns of difference vary depending on whether you look at weekends/holidays or weekdays. Compared to people reporting their race as non-Hispanic white, those self-reporting as non-Hispanic black report that on weekends and holidays they spend significantly more time in sleep and non-exercise leisure activities (21 and 48 more minutes, respectively), and less time in household and personal care activities, caring for others, and exercising (54, 17, and 7 fewer minutes, respectively). On weekdays, compared to non-Hispanic white respondents, non-Hispanic black respondents again spend more time sleeping and in non-exercise leisure activities (17 and 44 more minutes, respectively), and less time in household and personal care activities and caring for others (22 and 15 fewer minutes, respectively). Although there were no black/white differences in work time on weekends, we see that black respondents report about 23 fewer minutes of work than white respondents on weekdays. And while there were differences in time use for physical activity on weekends/holidays, there is no statistically significant difference in time use for physical activity on weekdays between black and white respondents. Hispanic respondents report both similar and different time use patterns from non-Hispanic white respondents. On weekends/holidays, Hispanic respondents report more time in sleep (23 minutes) and time working (16 minutes), and less time in caring for others (-16 minutes) and participating in non-exercise leisure activities (-22 minutes). There were no statistically significant differences in time for household and personal care activities or in time spent in physical activity. In stark comparison to weekend/holiday trends, on weekdays there are no statistically significant time use differences between Hispanic and non-Hispanic white respondents in any time use activity except for time spent caring for others, where Hispanic respondents report about 16 fewer minutes in this activity.

Educational attainment is one of the variables of most interest to us in looking at determinants of time use for physical activity. On weekends/holidays, each increment of educational attainment is associated with a higher level of physical activity. Compared to people with less than a high school degree, those with a high school degree, some college, a college degree, and an advanced degree report more time spent in physical activity, although this difference is only statistically significant for those who are college graduates (20 additional minutes of physical activity) or who have an advanced degree (28 additional minutes of physical activity). In contrast, on weekdays, there were no statistically significant associations between educational attainment and time spent on physical activity, net of other covariates. These positive associations between educational attainment and time allocated to physical activity are particularly interesting given that educational attainment is negatively related to time use for non-exercise leisure activities. Whereas more educated people have less time for leisure activity, they are still more likely to allocate more time for physical activity.

Other interesting results emerging from Table 6 are: the strong seasonal patterns of physical activity that are of approximately comparable magnitudes in both the weekend and weekday samples; the positive association of temperature with physical activity for both the weekend and weekday samples, particular noteworthy given that season is controlled; the negative association of state obesity rates with physical activity, suggestive of possible social context factors in individuals' choices regarding physical activity time patterns; and the important role of state unemployment rates as determinants of time working on weekends/holidays.

Gender Differences

Recalling that Figure 1 suggested some sizable differences in the marginal time use distributions of females and males, and given that gender affected all time use activities in Table 6 which controlled for many covariates, we now consider formal statistical testing for such differences in the context of our baseline econometric specifications. If there are meaningful differences by gender in the structure of time use determinants, the ultimate story about the role of human capital (and other) determinants may have to be qualified on a gender-specific basis. The results of the Wald tests of equality of the separate female and male coefficient vectors are summarized in Table 7.[11] In all cases there is strong evidence suggesting rejection of the null hypotheses of parameter equality—there are clear and consistent gender differences in determinants of time use.

Consequently, it is of some interest to investigate how the APEs differ by gender. Gender-specific results are displayed in Tables 8 and 9 for weekends/holidays and weekdays. Among the interesting gender differences or similarities seen in Table 8 for weekends/holidays are: males but not females exhibit negative age associations with time dedicated to physical activity; college or advance degree holders of both genders tend to engage in more physical activity,

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[11] The ideal approach here would be to test the null of gender equality of the APEs. To obtain reliable bootstrap estimates of the estimated APEs' covariance matrixes would require a significant increase in the number of bootstrap replications above what is feasible here. We will undertake this exercise in a subsequent version of the paper.

but the magnitudes of these effects are larger for males; having a spouse present in the household reduces the time spent on physical activity for males, with no effect for females; and the state obesity rates are negatively associated with physical activity time for both genders. The corresponding results for weekdays (Table 9) indicate: no strong role for educational attainment in determining physical activity patterns for either females or males, although the significance and magnitudes of the educational effects on sleep, personal care, work, and non-exercise leisure time are noteworthy; men with a spouse present in the household report less time for physical activity; higher temperature is associated with more physical activity in women but not men, whereas season affects physical activity for both men and women; living in a state with greater obesity rates is associated with less physical activity only in women; and no strong race/ethnicity patterns in physical activity are shown for males, although there are some clear patterns for females. Hispanic women, non-Hispanic black women, and women of other non-white racial groups report less time for physical activity than non-Hispanic white women on weekdays.

*Alternative Specifications of **t** and **x***

Several specifications were estimated to assess the sensitivity of our baseline specifications' assumptions to alternative definitions of **t** and **x**. In the first alternative, we redefined **t** in terms of *texerc2* instead of *texerc1* and *tnonexc1*, using the same covariates as appear in the baseline specification. Recall that *texerc1* is a more stringent characterization of "exercise" behavior than *texerc2* — *texerc1* excludes billiards, boating, bowling, fishing, hunting, and vehicle touring/racing as physical activities by moving them into non-exercise leisure time activities (*tnonexc1*). The main findings with respect to the *texerc2* outcomes relative to the *texerc1* findings reported in Table 6 are that for both the weekend/holiday and weekday samples the age, gender, race/ethnicity, and seasonal effects are larger, the educational attainment effects are smaller, and the temperature and state obesity effects become statistically insignificant.

The next three alternative specifications use the original **t** definition but consider alternative definitions of **x**. In the first of these, an indicator of whether there are any children under the age of 18 living in the household (*anyklt18*) is added to the covariates. For both weekends/holidays and weekdays, the estimated APEs for presence of a child indicate no statistically significant relationship with time in physical activity. However, presence of a child in the household had statistically significant but small negative associations with time sleeping, and statistically significant and large associations with time caring for others and time in non-exercise leisure activities (positive and negative, respectively).

The next alternative specifies a more-detailed set of household structure characteristics in **x**. Specifically, *anyklt18* is replaced with dummy variables indicating whether the youngest household child is aged 0-5 (*yghh0005*; approximately preschool) or aged 6-11 (*yghh0611*; approximately elementary school). For both weekends and weekdays, the statistically significant results indicate that having the youngest household child in either age category reduces time sleeping, working, and in non-exercise leisure activities, and increases time caring for others, with all these effects being larger in magnitude for the presence of the youngest household child being 0-5 (except for weekday sleep, where it is smaller than the effect for the youngest child being aged 6-11). Effects on time in physical activity are in all instances negative, but only statistically significant for presence of the youngest household child aged 0-5, and then only on weekdays.

Cognizant of the significant potential for introducing endogeneity bias, the final alternative specification adds to the covariates in the baseline specification dummy variable indicators of family income categories. Endogeneity considerations notwithstanding, it turns out that the various levels of family income tend to have only weak associations with the physical activity outcomes. Interestingly, larger family incomes are associated with reduced mean levels of sleep *even though* the magnitudes and significances of the estimated educational attainment effects on sleep remain impressive.

6. Discussion and Conclusions

This paper has attempted to take a comprehensive look at the structure of adults' time use patterns with a particular focus on whether individuals' economic endowments, human capital, demographic circumstances, and external environments influence time use choices in general and, specifically, with respect to time allocated to physical activity. Data from the American Time Use Surveys from 2005 and 2006 provide an ideal platform on which to build such an analysis. Our investigation suggests that time use patterns are driven in part by all the aforementioned factors. While few of our findings' signs are surprising (in the sense of departing from commonsense priors), we submit that our empirical results are particularly valuable for describing magnitudes (as measured empirically by the APEs) of such relationships in a systematic way that is novel and econometrically robust.

Our main priority was to examine the association between educational attainment and time use allocated for physical activity. We found that educational attainment was positively related to time allocated to physical activity on weekends/holidays, but not on weekdays, and these effects were stronger for men than for women. However, educational attainment was not related to time allocated to physical activity on weekdays for either men or women. This could be one place where offsetting effects of education may be at play, as the higher opportunity cost of time not spent at work may be most acutely felt during weekdays despite a greater demand for health via health investments like physical activity.

Consistent with prior research, our results show that people with less education spend more time in non-exercise leisure activities than do those with more education; however those with less education spend less time doing physical activity than do those with more education (Berry, 2007; Aguiar and Hurst, 2008). This contrast should be further examined in future work, to determine how and why total leisure time gets allocated to physical versus non-physical activities, and how this varies by educational attainment and other factors. Moreover, future work that controls for health may account for some of the positive relationship between low education and more time for leisure and between high education and more time for physical activity. In future analyses, we will examine whether educational attainment interacts with other variables in predicting time use for exercise, as it may be that some effects, such as family structure, differ by educational attainment.

