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Experiential wellbeing data from the American Time Use Survey: Comparisons with other methods and analytic illustrations with age and income

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Abstract

There has been a recent upsurge of interest in self-reported measures of wellbeing by official statisticians and by researchers in the social sciences. This paper considers data from a wellbeing supplement to the American Time Use Survey (ATUS), which parsed the previous day into episodes. Respondents provided ratings of five experiential wellbeing adjectives (happiness, stress, tiredness, sadness, and pain) for each of three randomly selected episodes. Because the ATUS Well-being module has not received very much attention, in this paper we provide the reader with details about the features of these data and our approach to analyzing the data (e.g., weighting considerations), and then illustrate the applicability of these data to current issues. Specifically, we examine the association of age and income with all of the experiential wellbeing adjective in the ATUS. Results from the ATUS wellbeing module were broadly consistent with earlier findings on age, but did not confirm all earlier findings between income and wellbeing. We conclude that the ATUS, with its measurement of time use, specific activities, and hedonic experience in a nationally representative survey, offers a unique opportunity to incorporate time use into the burgeoning field of wellbeing research.

Keywords

Daily Measurement; Evaluative Wellbeing; Experiential Wellbeing; Time Use

1. Introduction

There has been a recent upsurge of interest in self-reported measures of wellbeing (also known as subjective wellbeing measures), by official statisticians and by researchers in the social sciences. This is in part due to influential reports including by Stiglitz, Sen, and Fitoussi (2009), the Organization for Economic Cooperation and Development (OECD 2013), and the National Academy of Sciences (Stone and Mackie 2014) that have provided the rationale for supplementing standard economic measures of societal wellbeing, such as GDP, with peoples' subjective self-reports. Research documenting determinants of subjective wellbeing has primarily focused on evaluative measures of wellbeing, such as life satisfaction and the Cantril Ladder, which are the wellbeing measures most often used in large, national surveys (Krueger et al. 2009). Yet evaluative measures are only one aspect of subjective wellbeing, a component that reflects peoples' judgments about their current situation, which is framed in a context of their values and aspirations. Experiential wellbeing is another component of the wellbeing of individuals and groups. Experiential wellbeing is intended to assess peoples' everyday emotions, their joys, miseries, and pains, which have been shown to be only modestly associated with evaluative measures (Stone and Mackie 2014; Schimmack 2008; Luhmann et al. 2011). As will be discussed later, experiential measures that incorporate time-usage require greater respondent participation than evaluative measures, which has discouraged their widespread adoption in population surveys (Christodoulou et al. 2014). Identifying determinants of subjective wellbeing has also captured the interest of scientists, because determinants could be useful for developing interventions to enhance wellbeing and reduce suffering or for providing information to policy makers about their constituencies (O'Donnell et al. 2014).

In this paper we focus on the measurement of experiential wellbeing using the American Time Use Survey (ATUS) Wellbeing Module (WBM), a survey administered by the U.S. Bureau of Labor Statistics that has collected information on experiential wellbeing using a time-use data collection methodology with a sample representative of the United States. The paper has two goals. Our first, a methodological goal is to describe the ATUS WBM in considerable detail and the opportunities that arise from these data for a fine-grained examination of experiential wellbeing. Our second, a substantial goal is to use the ATUS data to examine relationships between experiential wellbeing and two variables – age and income -- that previously have received much attention in the prediction of evaluative wellbeing.

Regarding methodological issues pertinent to the ATUS, in the next section of this paper we describe how experiential wellbeing has been measured and highlight the methodological strengths of the technique compared with others to put the particular qualities of the ATUS into context as an approach for measuring experiential wellbeing. Regarding the substantive goal, we illustrate the qualities of the ATUS wellbeing data for understanding how age is associated with wellbeing; this question has far reaching implications for developing life course theories and for identifying consequences of the aging process, for example, how increased disease rates associated with aging affect us (Steptoe et al. 2015; Carstensen et al. 2000). We also examine the effects of income on subjective wellbeing, a topic that is of considerable interest for economists, some of whom view wellbeing as a proxy for utility, a

core construct in economics, as well as for those many non-economists who believe that wellbeing has little to do with money (Kahneman and Deaton 2010; Stevenson and Wolfers 2013). In a subsequent section of the paper we then provide brief reviews of prior literature about evaluative and experiential wellbeing and their relationships with age and income, and then move onto quantitative analyses using the ATUS wellbeing data. The last section of the paper presents analyses that test the associations between the two predictors and experiential wellbeing measured in the ATUS WBM.

2. Methodological Considerations in Assessing Experiential Wellbeing

For interpreting the experiential wellbeing findings, one needs to seriously consider how it is assessed. Experiential wellbeing concerns people's levels of their everyday emotions, which can include not only positive emotions, but also negative experiences such as pain and suffering; the assessment of such labile, emotional states presents challenges. Techniques of asking respondents how they "generally" feel or how they feel over long periods of time run the risk of bias, because answers to such questions are likely to reflect people's beliefs and expectations rather than actual experience (McFarland et al. 1989; Schwarz 1999). To obtain more accurate assessment of experiences, researchers have resorted to techniques that reduce recall bias by asking about current experiences using methods such as experience sampling (DeVries 1987) and ecological momentary assessment (Shiffman et al. 2008; Stone and Shiffman 1994). These techniques provide detailed and precise information about experience, but because they are burdensome for respondents and costly to implement for researchers, the techniques are better suited to small, intensive studies rather than large-scale studies intending to provide population estimates. Two solutions have been developed to overcome this problem.

The first solution is to obtain overall experiential ratings of yesterday; the method is simple and relatively quick. The technique is virtually the same as end-of-day diaries, which have been in use for many decades, but answered from the following day; questions like "Please rate your overall pain for yesterday" are used. Unlike most diary protocols, though, the yesterday ratings are typically only done for a single day, providing a single-day snapshot of experiential wellbeing. The assessments require only a few minutes and can be done anytime on the day following the targeted day (Christodoulou et al. 2014). Overall yesterday ratings have been used to collect experiential wellbeing data in the Gallup-Healthways Wellbeing Index (Harter and Gurley 2008) and have been used in a recent British Office for National Statistics' survey of wellbeing (<http://www.ons.gov.uk/ons/guide-method/user-guidance/well-being/index.html>).