Just as our educational attainment variables predicted time use differently on weekends and weekdays, so did many of our other covariates. Although we expected that time use itself would be distributed differently on weekends and weekdays (e.g., less work time on weekends), one of our main findings is that many of the covariates we examined operate quite differently on weekends than they do on weekdays. For example, women had less physical activity than men, but only on weekends/holidays—there were no gender differences in physical activity on weekdays.

We also highlight important findings about gender differences in time use. We found that men and women not only have different overall patterns of time use, which we expected based on prior work, but that there are predictors of that time use vary between men and women. For example, only for men, living with a spouse is associated with less time allocated to physical activity (on both weekends and weekdays). Indeed, some patterns vary specifically by both gender and weekend vs. weekday. For example, older age is associated with less time spent in physical activity, but only for males on weekends/holidays. As another example, although non-Hispanic black men and women both allocate less time to physical activity on weekends/holidays than do non-Hispanic white men and women, on weekdays this difference is only significant between black and white *women*, with no race differences for men.

The gender specificity of the results suggests that future research on time use should continue to separate analyses by gender, as the role of human capital and other determinants appears to be qualified on a gender-specific basis. Similarly, the variations in both time use and predictors of time use between weekends and weekdays suggests that we theorize more carefully about how people conceptualize their weeks, particularly how they think about time use trade-offs for different parts of the week (i.e., weekends versus weekdays), or how structural factors impinge on time use allocations differently on weekends versus weekdays. While such theorizing has implications for how we think about time use broadly, it may be particularly informative regarding the design of exercise intervention programs. For example, new initiatives might work for some groups better on weekends or weekdays, and this may vary by gender.

Also notable was our findings of some significant associations between physical and social environment variables and time use for physical activity. Season had a relatively robust relationship with physical activity, with summertime bringing with it greater physical activity allocations. In terms of the physical environment, higher temperature was related to higher physical activity in women, even controlling for season. Of course, it may be that those who want to exercise outdoors move to a place where this is more enjoyable. However, counterbalancing this potential selection effect is that people in ill health (i.e., asthma) also sometimes move to more temperate climates although they exercise little once they get there. Future analyses that control for self-rated health status will allow us to examine this and additional questions in more detail.

In terms of the social environment, living in a state with higher obesity rates was associated with less time in physical activity among men and women on weekends, and among women on weekdays. Although this is consistent with theory about the role of social norms and social context in determining health behaviors, it is surprising that this effect is captured using a state-level obesity variable rather than a more local measure. Given that we demonstrate statistically significant relationships despite the crude nature of this and other environmental measures, and while controlling for a range of covariates, we think further investigation is warranted into the exact nature of these relationships. Future research also needs to examine additional state- and local-level covariates.

In assessing both our results and the limitations of our analyses to date, we have a number of ideas of next research steps or considerations that may be productive. Our sensitivity analysis that examined alternative specifications of "physical activity" found that the specifications matter. Our main results used a specification of physical activity that is conservative—that excludes some activities, such as bowling, that may be less physically active than many other activities, and that excludes travel time for the activity. Indeed, when we examined a looser definition of physical activity that included less physically active recreational activities (such as bowling), the educational attainment effects became smaller, and the temperature and state obesity effects become insignificant. Future research will need to consider how to best categorize activities as "physical activity", attending as we did, to those activities that are truly physical versus those that are not.

In a related issue, we examined *total* time spent on physical activity in a day, but did not evaluate the *adequacy* of time spent on physical activity for each person on that day. Some studies on physical activity attempt to categorize the amount of time a person spends being physically active as sufficient or insufficient, per CDC exercise guidelines of approximately 30 minutes, or by some other guideline. Future research should examine not only predictors of total physical activity time, but also predictors of the adequacy of time spent on physical activity.

In addition, in attempting to measure time spent on actual physical activity, we did not include travel time for exercise in our measurement of time in physical activity. Although this means our physical activity measure better captures amount of exertion, it does not represent the total time that people allocate to physical activity (which would include travel time), and thus we may be underestimating actual time trade-offs made for physical activity for those physical activities that do not occur or begin and end at home.

In future phases of this work, we anticipate undertaking more formal statistical investigations of the characterizations and subsequent categorizations of exercise time vs. other time. Specifically, we plan to conduct formal tests of aggregation of outcomes along the lines suggested by Cramer and Ridder, 1991, and Hill, 1983, as well as to investigate a variety of data-driven approaches to category aggregation/disaggregation (see, e.g., Cotterman and Peracchi, 1992). Moreover, we plan to undertake some additional sensitivity analyses looking at how to handle "sports and exercise as part of job" under the work category. Also, there are activities that although coded under a primary activity elsewhere, may provide physical activity benefits, such as walking for travel purposes, housework, and some volunteer activities.

A potential limitation of time use data is that the one-day frame of the time diary means that time use activities that are not undertaken on a regular daily basis will be missed. Whether this presents any analytical concerns depends on the joint population distribution of activity frequency over days and the intensity of activities within days, and possibly on the mode of econometric analysis as well. For categories like time allocated to physical activity, such considerations may not be trivial. We hope to explore this issue in greater detail in future work, drawing on the literature that treats the analogous "purchase infrequency" or "consumption infrequency" problems in consumer demand analysis (Meghir and Robin, 1992; Robin, 1993).

In some of our sensitivity analyses, we investigated whether the presence of a child, and the age of the youngest child, affected time allocations to physical activity. Despite literature suggesting the importance of these factors (e.g., Kimmel and Connelly, 2007), our results showed non-significant or weak effects. Presence of a child when the youngest child was aged 0-5 had a small effect on lower time use for exercise on weekdays, with little other notable effects for related variables. However, future research should examine these specifications more closely, including looking at the role of secondary time use for childcare on physical activity.

In sum, our results demonstrate that time use for physical activity varies significantly by a number of individual and environmental variables, and varies notably by gender and by time of week (weekend vs. weekdays). Future work that attempts to further understand how and why time gets allocated for physical activity between different types of people is fertile ground for informing the design of exercise intervention messages and programs to target those in most need of increased physical activity. Moreover, simultaneously attending to *where* physical activity occurs may be important as well, as research indicates that people with less education have been spending more of their leisure time at home (Berry, 2007), putting opportunity or constraint on how that time might be translated into physical activity. The ATUS presents many opportunities for researchers to further this work in interesting and fruitful ways.

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Appendix: Estimation Details

Appealing to the estimation methods described by Papke and Wooldridge for the univariate case, one can set up a multinomial logit-like criterion function $Q(\boldsymbol{\beta}) = \prod_{i=1}^{N}\prod_{m=1}^{M}\mu_{im}(\mathbf{x})^{y_{im}}$ whose log is $J(\boldsymbol{\beta}) = \sum_{i=1}^{N}\sum_{m=1}^{M} y_{im} \times \log\left(\mu_{im}(\mathbf{x})\right)$, where $\boldsymbol{\beta}$ is either a kx(M-1) matrix or k(M-1)x1 vector depending on the particular reference. The corresponding estimating or score equations are:

$$\frac{\partial J(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}_m} = \sum_{i=1}^{N}\mathbf{x}_i'\left[y_{im} - \left(\frac{\exp(\mathbf{x}_i\boldsymbol{\beta}_m)}{1+\sum_{k=2}^{M}\exp(\mathbf{x}_i\boldsymbol{\beta}_k)}\right)\right],\ j=2,\ldots,M,$$

which are obviously the same solution equations as those corresponding to a standard multinomial logit estimator; note, however, that in this case the y_{im} are not binary.[12] Consistency of the resulting $\hat{\boldsymbol{\beta}}$ follows from standard arguments, in particular that $E\left[\frac{\partial J(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}_m}\right] = E_{\mathbf{x}}E\left[\frac{\partial J(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}_m}|\mathbf{x}\right] = \mathbf{0}$.

It should be noted that although estimating the model using MNL-type pseudo-likelihood methods will provide consistent estimates of the $\boldsymbol{\beta}_M$ parameters, the corresponding MNL covariance matrix will *not* be a consistent estimator of the true covariance matrix so long as $\Pr(y_{im} \in (0,1)|\mathbf{x}_i)>0$, which is to be expected in the time use data. In particular, the data in such cases will exhibit *underdispersion* relative to a maintained multinomial probability structure. It can be demonstrated formally that the difference between the MNL covariance estimator obtained as the negative inverse expected Hessian and the expected standard robust "sandwich" estimator is positive semidefinite so that, e.g., standard errors obtained using the MNL covariance estimator will tend to be *too large* relative to actual standard errors (a result opposite that more commonly found in the literature on overdispersion). See Mullahy, 2006, for details.

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[12] Standard canned multinomial logit estimation packages, like Stata's, do not readily accommodate nonbinary y_{im}. The estimates presented here are obtained using an author-written procedure written in Stata's Mata language, Version 9, which is available on request.