A second solution for collecting accurate experiential data in large-scale studies has been to combine well-known techniques for measuring time-usage, which has respondents parse the day into many episodes defined by activities, with other ratings of the episodes. This technique is called the Day Reconstruction Method (DRM; Kahneman et al. 2004; Krueger et al. 2009) and has been implemented by asking respondents to define episodes of their waking hours of yesterday (as is done in time-use studies) and then to return to each episode and rate several affective adjectives and pain for the period (though other characteristics of the episode could just as easily be rated). The process of recalling and reflecting upon

yesterday in this comprehensive manner is intended to help respondents recreate the feelings they actually had during those periods as opposed to relying on their general beliefs about occasions (Kahneman et al. 2004). Data from the DRM has been compared with data collected with momentary assessment methods, which are often considered the gold standard, and the correspondence between the methods is good (Christodoulou et al. 2014; Krueger et al. 2009), supporting the validity of the procedure.

More recently, a telephone interview version of a DRM-like interview has been developed and run by the Bureau of Labor Statistics (BLS) in their subjective wellbeing module, which was added to the ongoing ATUS. ATUS has been monitoring the time-use of Americans since January 2003 (<http://www.bls.gov/tus/overview.htm#1>). Participants are selected from the Current Population Survey and are interviewed for the ATUS within 2–5 months after their household has completed the Current Population Survey. Interviewers in the ATUS have respondents parse yesterday into discrete episodes and immediately code the activities in each using a three tier coding system. As with the DRM, the interviewers then obtain experiential wellbeing information about episodes; however, whereas the DRM collects wellbeing ratings for all episodes of the day, this was not feasible in the ATUS due to time and resource limitations. Instead, the computer-assisted telephone interview program in the ATUS randomly selected three episodes per person (out of usually about 20 episodes) for the wellbeing ratings, providing a partial DRM. Corresponding to the DRM and to overall yesterday diaries, the ATUS experiential wellbeing data is collected for a single day.

3. Illustrating the ATUS Wellbeing Module: Age, Income, and Experiential Wellbeing

With few exceptions, what we know about experiential wellbeing and its association with age and income are mainly from surveys of global yesterday assessments (Gallup-Healthways and the British Office for National Statistics wellbeing survey; Stone et al. 2010; Kahneman and Deaton 2010). Only a few studies have drawn upon the experiential wellbeing data from the ATUS to examine constructs and relationships that are well established through evaluative wellbeing measures (Kushlev et al. 2015; Schneider and Stone 2014; Dolan and Kudrna 2015; Lee et al. 2016; Flood and Genadek 2016; Dolan et al. in press). While it is not practically feasible to conduct a momentary data collection study with thousands of participants, if only because there are many important activities where people cannot respond (e.g., driving a car, taking a shower, being in office meetings), the availability of the BLS's ATUS data provides a way of collecting data that is similar to that obtained with real-time momentary assessments. Combined with time use information, it also enables a deeper understanding of experiential wellbeing, because activities, which are strongly related to daily affect (Krueger et al. 2009), can be considered in the analyses. Furthermore, because the ATUS is based on the current census, it provides a representative sampling of the people in the United States.

3.1. Age and Subjective Wellbeing

Researchers have long been interested in how subjective wellbeing changes with age. Early theories suspected that developmental trends in wellbeing would parallel those of physical

functioning, with both reaching their highest point in young to middle adulthood and declining thereafter (Bühler 1935; Frenkel-Brunswik 1968). In addition, older age was viewed as a period when people would question their purpose in life as they faced the reality of increasing losses and eventual mortality, which should lead to lower life satisfaction in older age (Scheibe and Carstensen 2010). But these theories have not been supported by empirical evidence: the so-called “paradox of wellbeing” (Gana et al. 2013) is that older people evaluate their lives as better than those at younger ages, especially so when compared with middle-aged people. The specific form of the age trend in life satisfaction is not entirely clear, but the predominant finding is that it is U-shaped over age, at least in rich English-speaking countries, with a nadir in satisfaction occurring in the late 40s to mid-50s (Steptoe et al. 2015).

Several life-span developmental theories provide possible explanations for findings of improved wellbeing with older age. One prominent theory, selective optimization with compensation (Baltes 2003), argues that, as people age, they invest their resources in goals more selectively and draw on the expertise accumulated in life to compensate for inevitable limitations and to optimize performance and wellbeing. Socioemotional Selectivity Theory (Carstensen et al. 2003) suggests that older people are more likely to prioritize emotional goals and invest more resources into meaningful social relationships, and that they derive increasingly greater life satisfaction from these selective investments. However, the majority of studies examining age-related trends in wellbeing have focused on evaluative wellbeing or have used retrospective assessments of wellbeing that tend to be associated with people’s implicit personal theories (Stone et al. 2010).

Turning to experiential wellbeing, only a few studies have investigated age effects (Carstensen et al. 2000; 2011). The available evidence suggests improvements with age for several aspects of experiential wellbeing such as daily negative affect and stress, but it also shows a complex pattern of age differences across different dimensions of experiential wellbeing. One study was based on the Gallup-Healthways Wellbeing Index, which is comprised of several hedonic adjectives that are dichotomously rated for whether or not there was “a lot” of the emotion yesterday (Stone et al. 2010). This study showed strong age gradients for almost all of the adjectives assessing experiential wellbeing; for example, the proportion of the respondents who said they experienced a lot of stress yesterday was fairly stable from age 18 to late 40s, and then plummeted during the period 50 through 70 years of age. Worry and anger had similar declining gradients, though with a more modest drop. Sadness did not vary much by age. Happiness and enjoyment displayed modest U-shape gradients. A later paper using the Gallup Organization’s World Poll (Steptoe et al. 2015) also showed age gradients for experiential wellbeing and the pattern varied according to the area of the world studied. For example, stress and worry showed an inverted U-pattern for high income, English-speaking countries whereas there was an ascending or flat pattern over age for countries of the former Soviet Union and Eastern Europe. Very recently, Dolan et al. (in press) analyzed data from the 2012–2013 ATUS WBM and found a modest U-shaped age-trend for happiness and an inverted U-pattern for negative wellbeing (a composite of sadness, stress, pain, and tiredness). Taken together, these results highlight the need to examine a range of specific dimensions of experiential wellbeing to obtain a nuanced characterization of life-span developmental trends in wellbeing.

3.2. Income and Subjective Wellbeing

With regard to income, there is some controversy about its association with evaluative wellbeing, with some scientists presenting a case for a strong linear association between evaluative wellbeing and the log of household income; others suggest an alternative perspective basing associations on income relative to those living in surrounding neighborhoods (Luttmer 2005); and, others claim an association only at the lower levels of the income distribution (Clark et al. 2008; 2009; Deaton 2008; Diener and Biswas-Diener 2002; Sacks et al. 2012). From a theoretical perspective, it has been argued that global evaluative wellbeing questions are potentially prone to exaggerate the importance of higher income for better subjective wellbeing (Kahneman and Deaton 2010; Kahneman et al. 2006). This is because standard survey questions that ask respondents how satisfied they are with their life overall may focus people's attention disproportionately to their material wellbeing when they respond to the question. On the other hand, people with greater income tend to devote considerable amounts of time to work and other activities that may be unpleasant, but such typical aspects of everyday life tend not to be salient in memory when answering evaluative wellbeing questions, whereas they may have a pronounced effect on experiential wellbeing (Kahneman et al. 2006). This suggests that experiential wellbeing may be much less positively impacted by higher income than evaluative wellbeing.

A recent study based on the experiential wellbeing questions in the Gallup-Healthways Wellbeing Index supports this supposition. In 2010, Kahneman and Deaton analyzed data from over 450,000 interviews from those data and showed a positive linear relationship between better experiential wellbeing and the logarithm of income until a income level of about \$75,000 was reached; thereafter, there was no association with income (Kahneman and Deaton 2010). This income association differed from that with the evaluative measure (the Cantril Ladder) in the same study, which had a linear rise with the logarithm of income, but did not plateau at higher incomes. The claim that experiential wellbeing ceases to rise after some level of income has been achieved suggests that beyond that point, the joys of daily life are not enhanced and the miseries are not diminished by more money is intriguing. Thus, confirming the association in the present study using another dataset, which has its own strengths and weaknesses, is timely.

Recently, Kushlev et al. (2015) used data from the 2010 ATUS WBM to examine the association between income and two affective adjectives, happy and sadness. Consistent with prior work, they found that greater income was associated with less sadness, but that income had no relationship with happiness. They furthermore explored the possible correlates of these associations by examining demographic variables and activities, but these variables did not explain the observed associations. In this paper we extend the analysis of income to all of the ATUS WBM adjectives to provide a more complete picture of the association of income with experiential wellbeing.

In summary, we will examine the relationships between two variables that are central to the social and behavioral sciences, age and income, with experiential wellbeing using recent data from the American Time Use Survey. Not only will we determine if the same gradients are observed as have been previously shown using yesterday assessments of wellbeing, we will be able to determine if the gradients are impacted by the daily activities reported by

individuals at different ages and at different income levels, that is, when their effects are statistically controlled. And these associations will be tested with a random sample of individuals from the Current Population Survey conducted by the Census Bureau.

4. Procedure and Materials

The data were collected by the BLS's ATUS project in 2010 with addition of the NIA-supported WBM. Extensive information about the methodology is available on the BLS website (<http://www.bls.gov/tus/wbdatafiles.htm>) including sample selection procedures, details about the Computer Assisted Telephone Interview and the training of the interviewers, wording of questions and skip patterns, and demographic information about the sample. Respondents were interviewed over the telephone and asked to provide a detailed time diary of the previous day. In a series of questions, the interviewer asked: "What were you doing?" "How long did you spend [ACTIVITY]?" "What did you do next?", starting at 4 AM of yesterday and ending at 4 AM on the interview day. Thus, episodes were defined based on the temporal sequence of yesterday's activities. The WBM was completed after the time use episodes were collected and three episodes were chosen at random (by a computer-assisted interview program), with the exception that the following episode categories were eliminated from consideration: sleeping, grooming, personal activities, don't know/can't remember, and refusal/none of your business. Also, to qualify for selection, an episode had to be at least 5 minutes in duration. After the completion of data collection, the BLS realized that there was a programming error in the selection of the three episodes for the WBM: it excluded the last episode of the day from being selected. We believe this adds only a very small error to analyses presented here, but do recognize that researchers interested in activities occurring late in the day will need to deal with this selection bias (BLS has also made available alternate sampling weights that may reduce bias associated with this error).

Items for the WBM were similar to those the Day Reconstruction Method and had the following form using happy as an example (administered by the interviewer): "From 0 to 6, where 0 means you were not happy and 6 means you were very happy, how happy did you feel at this time?" and the respondent was asked to provide a 0 to 6 response. The same format was used for adjectives stress, tired, and sad. For pain, the item was altered slightly: "From 0 to 6, where 0 means you did not feel any pain and 6 means you were in severe pain, how much pain did you feel during this time if any?" Items about the meaningfulness of the episode and whether or not there was a social interaction during episode were also collected, but are not analyzed here.

5. Analysis Plan

Because each episode has an equal chance of being selected, specific minutes of the day (or hours) do not: minutes that belong to longer episodes have a smaller chance of being selected, because they "share" their chances with more "other" minutes. Put differently, if we count each episode as a unit, irrespective of length, our measures will neglect the duration of the episode. A four-hour episode spent in misery is not the same as a five-minute episode spent in misery. For many wellbeing measures, such as the number of hours spent

being happy, or a U-index which is the fraction of the day spent in misery, we need to count each minute equally, not each episode equally. In this context, weighting is not an option but a necessity, and the BLS statisticians have supplied the appropriate weights to deal with this. Given that minutes in longer episodes have a smaller chance of being chosen, duration weighting is equivalent in this case to weighting by the inverse probability of selection, a familiar technique from survey sampling in general.

We begin with a brief description of the WBM participant sample: it is slightly different from the overall ATUS sample in 2010, whose characteristics are available on the BLS website. We next provide a description of the episodes reported in the module, including the number of episodes per person and average length of episodes. This is followed by a tabulation of the activities for episodes. We then turn to WBM questions about each activity and present basic descriptive statistics. Finally, we provide analyses of the relationships between respondent age and income and experiential wellbeing (happiness, stress, tiredness, sadness, and pain). Regression routines from STATA 13 were used and, when dealing with episodes as the units of analysis, cluster-robust standard errors (with respondents as clusters) were employed to adjust significance levels based on the non-independence induced by the fact that the 3 episodes are from the same respondent.

For the analyses of wellbeing differences by age and income, four sets of regression models were used. The first set of models tested linear and quadratic effects of an independent variable (age or log income) on wellbeing (happiness, stress, tiredness, sadness, or pain). Next, selected demographic variables (described below) were added as covariates to the models and the covariate-adjusted patterns of results for age and income were compared with the first models. In these models, when age was the predictor, income was included in the model and when income was the predictor, age was included. Third, given that age or income differences in wellbeing might be explained by daily activities (Kahneman et al. 2004), for example, if older people engaged in more pleasurable activities than middle-aged people, then controlling for activities could impact the age gradient for happiness. Therefore, a third model added the ATUS activity codes as a set of dummy variables and the resulting wellbeing patterns for age and income were again compared to the first model.