Table 1
Sample Summary Statistics (unweighted),
Time Use Variables, Measured in Minutes (N=16,217)

Weekends & Holidays (N=8,265)								
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**.25 Pctl**	**.50 Pctl**	**.75 Pctl**	**%=0**
tsleep	546.6	136.6	0	1360	470	540	625	0.17
thhpers	317.9	187.5	0	1440	175	295	435	0.34
tcare	52.0	101.6	0	1020	0	0	60	52.0
twork	83.0	183.5	0	1313	0	0	15	73.5
tnonexc1	427.4	206.1	0	1400	275	415	570	0.67
tnonexc2	422.0	204.7	0	1400	270	410	560	0.67
texerc1	13.2	45.4	0	610	0	0	0	86.6
texerc2	18.6	62.8	0	735	0	0	0	84.7

Weekdays (N=7,952)								
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**.25 Pctl**	**.50 Pctl**	**.75 Pctl**	**%=0**
tsleep	479.5	124.5	0	1436	415	475	540	0.05
thhpers	252.4	165.2	0	1400	135	210	328	0.14
tcare	53.3	97.4	0	1065	0	0	71.5	53.8
twork	335.0	263.9	0	1330	0	440	520	30.6
tnonexc1	309.3	182.2	0	1250	181	275	395	0.59
tnonexc2	307.2	180.4	0	1250	180	274	390	0.60
texerc1	10.5	34.5	0	837	0	0	0	84.9
texerc2	12.6	42.6	0	837	0	0	0	84.0

Table 2
Sample Summary Statistics (unweighted), Explanatory Variables (N=16,217)

Variable	Mean	Std. Dev.	Min	Max
female	.557	.497	0	1
age	43.378	10.506	25	64
blacknh	.119	.324	0	1
hispanic	.134	.34	0	1
otherre	.05	.218	0	1
whitenh	.697	.46	0	1
nohsgrad	.099	.299	0	1
hsgrad	.264	.441	0	1
somecoll	.291	.454	0	1
collgrad	.219	.414	0	1
advdeg	.127	.333	0	1
educ	13.931	2.933	0	20
widowed	.026	.159	0	1
divsep	.188	.39	0	1
nevmarr	.172	.377	0	1
married	.615	.487	0	1
sppreshh	.641	.48	0	1
hhsize	2.976	1.492	1	16
autumn	.238	.426	0	1
winter	.258	.438	0	1
spring	.267	.442	0	1
summer	.237	.425	0	1
sunday	.248	.432	0	1
monday	.103	.304	0	1
tuesday	.099	.298	0	1
wednesday	.097	.296	0	1
thursday	.099	.298	0	1
friday	.101	.301	0	1
saturday	.253	.435	0	1
yghh0002	.14	.347	0	1
yghh0305	.111	.315	0	1
yghh0611	.18	.384	0	1
yghh1214	.078	.268	0	1
yghh1517	.053	.223	0	1
pknhlt18	.015	.122	0	1
nkhhlt18	1.074	1.186	0	8

(continued)

Table 2 (continued)
Sample Summary Statistics (unweighted), Explanatory Variables (N=16,217)

Variable	Mean	Std. Dev.	Min	Max
fi0025	.203	.402	0	1
fi2550	.275	.447	0	1
fi5075	.094	.292	0	1
fi75100	.134	.341	0	1
fi100150	.11	.313	0	1
fi150up	.063	.243	0	1
temperature	55.365	16.292	5.8	84.4
precip	3.221	2.017	.01	15.69
uerate	4.894	1.012	1.8	11
ueratelg	4.927	1.014	2.2	11
stobover	36.604	.887	32.2	39.483
stobese	24.38	2.526	16.8	31.358

Note: N=16,123 for *temperature* and *precip* since data are not available for Alaska and Hawaii; and N=14,279 for the family income variables *fixxxx*.

Table 3
Weighted and Unweighted Sample Time Use Measures by Time of Week

	Means			
	Weekends & Holidays (N=8,265)		Weekdays (N=7,952)	
	Unweighted	Weighted	Unweighted	Weighted
tsleep	546.6	551.5	479.5	481.7
thhpers	317.9	307.6	252.4	249.9
tcare	52.0	43.4	53.3	41.9
twork	83.0	84.9	335.0	340.8
tnonexc1	427.4	439.7	309.3	315.7
texerc1	13.2	12.8	10.5	10.0

Table 4
Parameter Estimates, Baseline Specification: Weekends & Holidays (N=8,216)
(Robust t-statistics and FDR Rejection Recommendations)

	tsleep	thhpers	tcare	twork	texerc1
age	-.007	.001	-.04	-.014	-.015
t	10.491	1.268	15.301	5.284	3.881
fdr	1	0	1	1	1
female	.125	.379	.343	-.404	-.616
t	9.751	18.457	7.318	7.531	8.073
fdr	1	1	1	1	1
blacknh	-.071	-.291	-.489	-.005	-.823
t	3.324	8.387	5.831	.059	5.688
fdr	1	1	1	0	1
hispanic	.092	.048	-.301	.238	.002
t	4.421	1.509	3.527	2.8	.012
fdr	1	0	1	0	0
otherre	.118	.073	.066	.308	-.395
t	3.511	1.637	.652	2.664	2.365
fdr	1	0	0	0	0
hsgrad	-.006	.045	.321	.311	.41
t	.227	1.076	2.847	2.785	1.934
fdr	0	0	0	0	0
somecoll	.003	.137	.41	.48	.61
t	.103	3.287	3.638	4.325	2.968
fdr	0	1	1	1	1
collgrad	0	.162	.622	.307	1.162
t	.001	3.737	5.485	2.603	5.806
fdr	0	1	1	0	1
advdeg	.019	.207	.716	.225	1.398
t	.702	4.499	6.06	1.808	6.868
fdr	0	1	1	0	1
hhsize	.02	.038	.25	.031	-.015
t	3.416	4.374	13.738	1.383	.469
fdr	1	1	1	0	0
sppreshh	.004	.074	.306	-.091	-.18
t	.242	2.841	4.686	1.308	1.846
fdr	0	0	1	0	0
temperat	0	-.001	0	-.002	.009
t	.615	1.053	.199	.533	1.911
fdr	0	0	0	0	0

Table 4 (cont.)

	tsleep	thhpers	tcare	twork	texerc1
precip	0	-.001	.015	-.013	-.006
t	.019	.14	1.364	.997	.324
fdr	0	0	0	0	0
stobese	-.004	-.01	.003	-.007	-.07
t	1.362	2.285	.281	.601	4.263
fdr	0	0	0	0	1
ueratelg	-.002	-.002	.014	-.041	.109
t	.352	.167	.61	1.339	2.595
fdr	0	0	0	0	0
winter	-.031	-.098	.061	-.214	-.44
t	.985	2.005	.554	1.696	2.272
fdr	0	0	0	0	0
spring	-.013	-.025	.187	-.156	-.377
t	.578	.684	2.268	1.642	2.731
fdr	0	0	0	0	0
autumn	-.012	-.049	.051	-.133	-.371
t	.53	1.367	.624	1.424	2.82
fdr	0	0	0	0	0
sun	.022	-.108	-.153	-.456	-.087
t	1.71	5.425	3.435	8.329	1.142
fdr	0	1	1	1	0
cons	.533	-.4	-2.238	-.428	-2.113
t	5.983	2.766	6.207	1.139	3.975
fdr	1	0	1	0	1
Wald, All					
Chi-Sq	2013.398	1331.005	7694.526	3806.098	8612.045
d.f.	20	20	20	20	20
p	0	0	0	0	0
Wald, Slopes					
Chi-Sq	369.938	583.449	896.377	207.098	391.947
d.f.	19	19	19	19	19
p	0	0	0	0	0

Table 5
Parameter Estimates, Baseline Specification: Weekdays (N=7,907)
(Robust t-statistics and FDR Rejection Recommendations)

	tsleep	**thhpers**	**tcare**	**twork**	**texerc1**
age	-.008	.002	-.041	-.015	-.009
t	9.84	1.489	17.097	10.754	2.477
fdr	1	0	1	1	0
female	.11	.454	.892	-.285	.041
t	7.55	21.786	19.832	10.556	.533
fdr	1	1	1	1	0
blacknh	-.101	-.226	-.459	-.208	-.338
t	4.171	6.471	6.008	4.489	2.675
fdr	1	1	1	1	0
hispanic	.033	.044	-.318	.041	-.097
t	1.317	1.273	3.923	.907	.688
fdr	0	0	1	0	0
otherre	.015	.011	-.033	-.143	-.13
t	.427	.211	.334	2.256	.703
fdr	0	0	0	0	0
hsgrad	-.081	-.074	.049	.173	.008
t	2.73	1.675	.499	2.896	.032
fdr	0	0	0	0	0
somecoll	-.04	-.005	.229	.361	.413
t	1.349	.106	2.39	6.142	1.698
fdr	0	0	0	1	0
collgrad	.022	.049	.392	.52	.779
t	.724	1.093	4.034	8.735	3.232
fdr	0	0	1	1	1
advdeg	.063	.06	.446	.671	1.031
t	1.882	1.252	4.213	10.617	4.124
fdr	0	0	1	1	1
hhsize	.015	.032	.306	-.015	-.021
t	2.325	3.628	20.182	1.232	.601
fdr	0	1	1	0	0
sppreshh	.061	.16	.245	.098	.025
t	3.232	6.162	4.337	2.801	.255
fdr	1	1	1	0	0
temperat	0	0	0	0	.007
t	.111	.182	.001	.224	1.862
fdr	0	0	0	0	0