5.1. Sampling Weights

As previously described, the data from the WBM of ATUS requires weighting in order to estimate national means. Furthermore, the three episodes selected by the WBM are a sample of those from the day described in the ATUS. As such, BLS has created two sets of weights. The first set is applied when respondent is the unit of analyses (e.g., when examining the demographics of the sample) and the weights correct estimates for “the U.S. civilian, non-institutionalized population age 15 and over” (WUFINLWGT). BLS recommends that the second set of weights be used for episode-level wellbeing data: they are “designed to estimate average levels of affect for the population during activities eligible for the module. They can also be used to estimate population averages for functions such as ‘U-indexes’.” These are the weights that were described above that are designed to account for the differences in the duration of activities and for the probability of having a specific episode

selected given the varying numbers of episodes available for a respondent (WUFNACTWT, using the “pweight=” option), and they were used in the present analyses.

ATUS also offers the option of using replicate weights in combination with the sampling weights for computing the standard errors. Replicate weights contain all information about a complex (stratified and clustered) sampling design and provide standard error estimates that mimic the theoretical basis of standard errors while retaining all information about the complex sample design. For the present analyses, we have compared results using replicate weights with those using cluster robust standard errors in combination with the sampling weights; the two sets of results provided almost identical point estimates and standard errors (analyses not shown). Thus, the described results are based on the simpler method using sampling weights and cluster (here respondent) robust standard errors.

6. Results

6.1. Respondents

Participants in the ATUS 2010 WBM were 12,829 adults in the US. A total of 38,160 episodes were collected, or an average of 2.97 episodes per person, slightly less than the protocol specification of 3 episodes per person. The breakdown of number of episodes per person is that 12,518 respondents had 3 episodes (97.6%), 295 had 2 (2.3%), and 16 had 1 (0.1%). The sample was 44% female, 12% had less than a high school education and 61% had at least some college. Average age was 48.1 (SD=16.8), 79% of the sample was white, and 52% of the sample was married. For the subsequent analyses, we included participants who were 18 years of age and older and who had at least 2 episodes reported in the WBM (the decision to include or exclude respondents with missing episodes did not alter the results).

6.2. Description of Episodes

The average episode length was just over an hour ($M = 1.12$, $SD = 1.60$, Median = .50, $n = 36,449$, with a minimum of 5 minutes and a maximum of just over 23.5 hours (i.e., the entire day; this respondent indicated that he/she was engaged in a work-related activity for almost the entire day, with the other brief episode reported by the person being eating/drinking; excluding this respondent from the analyses did not change the results). It is also useful to consider how many hours in total were covered by the (usually) three episodes per person. The average was 3.22 hours ($SD = 2.76$; $n = 12,259$ respondents), with a low of 5 minutes to a high of just under 24 hours.

6.3. Activities

BLS categorizes episode activities with a three-level nested coding system, where the first level is the broadest description and the third level is the most detailed (Shelley 2005). For example, the activity code for “vacuuming” (third level) is nested in “housework” (second level), which is nested in the code for “household activities” (first level). Table 1 shows the frequencies and duration of first level activities in the WBM, that is, activities for just under 3 episodes per day. The first column presents the raw, unweighted frequencies and percentage of total, whereas the second column applies weights to the frequencies.

Differences in the percentages between columns 1 and 2 are due to the sampling protocol in the WBM, which over-sampled weekends and under-sampled episodes of long duration. For example, 24% of the episodes in the raw data were coded as traveling, but because they are relatively brief, the weighted frequency data shows that traveling is only 9% of all episodes. The last column of the table presents the average duration of each activity, again, weighted. The weighted frequency data presented here are very similar to the frequencies based on the full ATUS as presented on the ATUS website.

6.4. Wellbeing Module

Table 2 presents the question content and descriptive statistics at an episode level for the experiential wellbeing questions considered here (note there was randomization of the order of the five experiential wellbeing adjectives for each respondent and the order was the same for the three WBM episodes each respondent rated). Experiences (happy, tired, pain, sad, stress) were rated using 0 (not at all) to 6 (very) response scales; happy was, on average, rated towards the upper end of the scale whereas sad received the lowest rating, and pain and stress were rated somewhat higher than sadness, followed by tired being rated a little higher. The table also presents a characteristic of the distributions, skewness, where negative values indicate a long tail to the left of the distribution (toward lower values) and positive values indicate a long tail to the right (toward higher values). Pain, sadness, and stress were positively skewed, whereas happy was negatively skewed. Tired showed a generally symmetrical distribution. Correlations between the different wellbeing questions were small to moderate in magnitude (average $r = .31$, range .16 to .47, $p < .001$ for all correlations, see Table 2), suggesting that they captured relatively distinctive aspects of experiential wellbeing. This is consistent with the notion that wellbeing is best characterized as a profile of indicators across multiple domains, rather than as a single global concept (Forgeard et al. 2011; Ryff and Keyes 1995; Stone and Mackie 2014). Thus, each wellbeing variable was considered separately in subsequent analyses.

6.5. Age and Experienced Wellbeing

To determine if there were linear or quadratic effects of age in the ATUS data, the five ATUS hedonic variables were regressed on age (linear) and age squared (quadratic); the results are labeled Model 1 and are shown in the upper panel of Table 3. For all of the models, the first row presents the F-value for the entire model and subsequent rows show the regression coefficients for the linear and quadratic terms (and significance levels) and for other variables in the model (error terms were clustered at the level of the individual, and activity weights were used). F-tests for all of the outcomes showed significant linear and quadratic associations with age, with the strongest associations for pain and stress (see Fig 1). Specifically, happiness showed a slight decrease by .12 points (on the 0 to 6 scale) from ages 18 to 40, with a subsequent increase by .47 scale points from ages 40 to 80. Stress increased by .38 points from ages 18–40, with a decrease by 1.03 points from ages 40–80. Tiredness and pain showed near linear associations with age but in opposite directions: whereas pain increased by .77 scale points from ages 18–80, tiredness decreased by .57 points over the same age range. Finally, sadness showed a slight increase (.26 points) over the 18–80 year age range.

Sociodemographic differences over age could account for the patterns shown above. The controls used here are similar to the ones used by Kahneman and Deaton (2011) in their analyses of wellbeing and income and we use the selected control variables for consistency and to achieve comparability with this prior research. They were income (log of the income variable that is described in the next section), education (some college or less=0, associate college degree or more=1), sex (female=0, male=1), presence of disability (no=0, yes=1), weekend (weekday=0, weekend=1), and marital status (not married=0, married=1). As expected (see Model 2), many of these variables were strongly associated with the outcomes. For example, weekends had greater levels of happiness and lower levels of stress and tiredness and disability was strongly associated with much lower levels of wellbeing on all of the experiential variables. Although there were many variables associated with experiential variables, the associations between age and each of the wellbeing variables remained very similar, and in some cases the main linear effect of age was increased, after controlling for these demographics.