Table 5 (cont.)

	tsleep	thhpers	tcare	twork	texerc1
precip	0	.002	.018	0	.001
t	.103	.455	1.732	.038	.06
fdr	0	0	0	0	0
stobese	-.002	-.002	-.003	-.005	-.044
t	.775	.343	.346	.778	2.79
fdr	0	0	0	0	0
ueratelg	-.014	-.012	-.005	-.05	-.008
t	1.891	1.077	.228	3.397	.233
fdr	0	0	0	1	0
winter	-.019	-.041	.132	-.017	-.515
t	.541	.843	1.27	.269	2.99
fdr	0	0	0	0	0
spring	.016	.013	.165	.057	-.305
t	.596	.368	2.127	1.19	2.412
fdr	0	0	0	0	0
autumn	.006	-.078	.153	.015	-.639
t	.234	2.236	2.008	.319	5.287
fdr	0	0	0	0	1
tue	.024	.003	-.055	.06	.074
t	1.058	.08	.855	1.38	.597
fdr	0	0	0	0	0
wed	.019	.037	-.052	.089	.083
t	.801	1.098	.779	2.037	.679
fdr	0	0	0	0	0
thu	.013	.018	-.075	.061	.202
t	.557	.536	1.168	1.429	1.625
fdr	0	0	0	0	0
fri	-.129	-.09	-.226	-.101	-.101
t	5.683	2.828	3.287	2.38	.774
fdr	1	0	1	0	0
cons	.811	-.594	-1.915	.828	-2.417
t	7.984	4.198	6.205	4.334	3.687
fdr	1	1	1	1	1
Wald, All					
Chi-Sq	4376.61	979.663	6097.943	691.824	8777.272
d.f.	23	23	23	23	23
p	0	0	0	0	0
Wald, Slopes					
Chi-Sq	405.933	660.06	1476.48	580.297	275.435
d.f.	22	22	22	22	22
p	0	0	0	0	0

Table 6
Estimated APEs, Baseline Specification, by Time of Week
(.95-CI Estimated using Hansen C2 Method and 500 Bootstrap Iterations)

Weekends & Holidays (N=8,216)						
	tsleep	**thhpers**	**tcare**	**twork**	**texerc1**	**tnonexc1**
age	-1.178	1.883	-1.797	-.742	-.131	1.965
ci-L	-1.51	1.489	-2.016	-1.173	-.236	1.567
ci-U	-.889	2.271	-1.575	-.333	-.03	2.403
female	6.809	82.55	11.508	-43.205	-9.583	-48.079
ci-L	.613	74.781	7.459	-51.254	-11.707	-57.196
ci-U	12.614	91.191	15.546	-34.289	-7.603	-38.739
blacknh	20.686	-53.629	-16.692	8.81	-7.095	47.92
ci-L	8.931	-66.5	-22.82	-7.356	-9.348	33.966
ci-U	32.903	-40.422	-10.659	22.757	-4.976	64.188
hispanic	22.68	-.826	-15.969	16.409	-.649	-21.644
ci-L	13.275	-13.455	-22.73	2.753	-3.859	-35.98
ci-U	33.07	11.441	-9.576	29.313	2.565	-7.938
otherre	20.794	-2.475	-.802	20.75	-5.099	-33.168
ci-L	5.901	-19.423	-10.159	-1.306	-8.196	-52.066
ci-U	36.335	15.686	8.589	41.076	-1.828	-12.575
hsgrad	-26.424	.515	15.186	23.414	5.376	-18.067
ci-L	-39.446	-16.981	.796	3.823	-3.047	-36.799
ci-U	-13.054	18.305	26.721	40.354	10.926	.954
somecoll	-43.429	16.99	17.794	35.358	8.037	-34.75
ci-L	-54.603	.361	2.837	16.832	-1.325	-50.719
ci-U	-29.479	34.164	28.37	53.327	13.808	-14.342
collgrad	-50.773	21.171	30.966	18.296	19.581	-39.241
ci-L	-62.157	4.161	14.81	-1.594	6.386	-54.763
ci-U	-36.475	39.987	43.856	36.687	27.552	-20.054
advdeg	-53.322	27.614	37.871	8.571	28.001	-48.735
ci-L	-65.285	8.304	18.43	-12.597	10.873	-68.53
ci-U	-37.532	49.207	52.242	25.535	38.1	-28.194
hhsize	-3.738	3.556	11.389	.402	-.542	-11.067
ci-L	-6.11	.074	9.595	-2.525	-1.272	-14.78
ci-U	-1.387	6.775	13.002	3.81	.314	-6.957

Weekdays (N=7,907)						
	tsleep	**thhpers**	**tcare**	**twork**	**texerc1**	**tnonexc1**
age	-.142	2.232	-1.771	-2.526	-.017	2.223
ci-L	-.432	1.889	-1.981	-3.078	-.089	1.804
ci-U	.15	2.604	-1.53	-2.002	.057	2.664
female	15.132	91.936	39.134	-121.736	-.351	-24.113
ci-L	9.526	85.036	35.251	-133.397	-1.926	-31.701
ci-U	20.766	98.669	43.147	-109.9	1.326	-15.925
blacknh	17.412	-21.658	-14.736	-23.094	-1.932	44.008
ci-L	6.97	-33.695	-21.252	-41.684	-4.21	31.071
ci-U	27.811	-11.581	-8.751	-4.931	.312	57.766
hispanic	7.473	6.915	-15.542	7.856	-1.146	-5.556
ci-L	-2.355	-5.125	-21.679	-11.595	-3.819	-20.174
ci-U	16.538	18.64	-10.28	26.693	1.424	8.341
otherre	20.313	9.28	-.356	-36.415	-1.011	8.19
ci-L	7.038	-7.969	-9.676	-61.837	-4.377	-11.051
ci-U	33.289	27.314	8.485	-11.558	2.229	27.25
hsgrad	-39.887	-18.774	2.401	57.488	-.002	-1.225
ci-L	-52.074	-35.36	-7.385	30.574	-5.56	-20.327
ci-U	-27.087	-3.916	10.797	87.073	4.502	15.055
somecoll	-58.646	-21.763	7.635	94.958	3.609	-25.793
ci-L	-71.403	-37.539	-2.149	68.799	-3.428	-44.178
ci-U	-44.568	-7.562	17.074	124.814	9.031	-10.17
collgrad	-67.649	-28.662	12.241	126.149	7.456	-49.535
ci-L	-80.029	-44.636	2.097	98.565	-1.663	-67.473
ci-U	-53.7	-13.988	20.916	156.437	13.208	-32.805
advdeg	-79.193	-41.28	11.512	165.279	10.999	-67.317
ci-L	-92.633	-57.95	1.109	132.136	-.806	-86.696
ci-U	-64.223	-25.85	21.735	196.648	18.867	-50.035
hhsize	-1.465	3.104	14.889	-10.736	-.407	-5.385
ci-L	-4.149	.324	13.428	-15.337	-1.09	-8.996
ci-U	1.055	6.403	16.304	-5.996	.295	-1.988

Table 6 (cont.)