Observed age patterns might also be explained by the content of daily activities. Activity content is known to impact experiential variables (Kahneman et al. 2004), but it must also be acknowledged that choice of activity is likely to be influenced by hedonic state, so we are not claiming a causal association between activities and wellbeing. Thus, in Model 3 we added activity categories as covariates, represented by dummy variables for the first tier of coding of the ATUS, to the previous model (including demographics). As with the demographic variables, many of the activities had reasonable associations with the experiential variables, for example, religious activities were associated with more happiness and with less stress and tiredness. Although activities were related to the outcomes, the overall patterns of age differences (and significance levels) were again only slightly affected by the addition of activities to the model.

6.6. Income and Experienced Wellbeing

We now turn to the association between experienced wellbeing and family income reported in the paper by Kahneman and Deaton (2010) using the same Gallup survey as Stone et al. (2010). Of the 12,259 individuals who participated in the ATUS WBM, household income was available for, depending on the experiential outcome, between 11,703 and 11,721 (95%) respondents; they comprise the sample for the following analyses. We transformed the categorical income information to a continuous variable by assigning values to the ATUS categories of: 4,000; 6,250; 8,750; 11,250; 13,750; 17,500; 22,500; 27,500; 32,500; 37,500; 45,000; 55,000; 67,500; 87,500; 125,000; and, 180,000. These values correspond to the midpoints of the income category ranges. They were log-transformed for the subsequent regressions.

The five experiential outcome variables were each regressed on the log income variable (treated as continuous, and testing linear and quadratic effects). Without sociodemographic control variables, no associations were evident for happy, stress, or tired. Significant linear (in logarithms) effects were evident for sad and pain: as illustrated in Fig 2, a doubling in income was associated with a 0.10 scale point reduction in sadness and with a 0.20 scale point reduction in pain on the 0–6 scale. Similarly, stress showed no association with income

in the ATUS data while falling and then rising with income in the Gallup data. However, sadness in both Gallup and ATUS data showed a downward trend as income increased.

As was the case for the age analyses, the addition of demographic and activity variables had little impact on the results, though the effects of income were slightly diminished in the presence of these controls (see Table 3; the results for Models 2 and 3 are shown in the sections labeled Model 2 and Model 3 following in the Age section of the table).

7. Discussion

The first of the two goals articulated at the outset was achieved by presenting a detailed description of how the ATUS Wellbeing Module compares with other techniques for measuring experiential wellbeing. Relatedly, we presented a detailed description of our approach to the data analysis and described several issues associated with using these data for addressing questions of relevance for social and behavioral scientists. The second goal was to illustrate the usefulness of the ATUS data by examining associations of age and income with experiential wellbeing. We did this in a sequential fashion by adding demographic control variables and, in the last step, activity controls in the analysis of each of the wellbeing adjectives. We now discuss how the ATUS data compared with data collected by similar techniques and then turn to the substantive findings. We close with some thoughts about how these data may serve the social and behavioral sciences and discuss limitations of the methodology.

Episode and wellbeing data collected with the ATUS WBM module were generally consistent with expectations based on our experience with DRM studies conducted by us and by others. The number of episodes reported by ATUS respondents was in accord with prior DRM research with more selective populations, that is, on average between 15 and 20 episodes were reported per respondent. And new data from the WBM on subjective experience are similar to those from previous investigations of comparable concepts (Kahneman et al. 2004; Stone et al. 2010). For example, happiness was rated well into the upper half of the scale range, whereas negative emotions were reported at much lower levels, a common finding in daily measurement of these constructs. Thus, there are several indications that the WBM module has produced reasonable data.

We examined how age and income were associated with the five ATUS ratings of episodic wellbeing experience. Based on prior research (Stone et al. 2010; Carstensen et al. 2000; Carstensen et al. 2011), we expected that several aspects of experiential wellbeing (in particular, stress and emotional wellbeing) would show improvements in older age, but we also expected pronounced variation in the age patterns across different wellbeing dimensions. Our results largely confirmed previous findings for age differences in wellbeing that were based on overall experiential ratings of yesterday used in Gallup (Stone et al. 2010), although specific patterns over age were slightly different. As in Gallup, ATUS happiness yesterday showed a U-shaped distribution with a higher right-hand (older) tail (Fig 1; based on Model 1 results), suggesting improvements in happiness in older age. This finding differs somewhat from previous studies using ecological momentary assessments to measure experiential wellbeing and that provided mixed results on associations between age

and positive affect, with some finding significantly positive relationships (English and Carstensen 2014), and others finding no age effects (Carstensen et al. 2000). The relatively modest sample sizes afforded by ecological momentary assessment studies may have contributed to these discrepant previous findings, which highlights the need for experiential wellbeing data assessed in relatively large and nationally representative samples as provided by ATUS. Consistent with prior studies (English and Carstensen 2014; Stone et al. 2010), sadness showed a significant inverse U-shaped relationship with age, although the association was the weakest of all five outcomes and the graphic shows a very modest curvilinear increase over age. Together, though, the findings on affective dimensions of experiential wellbeing support the theoretical argument that emotional wellbeing in daily life improves in older age (Carstensen et al. 2003; Baltes 2003).

Experiences of pain, stress, and tiredness showed remarkably divergent age patterns. The level of daily pain was positively associated with age, which may be expected given deteriorating health as people age. Interestingly, the rate of increase in pain became less pronounced in older age (past 60 years of age), which replicates previous findings on life-span developmental trends in daily pain intensity ratings using an assessment method paralleling the ATUS (Krueger and Stone 2008). Daily stress measured by ATUS showed high levels prior to age 50 and a steep, linear decline thereafter, which was very similar to the pattern found in the Gallup data (Stone et al. 2010). A slight difference is the increase in stress from age 20 to 50 shown in ATUS, which was not evident in Gallup. Experiences of tiredness showed a similarly pronounced decline with age. Even though perceived stress and tiredness both have important links to health outcomes, including immunological processes (Cohen et al. 1992) and morbidity (Steptoe and Kivimäki 2012; Junghaenel et al. 2011), relatively scant attention has been paid to patterns of stress and tiredness over the life span and to explore what might cause it. Our findings suggest that fully documenting the nature of developmental trajectories in emotional, somatic, and physical symptom experiences could advance a more comprehensive understanding of wellbeing over the course of life.

Our analysis of household income and experiential wellbeing was less consistent with the prior Gallup study (Kahneman and Deaton 2010). Unlike prior work with “yesterday” global diaries, which showed that income was positively associated with wellbeing, at least from low to moderate income levels, the ATUS WBM data indicated no relationship with happiness. However, negative emotions from the WBM were more consistent with prior work, providing an overall mixed picture of the concordance between findings based on the Gallup data versus those from the ATUS. As would be expected, the results for happy and sad confirm the findings of Kushlev, Dunn, & Lucas (2015). Higher income had a pronounced negative relationship with daily pain, which may be in part reflecting differences in occupation, medical care, or health behaviors across income groups (Pampel et al. 2010). On the other hand, experiences of stress and tiredness did not systematically differ by income, which seems surprising in view of the fact that lower income is associated with numerous environmental and social conditions that constitute enduring stressors in daily life (Baum et al. 1999; Santiago et al. 2011). As for age, these results patterns suggest that multiple dimensions of people’s life experience should be considered in concert to gain a comprehensive understanding of the association between income and wellbeing.

Our findings could be viewed as evidence that the amount of money people earn may have only little bearing on several dimensions of wellbeing experienced during the episodes of a given day, whereas stronger positive relationships between income and subjective wellbeing occur when people make global evaluative judgments (Kahneman et al. 2006), and to some extent when they make global assessments of yesterday's experiential wellbeing (Kahneman and Deaton 2010). The differences between the present findings from the ATUS and previous Gallup study could be regarded as a challenge to the idea that data collected with yesterday global diaries are equivalent to those collected with DRM-type data, where the day is reconstructed and affect (and other experiential data) is subsequently obtained about the entire day. Apart from the higher "resolution" provided by DRM-data, the rationale for the WBM reinstatement methodology was to possibly provide more accurate data (Schwarz 2012). The DRM method encourages people to "re-live" each episode of the day in order to avoid the recall and summary biases that may be inherent in recalling and summarizing the emotions for an entire day. That is, the procedure was specifically developed to evoke the contextual experience, as opposed to the semantic and decontextualized information involved in one's beliefs about emotions (Kahneman et al. 2004). Admittedly, the generation of time-use data used in the ATUS was not as specific as the DRM protocol. Nevertheless, the technique of recalling and reporting the activities of yesterday should engender at least some reinstatement and likely much more than with "overall" day recall methods. Nevertheless, we do not claim that DRM data are more accurate than data from yesterday recall methods, because this study did not directly address that question.

There are other possibilities for the differences observed between income and wellbeing here compared to prior findings. One is that the variability or random error introduced by having experiential wellbeing data for only 3 episodes per day brought a high level of variability within each respondent and so obscured the true association. We expect smaller standard errors from a full DRM, where emotions for all daily episodes are assessed and are subsequently used in analyses (about five times the total number of episodes than were collected in ATUS WBM). While it is possible that high variability obscured associations, we are not sure how likely this is given the relatively large sample size and the fact that the ATUS data replicated the prior age effects derived from diary recall. We also note here that it is essential that the proper weights be applied to the WBM data given the undersampling of lengthy episodes. Finally, the population sampling strategies of the studies varied, with Gallup's survey being based on random-digit dial interviews whereas the ATUS based on the individuals sampled from the Current Population Survey, which was conducted 2–5 months earlier. But, again, we have no evidence that this is causing the discrepant results.

More generally, we speculate on how the ATUS WBM data could be used to address issues in the social sciences, economics, medicine, and policy research. As mentioned earlier, the time use data are already serving those disciplines, but time use combined with subjective experiences in episodes has even greater potential to more deeply tackle important issues. A few examples: When an individual is out of work and looking for a job, what happens to their daily experience [a question addressed in recent work by Krueger and Mueller (2012a, 2012b)]? Or what is the daily experience of individuals with chronic diseases, in terms of activities, emotions, and pain? What is the impact of climate in different parts of the country on daily experience? How are activities and emotion related to presence of children in the

household? What is the wellbeing of those who are married versus those who are divorced and do daily activities moderate that difference?

Another facet of the WBM that should be appreciated is that the specific aspects of experience that are included in the module are *not inherently* limited to those concepts mentioned here. The method of reconstructing a day and questioning individuals about what happened and how they felt during the identified episodes is generic in the sense that future uses could include other content. For instance, if the focus was on health, one could imagine a set of episode-level questions that asked about symptoms and health-related behaviors that were pre-identified from other surveys. Or if the focus was on consumption, then questions about consumption within episodes could be developed.

Although this paper has highlighted many of the positive attributes of the ATUS WBM data, we hasten to add that it, and the DRM on which it is based, have limitations. Perhaps the main one is that the data is based on up to 24-hour retrospection; though this is much shorter than many other wellbeing assessments, it is likely that some aspect of yesterday's experiences are forgotten or distorted by cognitive processes. Research comparing the DRM to momentary data capture for the same days has yielded promising results (Dockray et al. 2010; Krueger et al. 2009), but additional research is needed to confirm these findings. Second, the method is still relatively new and it is likely that modifications to the procedure could enhance its validity, for example, in the process of recreating the events of yesterday and in the selection of adjectives that best characterize daily experience.

In closing, we turn to the policy implications that the measurement of experiential SWB could inform and we reference a chapter from the National Academy of Sciences report (Stone and Mackie 2014) and a report from the OECD (2013) touching on this issue. Because experiential SWB is associated with biological states and is predictive of later morbidity and mortality (Steptoe et al. 2015; 2005), policies to improve wellbeing could impact the nation's health. Monitoring of wellbeing has the possibility of informing policy decisions pertaining to economic progress, health behaviors, loss of employment, the impact of civic projects, retirement, childcare, and employment benefits, to name just a few areas. In fact, a prominent economist has advocated for a national time accounts that include experiential wellbeing (Krueger et al. 2009).

In sum, the value of the ATUS has been enhanced by the addition of the WBM and we have attempted to demonstrate this with concrete examples how the ATUS wellbeing questions, and more generally the DRM methodology, can deepen our understanding of daily experience and address topics of interest to the scientific community.

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References

Baltes PB. Extending longevity: Dignity gain -- or dignity drain? *MaxPlanck Research*. 2003; 3:14–19.