Weekends & Holidays (N=8,216)						
	tsleep	**thhpers**	**tcare**	**twork**	**texerc1**	**tnonexc1**
sppreshh	-9.304	16.498	13.598	-9.345	-2.705	-8.743
ci-L	-17.148	6.327	8.405	-19.063	-5.425	-20.42
ci-U	-1.519	25.834	19.313	2.055	.182	4.026
temperat	.008	-.221	-.001	-.089	.119	.183
ci-L	-.301	-.651	-.235	-.509	.011	-.329
ci-U	.335	.191	.217	.323	.218	.614
precip	.245	-.1	.781	-1.04	-.068	.181
ci-L	-1.103	-2.008	-.294	-2.968	-.457	-1.938
ci-U	1.732	1.675	1.908	.883	.376	2.117
stobese	.457	-1.784	.393	-.204	-.855	1.993
ci-L	-.929	-3.66	-.494	-1.838	-1.248	-.097
ci-U	1.668	-.164	1.301	1.681	-.403	3.946
ueratelg	-.142	.105	.847	-3.199	1.463	.927
ci-L	-3.397	-3.946	-1.668	-7.413	.385	-3.331
ci-U	3.234	3.79	2.921	.949	2.552	5.34
winter	8.56	-16.29	5.691	-13.273	-4.65	19.961
ci-L	-5.314	-36.534	-5.983	-32.087	-8.838	-3.701
ci-U	23.377	1.868	16.682	3.405	-.989	39.976
spring	1.162	-3.26	10.859	-11.183	-4.375	6.797
ci-L	-8.777	-18.245	2.346	-25.753	-7.497	-10.243
ci-U	12.239	11.524	19.427	1.617	-1.575	22.769
autumn	6.478	-7.828	3.912	-8.71	-4.176	10.324
ci-L	-3.176	-21.999	-4.178	-22.209	-7.021	-5.678
ci-U	15.89	6.152	11.426	3.099	-1.39	24.647
sun	37.793	-19.138	-5.312	-33.086	-.483	20.225
ci-L	32.145	-26.92	-9.46	-40.583	-2.523	11.915
ci-U	43.26	-11.312	-1.63	-25.201	1.448	30.322

Weekdays (N=7,907)						
	tsleep	**thhpers**	**tcare**	**twork**	**texerc1**	**tnonexc1**
sppreshh	-9.163	19.949	8.209	6.229	-.585	-24.638
ci-L	-15.976	10.425	3.034	-7.167	-2.363	-34.748
ci-U	-2.52	28.865	13.074	21.42	1.523	-14.364
temperat	-.104	.016	-.007	.061	.074	-.04
ci-L	-.394	-.304	-.215	-.502	0	-.45
ci-U	.179	.377	.217	.637	.152	.366
precip	-.359	.276	.86	-.447	0	-.331
ci-L	-1.777	-1.572	-.116	-3.493	-.368	-2.276
ci-U	.94	2.106	1.838	2.545	.369	1.581
stobese	.053	.261	-.035	-.634	-.43	.785
ci-L	-1.144	-1.28	-.809	-3.343	-.741	-.937
ci-U	1.291	1.821	.927	1.58	-.106	2.406
ueratelg	2.087	1.631	.681	-10.227	.111	5.717
ci-L	-.66	-2.278	-1.64	-16.397	-.644	1.718
ci-U	4.843	5.143	2.769	-3.694	.895	10.309
winter	-1.528	-6.287	7.954	-.484	-4.611	4.956
ci-L	-13.233	-21.117	-3.539	-25.536	-7.55	-15.009
ci-U	12.142	9.706	18.993	27.55	-1.746	23.045
spring	-4.427	-2.94	7.515	10.584	-3.249	-7.484
ci-L	-14.327	-14.023	-.535	-7.634	-5.558	-21.313
ci-U	4.839	8.021	14.822	31.938	-.875	4.105
autumn	5.776	-17.79	8.667	6.993	-5.636	1.99
ci-L	-3.798	-29.855	.618	-12.07	-7.45	-11.184
ci-U	15.189	-7.447	15.951	26.923	-3.852	15.615
tue	1.575	-4.492	-3.881	12.736	.551	-6.488
ci-L	-6.407	-14.552	-9.296	-7.403	-2.352	-20.834
ci-U	10.321	6.572	1.606	31.2	2.872	6.782
wed	-6.228	1.223	-4.282	18.72	.524	-9.956
ci-L	-14.199	-10.137	-9.503	-.816	-1.983	-23.285
ci-U	3.632	12.098	1.759	35.138	2.852	3.731
thu	-3.661	-.642	-4.826	13.513	1.99	-6.374
ci-L	-12.393	-10.402	-10.386	-4.681	-.755	-19.356
ci-U	4.851	10.069	.531	30.983	4.559	6.254
fri	-18.453	.282	-6.689	-3.531	-.109	28.501
ci-L	-27.126	-9.923	-13.141	-22.93	-2.686	15.969
ci-U	-9.714	11.632	-.807	12.881	2.344	41.975

Table 7
Wald Test Results for Female-Male Parameter Equality, Baseline Specification

	Weekends & Holidays			Weekdays		
	X^2	d.f.	p-value	X^2	d.f.	p-value
All Parameters	736.7	95	<.0001	1441.1	110	<.0001
Slopes Only	148.6	90	<.0002	369.5	105	<.0001

Table 8
Estimated APEs, Baseline Specification by Gender: Weekends & Holidays
(.95-CI Estimated using Hansen C2 Method and 100 Bootstrap Iterations)

Females (N=4,655)

	tsleep	**thhpers**	**tcare**	**twork**	**texerc1**	**tnonexc1**
age	-1.343	2.234	-2.183	-.724	-.088	2.103
ci-L	-1.709	1.776	-2.482	-1.207	-.189	1.298
ci-U	-.98	2.832	-1.878	-.35	.016	2.583
blacknh	27.177	-46.277	-22.438	1.919	-5.838	45.457
ci-L	14.056	-62.732	-30.665	-13.971	-8.094	25.173
ci-U	47.025	-28.877	-14.507	18.168	-4.098	60.892
hispanic	31.818	4.175	-19.688	1.685	-1.463	-16.526
ci-L	23.884	-13.852	-30.689	-14.297	-5.13	-34.847
ci-U	44.117	21.96	-12.057	18.068	1.209	-.997
otherre	20.127	-7.927	1.159	26.17	-3.3	-36.229
ci-L	-4.625	-27.818	-14.711	.519	-7.59	-69.545
ci-U	39.991	18.671	12.359	54.521	.233	-9.212
hsgrad	-38.517	8.382	27.35	23.575	9.288	-30.078
ci-L	-65.488	-22.938	-.1	-11.379	-2.169	-56.681
ci-U	-10.085	40.423	45.718	49.335	15.912	5.429
somecoll	-47.585	18.889	28.617	24.847	12.638	-37.406
ci-L	-72.044	-8.14	4.883	-4.381	-.925	-65.256
ci-U	-21.468	52.704	47.043	51.044	20.507	-5.044
collgrad	-59.474	22.384	40.404	19.07	20.246	-42.63
ci-L	-86.298	-4.838	11.536	-10.454	4.582	-73.756
ci-U	-28.276	52.946	62.074	47.665	29.766	-11.731
advdeg	-66.353	19.409	48.999	19.901	26.89	-48.846
ci-L	-92.586	-13.939	13.653	-13.859	.135	-77.229
ci-U	-34.787	51.831	78.615	47.63	40.796	-14.189
hhsize	-5.403	5.949	13.177	-1.138	-.569	-12.016
ci-L	-8.174	2.371	11.115	-5.868	-1.359	-16.51
ci-U	-1.698	10.8	15.696	3.005	.251	-6.865
sppreshh	-7.031	22.339	8.303	-19.974	-.525	-3.112
ci-L	-19.314	11.191	1.579	-32.305	-2.608	-21.8
ci-U	1.849	39.404	15.559	-6.971	1.175	9.624

Males (N=3,561)

	tsleep	**thhpers**	**tcare**	**twork**	**texerc1**	**tnonexc1**
age	-.915	1.457	-1.349	-.919	-.178	1.903
ci-L	-1.346	.893	-1.722	-1.58	-.372	1.157
ci-U	-.429	2.023	-.951	-.309	-.005	2.547
blacknh	25.92	-65.797	-15.914	22.151	-9.267	42.906
ci-L	.02	-87.014	-25.235	-6.049	-13.464	16.938
ci-U	49.982	-46.799	-8.129	49.683	-4.863	65.513
hispanic	19.72	-24.257	-15.764	38.958	-1.894	-16.763
ci-L	3.533	-48.079	-25.683	14.417	-8.247	-41.096
ci-U	30.437	-8.278	-5.599	66.657	4.15	7.825
otherre	33.578	-12.345	-10.581	21.093	-9.713	-22.033
ci-L	10.24	-36.418	-21.587	-10.521	-14.581	-50.988
ci-U	57.575	7.82	.029	48.215	-4.28	21.353
hsgrad	-72.246	31.845	28.777	52.115	14.334	-54.825
ci-L	-96.933	-8.555	.397	3.267	-7.307	-98.688
ci-U	-47.433	84.627	56.465	90.311	25.521	-16.682
somecoll	-88.481	45.747	29.771	68.987	15.49	-71.515
ci-L	-115.973	10.754	.33	5.168	-4.566	-112.601
ci-U	-62.117	97.165	52.298	109.403	28.38	-31.354
collgrad	-93.372	52.008	41.602	49.812	28.998	-79.047
ci-L	-122.61	12.403	9.85	-3.39	.581	-119.215
ci-U	-64.947	104.214	65.452	90.759	45.957	-32.93
advdeg	-99.34	70.675	49.814	30.975	42.86	-94.984
ci-L	-125.465	25.843	11.077	-21.128	5.585	-145.382
ci-U	-64.447	133.412	80.672	70.138	62.742	-42.866
hhsize	-1.393	.849	8.253	1.407	-.432	-8.684
ci-L	-5.271	-4.563	5.464	-3.517	-2.019	-15.016
ci-U	3.686	5.861	10.968	7.38	.92	-4.264
sppreshh	-14.071	9.769	22.078	6.455	-6.181	-18.05
ci-L	-28.363	-6.436	14.189	-12.981	-11.617	-36.161
ci-U	-1.574	26.63	30.943	27.521	-.303	2.505

Table 8 (cont.)