- Baum A, Garofalo J, YALI A. Socioeconomic status and chronic stress: does stress account for SES effects on health? *Annals of the New York Academy of Sciences*. 1999; 896(1):131–144. [PubMed: 10681894]
- Bühler C. The curve of life as studied in biographies. *Journal of applied psychology*. 1935; 19(4):405–409.
- Carstensen LL, Fung HH, Charles ST. Socioemotional selectivity theory and the regulation of emotion in the second half of life. *Motivation and Emotion*. 2003; 27:103–123.
- Carstensen LL, Pasupathi M, Mayr U, Nesselroade JR. Emotional experience in everyday life across the adult life span. *Journal of personality and social psychology*. 2000; 79(4):644–655. [PubMed: 11045744]
- Carstensen LL, Turan B, Scheibe S, Ram N, Ersner-Hershfield H, Samanez-Larkin GR, et al. Emotional Experience Improves With Age: Evidence Based on Over 10 Years of Experience Sampling. *Psychology and Aging*. 2011; 26(1):21–33. [PubMed: 20973600]
- Christodoulou C, Schneider S, Stone A. Validation of a Brief Yesterday Measure of Hedonic Well-Being and Daily Activities: Comparison with the Day Reconstruction Method. *Social Indicators Research*. 2014; 115:907–917. [PubMed: 24683288]
- Clark AE, Frijters P, Shields MA. Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. *Journal of Economic Literature*. 2008; 46:95–144.
- Clark AE, Kristensen N, Westergaard-Nielsen N. Economic satisfaction and income rank in small neighbourhoods. *Journal of the European Economic Association*. 2009; 7:519–527.
- Cohen S, Tyrrell DAJ, Smith AP. Psychological stress and the common cold. *New England Journal of Medicine*. 1992; 326:645–646. [PubMed: 1734261]
- Deaton A. Income, health, and well-being around the world: Evidence from the Gallup World Poll. *Journal of Economic Perspectives*. 2008; 22:53–72. [PubMed: 19436768]
- DeVries M. Investigating mental disorders in their natural settings: Introduction to the special issue. *Journal of Nervous and Mental Disease*. 1987; 175:509–513.
- Diener E, Biswas-Diener R. Will money increase subjective well-being? *Social Indicators Research*. 2002; 57:119–169.
- Dockray S, Grant N, Stone AA, Kahneman D, Wardle J, Steptoe A. A comparison of affect ratings obtained with ecological momentary assessment and the day reconstruction method. *Social Indicators Research*. 2010; 99:269–283. [PubMed: 21113328]
- Dolan P, Kudrna L. More years, less yawns: fresh evidence on tiredness by age and other factors. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*. 2015; 70(4):576–580.
- Dolan P, Kudrna L, Stone A. The Measure Matters: An Investigation of Evaluative and Experience-Based Measures of Wellbeing in Time Use Data. *Social Indicators Research*. in press.
- English T, Carstensen LL. Emotional experience in the mornings and the evenings: consideration of age differences in specific emotions by time of day. *Frontiers in Psychology*. 2014; 5:185. [PubMed: 24639663]
- Flood SM, Genadek KR. Time for each other: Work and family constraints among couples. *Journal of Marriage and Family*. 2016; 78(1):142–164. [PubMed: 26778856]
- Forgeard MJ, Jayawickreme E, Kern ML, Seligman ME. Doing the right thing: Measuring wellbeing for public policy. *International Journal of Wellbeing*. 2011; 1:79–106.
- Frenkel-Brunswick, E. Adjustments and reorientation in the course of the life span. In: Neugarten, BL., editor. *Middle Age and Aging*. Chicago: University of Chicago Press; 1968. p. 77–84.
- Gana K, Bailly N, Saada Y, Joulain M, Alaphilippe D. Does Life Satisfaction Change in Old Age: Results From an 8-Year Longitudinal Study. *Journals of Gerontology Series B-Psychological Sciences and Social Sciences*. 2013; 68:540–552.
- Harter JK, Gurley VF. Measuring health in the United States. *APS Observer*. 2008; 21:23–26.
- Jungaenel DU, Christodoulou C, Lai JS, Stone AA. Demographic correlates of fatigue in the US general population: Results from the patient-reported outcomes measurement information system (PROMIS) initiative. *Journal of psychosomatic research*. 2011; 71(3):117–123. [PubMed: 21843744]

- Kahneman D, Deaton A. High income improves evaluation of life but not emotional well-being. *Proceedings of the National academy of Sciences of the United States of America*. 2010; 107:16489–16493. [PubMed: 20823223]
- Kahneman D, Krueger AB, Schkade D, Schwarz N, Stone AA. Would you be happier if you were richer? A focusing illusion. *Science*. 2006; 312(5782):1908–1910. [PubMed: 16809528]
- Kahneman D, Krueger AB, Schkade DA, Schwarz N, Stone AA. A survey method for characterizing daily life experience: the day reconstruction method. *Science*. 2004; 306:1776–1780. [PubMed: 15576620]
- Krueger, A., Kahneman, D., Schkade, D., Schwarz, N., Stone, A. *Measuring the Subjective Well-Being of Nations: National Accounts of Time Use and Well-Being: National Time Accounting: The Currency of Life*. Chicago, IL: University of Chicago Press; 2009. NBER Working Paper No. c5053
- Krueger AB, Mueller AI. The lot of the unemployed: A time use perspective. *Journal of the European Economic Association*. 2012a; 10:765–794.
- Krueger AB, Mueller AI. Time Use, Emotional Well-Being, and Unemployment: Evidence from Longitudinal Data. *American Economic Review*. 2012b; 102:594–599.
- Krueger AB, Stone AA. Assessment of pain: a community-based diary survey in the USA. *The Lancet*. 2008; 371(9623):1519–1525.
- Kushlev K, Dunn EW, Lucas RE. Higher income is associated with less daily sadness but not more daily happiness. *Social Psychological and Personality Science*. 2015; 6(5):483–489.
- Lee Y, Hofferth SL, Flood SM, Fisher K. Reliability, Validity, and Variability of the Subjective Well-Being Questions in the 2010 American Time Use Survey. *Social Indicators Research*. 2016; 126(3):1355–1373. [PubMed: 27026752]
- Luhmann M, Schimmack U, Eid M. Stability and variability in the relationship between subjective well-being and income. *Journal of Research in Personality*. 2011; 45(2):186–197.
- Luttmer EFP. Neighbors as negatives: Relative earnings and well-being. *Quarterly Journal of Economics*. 2005; 120:963–1002.
- McFarland C, Ross M, DeCourville N. Women's theories of menstruation and biases in recall of menstrual symptoms. *J Pers Soc Psychol*. 1989; 57:522–531. [PubMed: 2778636]
- O'Donnell, G., Deaton, A., Durand, M., Halpern, D., Layard, R. *Wellbeing and policy*. London, UK: Legatum Limited; 2014.
- OECD. *OECD Guidelines on Measuring Subjective Well-being*. Paris, FR: OECD Publishing; 2013.
- Pampel FC, Krueger PM, Denney JT. Socioeconomic disparities in health behaviors. *Annual review of sociology*. 2010; 36:349–370.
- Ryff CD, Keyes CLM. The structure of psychological well-being revisited. *Journal of personality and social psychology*. 1995; 69:719–727. [PubMed: 7473027]
- Sacks DW, Stevenson B, Wolfers J. The New Stylized Facts About Income and Subjective Well-Being. *Emotion*. 2012; 12:1181–1187. [PubMed: 23231724]
- Santiago CD, Wadsworth ME, Stump J. Socioeconomic status, neighborhood disadvantage, and poverty-related stress: Prospective effects on psychological syndromes among diverse low-income families. *Journal of Economic Psychology*. 2011; 32(2):218–230.
- Scheibe S, Carstensen LL. Emotional aging: Recent findings and future trends. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*. 2010:gbp132.
- Schimmack, U. The structure of subjective well-being. In: Eid, M., Larsen, R., editors. *The Science of Subjective Well-Being*. New York: Guilford Press; 2008. p. 97-123.
- Schneider S, Stone AA. Distinguishing between frequency and intensity of health-related symptoms from diary assessments. *Journal of psychosomatic research*. 2014; 77(3):205–212. [PubMed: 25149030]
- Schwarz N. Self-reports. How the questions shape the answers. *American Psychologist*. 1999; 54:93–105.
- Schwarz, N. Why researchers should think "real-time": A cognitive rationale. In: Mehl, MR., Conner, TS., editors. *Handbook of research methods for studying daily life*. New York: Guilford; 2012. p. 22-42.