Females (N=4,655)	tsleep	thhpers	tcare	twork	texerc1	tnonexc1
temperat	-.204	.022	.075	-.232	.121	.219
ci-L	-.585	-.555	-.172	-.673	.002	-.318
ci-U	.146	.523	.402	.209	.201	.776
precip	.005	2.34	.521	-1.693	-.417	-.756
ci-L	-1.821	.056	-.912	-4.145	-.783	-2.868
ci-U	1.919	4.975	2.011	1.52	.072	2.22
stobese	.596	-1.497	-.143	.026	-.736	1.754
ci-L	-1.01	-4.165	-1.154	-2.362	-1.123	-.644
ci-U	2.507	.604	1.197	2.072	-.332	4.298
ueratelg	-2.52	-1.902	1.147	-.99	.302	3.964
ci-L	-6.484	-8.171	-1.557	-6.131	-.714	-2.347
ci-U	1.554	3.711	3.856	2.583	1.439	10.133
winter	.179	10.575	10.174	-22.632	-4.473	6.177
ci-L	-28.92	-24.657	-5.395	-54.075	-10.234	-30.437
ci-U	23.011	35.062	24.041	8.153	.65	47.312
spring	.239	7.402	14.824	-21.991	-5.668	5.194
ci-L	-20.243	-19.398	4.039	-49.959	-9.744	-23.015
ci-U	17.313	31.597	28.626	6.016	-.945	34.393
autumn	4.669	7.736	10.163	-17.774	-4.568	-.226
ci-L	-18.187	-19.145	-3.764	-45.176	-9.044	-30.908
ci-U	25.151	28.173	22.82	17.061	-.302	28.061
sun	37.719	-28.126	-4	-23.79	.494	17.703
ci-L	29.886	-36.658	-9.301	-32.243	-1.175	5.853
ci-U	44.13	-17.417	.868	-14.514	2.009	26.883

Males (N=3,561)	tsleep	thhpers	tcare	twork	texerc1	tnonexc1
temperat	.293	-.571	-.106	.11	.131	.144
ci-L	-.11	-1.226	-.458	-.699	-.065	-.443
ci-U	.882	-.067	.162	.712	.392	.956
precip	.61	-2.979	1.084	-.401	.4	1.285
ci-L	-1.753	-5.922	-.544	-3.055	-.45	-1.954
ci-U	2.497	-.562	2.741	3.161	1.149	4.213
stobese	.317	-2.209	1.024	-.532	-1.001	2.401
ci-L	-1.551	-4.893	-.381	-3.418	-1.573	-.8
ci-U	2.093	.382	2.603	2.759	-.259	4.998
ueratelg	2.952	3.35	.711	-6.247	2.98	-3.746
ci-L	-2.233	-2.231	-2.717	-14.769	.775	-9.731
ci-U	7.619	9.312	3.773	1.139	4.945	3.97
winter	25.349	-58.517	7.821	-13.097	-10.019	48.464
ci-L	-9.256	-93.167	-13.82	-53.258	-19.142	12.535
ci-U	56.393	-19.632	25.502	24.793	2.459	87.193
spring	13.196	-32.753	10.887	-11.185	-7.808	27.662
ci-L	-14.054	-60.455	-9.118	-40.897	-15.182	-2.687
ci-U	38.673	1.743	28.155	24.464	2.936	59.059
autumn	16.121	-40.253	5.184	-13.146	-9.114	41.208
ci-L	-16.233	-68.235	-12.816	-51.194	-15.558	6.049
ci-U	37.867	-6.951	20.42	24.879	2.185	73.193
sun	38.264	-7.69	-7.08	-45.117	-1.593	23.216
ci-L	28.004	-17.872	-12.542	-58.677	-6.337	10.058
ci-U	46.942	3.819	-.23	-29.165	2.901	37.952

Table 9
Estimated APEs, Baseline Specification by Gender: Weekdays
(.95-CI Estimated using Hansen C2 Method and 100 Bootstrap Iterations)

Females (N=4,317)

	tsleep	thhpers	tcare	twork	texerc1	tnonexc1
age	-.262	2.583	-2.678	-1.742	.01	2.09
ci-L	-.706	2.014	-3.035	-2.471	-.07	1.588
ci-U	.13	3.049	-2.338	-.895	.097	2.647
blacknh	22.235	-21.056	-21.95	1.168	-5.861	25.463
ci-L	11.294	-39.04	-30.679	-23.986	-8.244	6.016
ci-U	36.166	-3.016	-13.813	25.473	-3.621	37.821
hispanic	11.515	14.474	-19.675	4.498	-4.45	-6.361
ci-L	-2.363	-8.1	-28.785	-20.295	-7.392	-23.481
ci-U	24.612	29.222	-10.047	34.236	-1.432	11.072
otherre	34.114	10.533	-9.768	-28.886	-3.606	-2.386
ci-L	15.277	-20.074	-21.38	-61.829	-5.905	-28.555
ci-U	51.578	37.807	4.37	10.335	-.83	21.305
hsgrad	-98.734	-61.353	9.517	179.862	4.25	-33.542
ci-L	-127.708	-93.144	-13.945	130.571	-5.147	-69.512
ci-U	-71.925	-28.649	30.077	230.654	11.416	4.335
somecoll	-103.86	-65.881	13.419	198.391	5.799	-47.868
ci-L	-127.684	-93.326	-5.741	145.101	-4.222	-77.228
ci-U	-76.964	-37.579	33.044	253.312	13.619	-16.601
collgrad	-121.13	-74.734	18.389	238.348	6.787	-67.66
ci-L	-148.779	-109.292	-7.792	195.867	-1.708	-100.94
ci-U	-95.115	-44.925	39.459	297.161	15.332	-29.514
advdeg	-135.181	-85.947	18.418	273.484	10.695	-81.468
ci-L	-164.379	-119.886	-8.973	215.743	-5.597	-120.621
ci-U	-106.68	-49.873	40.949	335.579	19.68	-47.274
hhsize	-2.1	10.262	20.081	-26.065	.153	-2.332
ci-L	-4.89	6.131	17.549	-33.309	-.78	-6.934
ci-U	1.076	14.208	21.735	-19.399	1.013	2.089
sppreshh	-1.136	31.752	5.325	-18.562	1.335	-18.714
ci-L	-9.58	19.221	-1.943	-34.42	-.636	-33.677
ci-U	8.302	45.171	11.791	.833	3.955	-5.379

Males (N=3,590)

	tsleep	thhpers	tcare	twork	texerc1	tnonexc1
age	.187	2.069	-.728	-4.122	-.019	2.614
ci-L	-.284	1.704	-1.023	-5.145	-.148	1.999
ci-U	.62	2.548	-.499	-3.286	.114	3.464
blacknh	18.013	-20.247	-13.445	-56.355	3.477	68.557
ci-L	-2.397	-37.509	-20.187	-84.395	-1.203	48.651
ci-U	35.953	-6.888	-7.912	-27.84	7.579	95.382
hispanic	9.516	-10.557	-14.413	6.311	2.439	6.704
ci-L	-2.775	-24.712	-23.468	-22.124	-3.784	-12.748
ci-U	20.584	6.904	-7.165	35.37	6.823	28.909
otherre	11.127	2.766	1.163	-46.73	1.445	30.229
ci-L	-8.94	-19.93	-9.581	-82.648	-7.41	2.71
ci-U	32.684	22.291	11.151	-11.141	8.521	55.872
hsgrad	-63.572	-9.55	7.788	84.676	1.764	-21.107
ci-L	-89.272	-39.048	-12.018	28.594	-10.286	-54.211
ci-U	-36.616	26.262	27.124	141.542	11.656	14.153
somecoll	-83.152	-4.719	9.974	111.544	6.366	-40.013
ci-L	-107.69	-33.004	-13.463	53.885	-11.952	-80.345
ci-U	-53.45	32.421	29.955	178.906	18.024	2.783
collgrad	-87.481	-11.434	12.795	133.667	12.951	-60.499
ci-L	-114.197	-38.856	-10.651	75.281	-9.674	-97.766
ci-U	-60.157	27.677	32.955	189.771	25.695	-22.874
advdeg	-106.22	-25.814	13.162	189.731	16.674	-87.534
ci-L	-139.652	-54.201	-15.367	136.429	-14.269	-116.433
ci-U	-75.848	13.943	36.918	258.201	33.201	-49.215
hhsize	.974	-4.224	8.066	2.616	-.65	-6.781
ci-L	-2.446	-8.522	6.433	-5.543	-1.761	-10.837
ci-U	4.72	-1.065	9.624	8.731	.472	.059
sppreshh	-23.524	3.805	13.635	45.873	-3.868	-35.922
ci-L	-34.481	-8.505	8.217	22.959	-7.433	-58.568
ci-U	-13.204	17.65	20.113	71.15	-.347	-20.44

Table 9 (cont.)

	Females (N=4,317)						Males (N=3,590)					
	tsleep	**thhpers**	**tcare**	**twork**	**texerc1**	**tnonexc1**	**tsleep**	**thhpers**	**tcare**	**twork**	**texerc1**	**tnonexc1**
temperat	.044	.177	-.037	-.271	.112	-.025	-.297	-.176	.017	.495	.028	-.067
ci-L	-.385	-.308	-.451	-1.048	.034	-.529	-.679	-.639	-.177	-.445	-.086	-.87
ci-U	.401	.745	.242	.542	.203	.64	.177	.277	.278	1.417	.165	.636
precip	-1.444	-.09	1.422	1.602	.212	-1.702	.854	.757	.388	-2.726	-.332	1.059
ci-L	-2.835	-2.885	.106	-1.166	-.348	-4.487	-1.767	-1.348	-.825	-7.438	-.795	-2.755
ci-U	.565	2.627	2.475	5.813	.793	.394	2.925	2.854	1.518	3.265	.234	4.074
stobese	.011	.919	.26	-1.344	-.629	.783	.201	-.214	-.49	-.268	-.122	.892
ci-L	-1.898	-1.555	-1.131	-5.229	-1.057	-1.715	-1.757	-1.979	-1.512	-3.331	-.594	-1.697
ci-U	2.007	3.126	1.664	2.569	-.28	2.695	1.843	1.29	.634	2.602	.383	3.556
ueratelg	1.599	-1.365	.762	-10.015	.308	8.711	2.618	4.51	.461	-9.872	-.084	2.367
ci-L	-2.009	-6.238	-2.778	-17.343	-.571	4.774	-2.871	-.656	-1.667	-20.612	-1.241	-4.295
ci-U	5.466	4.212	4.724	-2.787	1.201	12.764	8.663	8.286	2.454	-1.433	.917	9.515
winter	-1.183	-2.753	15.579	4.323	-5.26	-10.706	-2.249	-21.299	7.666	6.434	-9.874	19.323
ci-L	-23.15	-35.849	-10.016	-41.95	-9.254	-43.15	-27.034	-46.706	-7.053	-49.461	-15.809	-29.68
ci-U	20.919	25.86	30.229	46.628	-.219	21.706	28.398	3.471	22.742	56.123	-3.051	65.931
spring	-.71	-7.936	17.747	12.076	-4.978	-16.199	-6.809	-10.629	3.786	15.88	-7.762	5.533
ci-L	-20.407	-35.887	-1.017	-26.628	-8.504	-39.791	-25.503	-33.473	-7.407	-22.944	-12.869	-37.418
ci-U	17.655	17.095	29.835	57.018	.139	11.764	18.251	15.425	15.191	61.277	-1.663	42.14
autumn	3.787	-17.181	16.844	14.611	-6.351	-11.71	5.253	-23.144	7.209	4.866	-10.246	16.062
ci-L	-16.701	-47.293	-2.245	-21.658	-10.287	-40.394	-12.258	-44.148	-6.762	-39.019	-15.657	-23.627
ci-U	19.877	4.7	30.152	63.15	-1.751	15.194	27.563	.377	20.033	49.381	-3.678	54.641
tue	-6.237	-3.753	-10.86	20.91	.503	-.563	-.766	-5.322	-2.769	14.451	1.552	-7.146
ci-L	-23.102	-23.567	-23.716	-16.008	-3.511	-20.67	-17.868	-26.639	-11.524	-17.06	-4.84	-29.77
ci-U	7.753	21.71	2.634	57.341	3.769	20.446	15.914	11.374	4.69	47.506	6.712	15.508
wed	-15.72	-8.276	-11.699	36.04	1.727	-2.071	-3.228	10.504	-2.789	6.425	.277	-11.189
ci-L	-30.848	-24.325	-24.457	4.47	-2.253	-28.312	-19.193	-9.679	-12.757	-19.767	-6.081	-34.521
ci-U	-.77	12.387	1.941	69.995	5.477	19.721	12.04	25.03	4.758	41.005	5.641	9.362
thu	-9.472	-2.59	-11.717	24.127	1.397	-1.745	-6.185	.915	-2.839	12.284	2.823	-6.997
ci-L	-23.521	-22.211	-24.291	-5.543	-1.449	-27.126	-23.874	-21.341	-11.699	-20.386	-5.127	-35.084
ci-U	3.377	19.34	1.274	61.022	4.966	18.797	10.302	19.615	5.886	41.279	8.73	14.077
fri	-24.071	-5.6	-13.809	13.109	1.122	29.25	-14.098	6.285	-3.403	-5.764	-.601	17.582
ci-L	-38.629	-25.274	-28.695	-16.616	-2.734	6.146	-32.895	-16.961	-11.237	-36.191	-7.868	-7.248
ci-U	-11.856	16.258	-.043	48.894	4.522	54.817	2.13	25.09	4.148	27.539	4.976	39.055

Figure 1
Time Use Patterns by Gender, Time of Week, and Physical Activity Measurement (Unweighted)

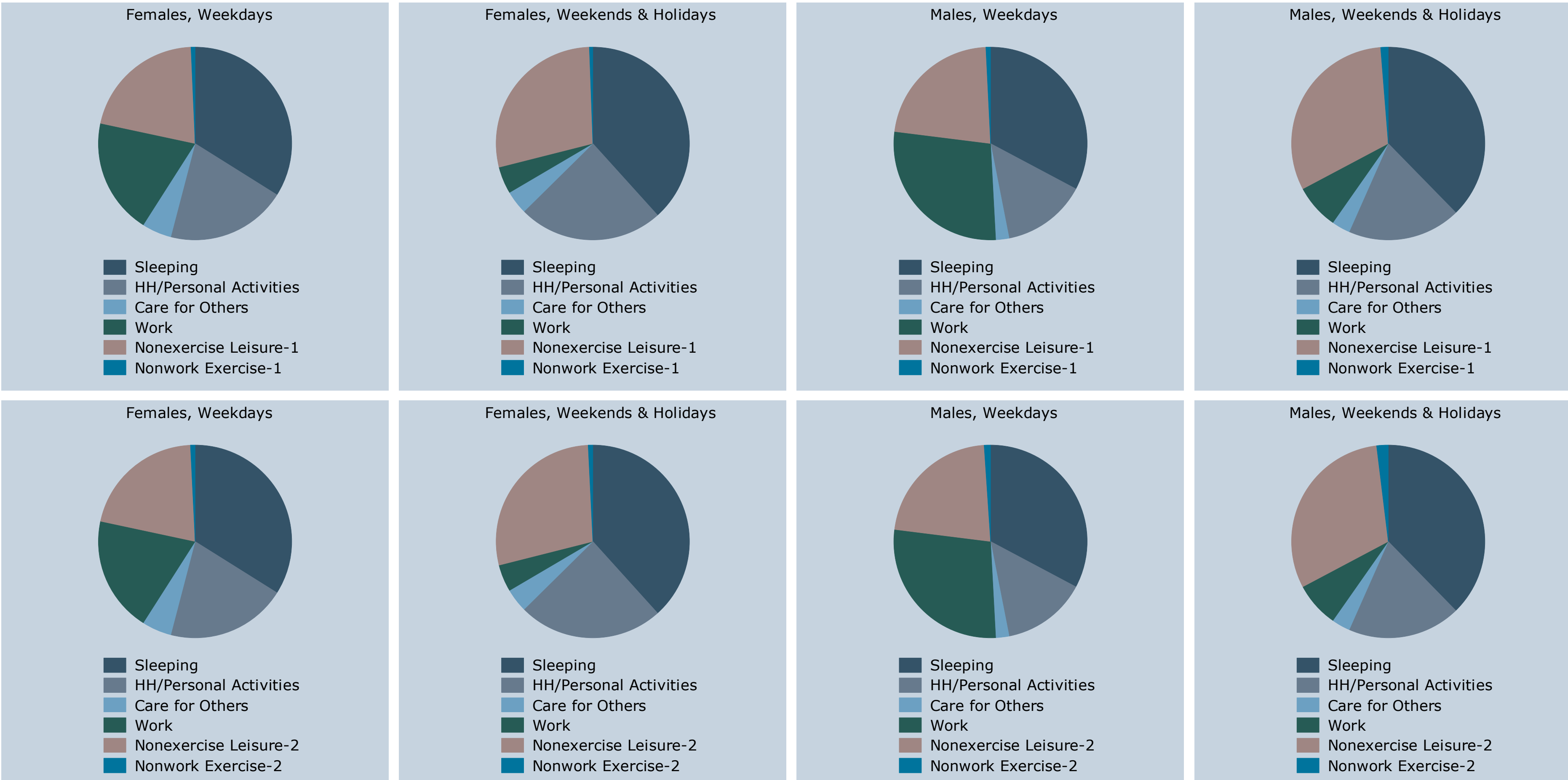

Figure 2
Time Use Patterns by Educational Attainment and Time of Week (Unweighted)

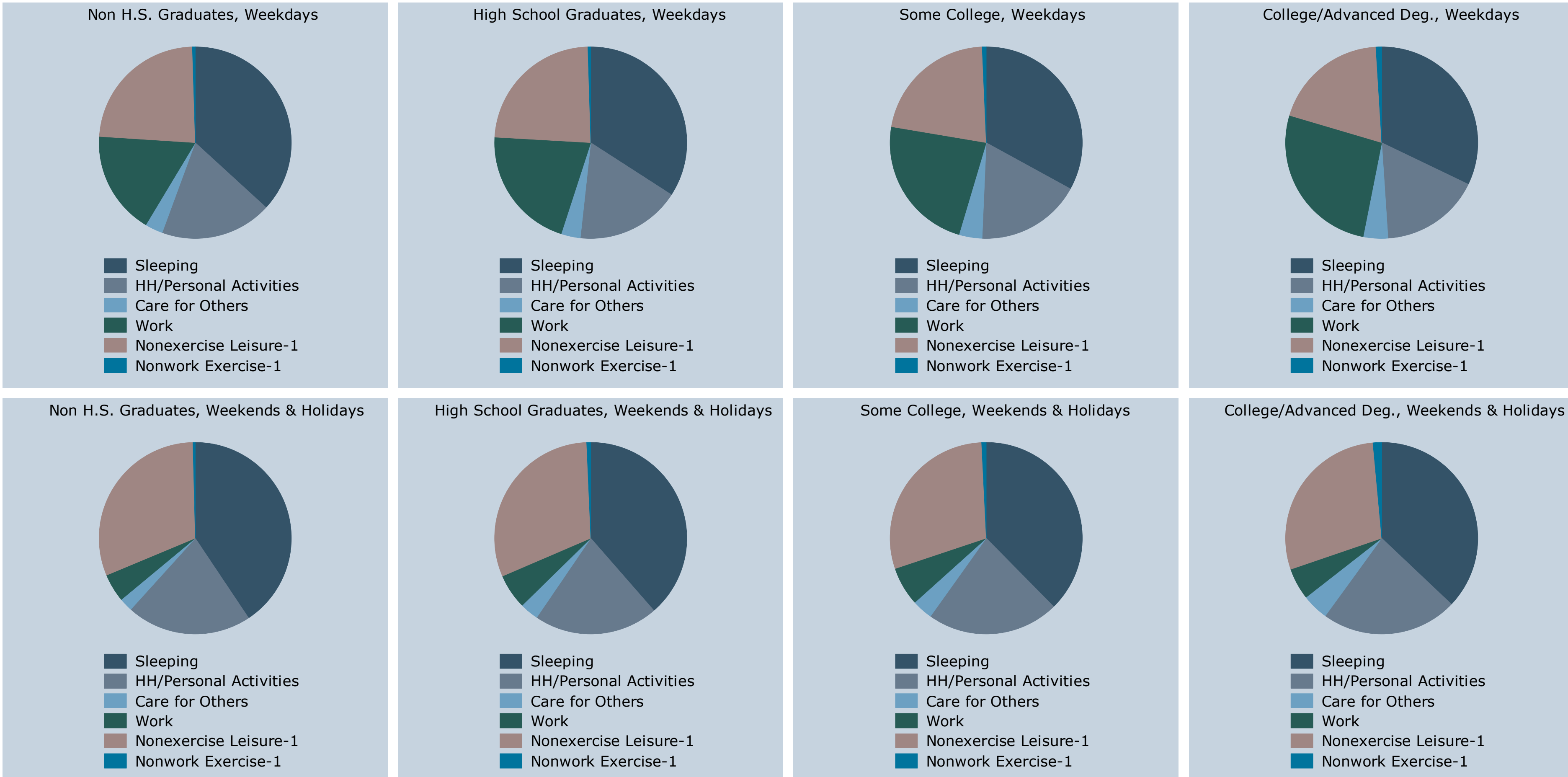

Figure 3a

Full-Sample Distributions of Time Use Measures by Time of Week: *tsleep*, *thhpers*, *tcare* (Unweighted)

(Note: y-scales differ across categories but not within categories)

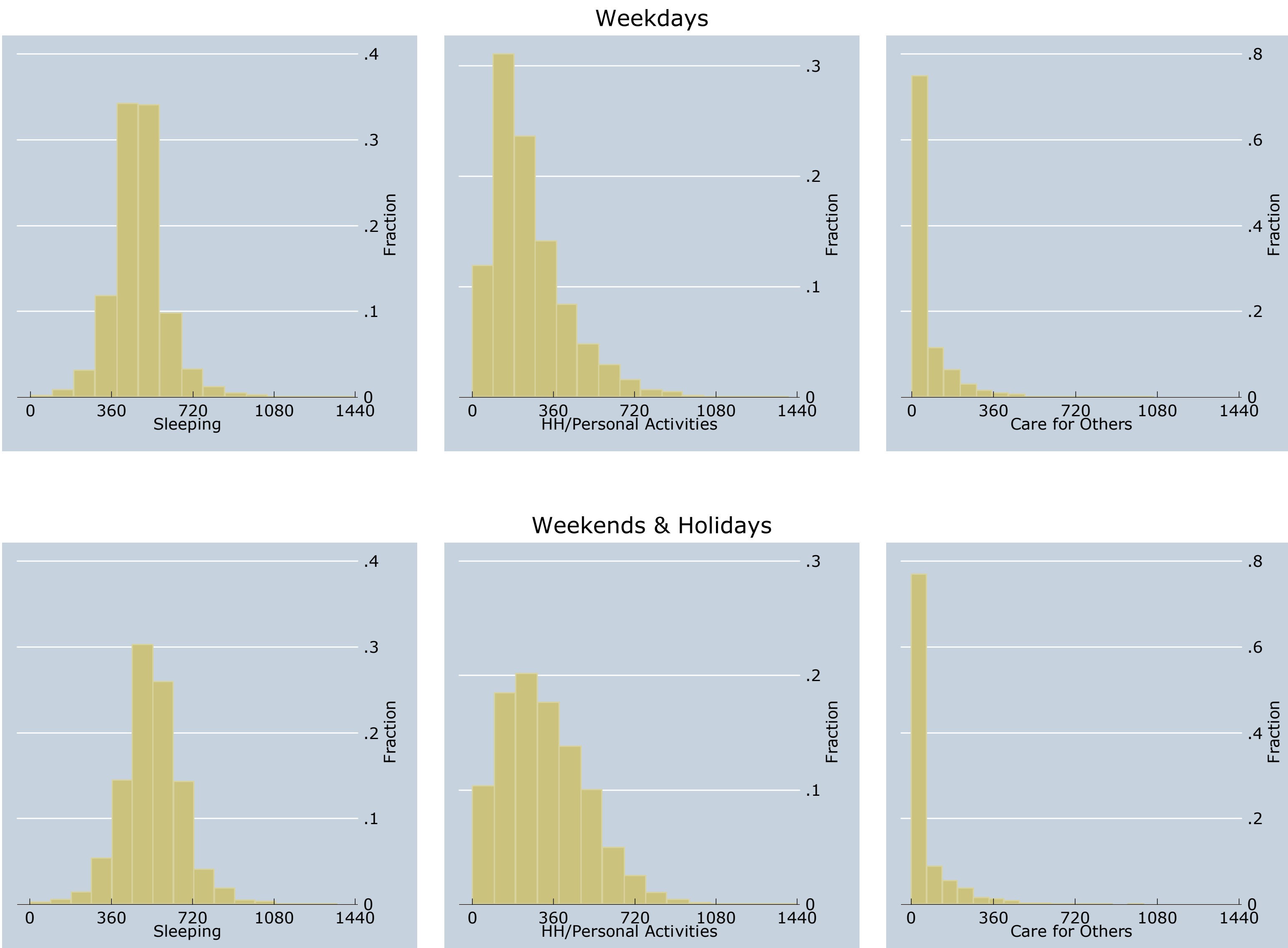

Figure 3b
Full-Sample Distributions of Time Use Measures by Time of Week: *twork*, *tnonexc1*, *texerc1* (Unweighted)
(Note: y-scales differ across categories but not within categories)