- Shelley KJ. Developing the American time use survey activity classification system. *Monthly Lab Rev.* 2005; 128:3–15.
- Shiffman S, Stone AA, Hufford MR. Ecological momentary assessment. *Annu Rev Clin Psychol.* 2008; 4:1–32. [PubMed: 18509902]
- Steptoe A, Deaton A, Stone AA. Subjective wellbeing, health, and ageing. *Lancet.* 2015; 385:640–648. [PubMed: 25468152]
- Steptoe A, Kivimaki M. Stress and cardiovascular disease. *Nat Rev Cardiol.* 2012; 9(6):360–370. [PubMed: 22473079]
- Steptoe A, Wardle J, Marmot M. Positive affect and health-related neuroendocrine, cardiovascular, and inflammatory processes. *Proceedings of the National academy of Sciences of the United States of America.* 2005; 102:6508–6512. [PubMed: 15840727]
- Stevenson B, Wolfers J. Subjective well-being and income: Is there any evidence of satiation? *The American Economic Review.* 2013; 103(3):598–604.
- Stiglitz, JE., Sen, A., Fitoussi, JP. Report by the Commission on the Measurement of Economic Performance and Social Progress (CMEPSP). 2009. <http://www.stiglitz-sen-fitoussi.fr/en/documents.htm>
- Stone, AA., Mackie, C. Subjective Well-Being: Measuring Happiness, Suffering, and Other Dimensions of Experience. Washington, DC: National Academies Press; 2014.
- Stone AA, Schwartz JE, Broderick JE, Deaton A. A snapshot of the age distribution of psychological well-being in the United States. *Proc Natl Acad Sci U S A.* 2010; 107:9985–9990. [PubMed: 20479218]
- Stone AA, Shiffman S. Ecological Momentary Assessment (EMA) in behavioral medicine. *Annals of Behavioral Medicine.* 1994; 16:199–202.

Fig 1. Age predicting Happy (left panel), Stress, Tired, Sad, and Pain (right panel).

Fig 2.
Income predicting Happy (left panel), Stress, Tired, Sad, and Pain (right panel).

Table 1

Frequency and average duration of WBM episodes and Frequency of ATUS episodes

Activity	N episodes in Wellbeing Module	N episodes in Wellbeing Module, weighted	Average Duration of Wellbeing Module Episodes, weighted (hours)
1. Personal Care	221 (1%)	182 (1%)	3.73
2. Household Activities	6,660 (19%)	5,331 (15%)	1.90
3. Caring for/Helping Household Members	1,990 (6%)	1,244 (3%)	1.31
4. Caring for/Helping Non-Household members	366 (1%)	445 (1%)	3.19
5. Work & Work-related Activities	2,529 (7%)	8,959 (25%)	4.80
6. Education	177 (1%)	540 (2%)	2.93
7. Consumer Purchases	1,447 (4%)	1,033 (3%)	1.42
8. Professional & Personal Services	213 (1%)	250 (1%)	1.85
11. Eating & Drinking	5,585 (16%)	3,125 (9%)	1.05
12. Socializing, Relaxing, Leisure	6,520 (18%)	9,708 (27%)	2.78
13. Sport, Exercise, Recreation	577 (2%)	732 (2%)	2.26
14. Religious & Spiritual Activities	434 (1%)	431 (1%)	2.16
15. Volunteer Activities	273 (1%)	425 (1%)	2.81
16. Telephone Calls	370 (1%)	232 (1%)	1.11
17. Traveling	8,574 (24%)	3,204 (9%)	0.81

Table 2

Descriptive statistics for the WBM questions

Question about an episode ^a	Mean (SD)	N _{episodes}	Skewness	Correlation ^b			
				Happy	Tired	Pain	Sad
Happy	4.33 (1.67)	36,226	-.96				
Tired	2.20 (1.99)	36,337	0.36	-.17			
Pain	.93 (1.68)	36,349	1.63	-.16	.36		
Sad	.66 (1.42)	36,340	2.29	-.29	.28	.36	
Stress	1.33 (1.78)	36,348	1.14	-.31	.36	.31	.47

Notes: From 0 to 6, where a 0 means you were not (happy/tired/sad/stressed/did not feel any pain) at all and a 6 means you were (very happy/tired/sad/stressed/in severe pain), how (happy/tired/sad/stressed/how much pain) did you feel during this time?

^aThe order of the first five adjectives was randomized by participant by the interview program.

^bCorrelations were determined using episode-level sampling weights; all correlations are significant at $p < .001$.

Table 3

Regression models predicting Happy, Stress, Tired, Sad, and Pain from Age (upper panel) and Log Income (lower panel). (F-values for the model, followed by regression coefficients for predictors.)

	Happy	Stress	Tired	Sad	Pain
Models for Age					
Model 1	F=24.22 ***	F=96.04 ***	F=29.41 ***	F=12.58 ***	F=46.48 ***
Age	-.0213 **	.0570 ***	.0152	.0220 **	.0357 ***
Age squared	.0003 ***	-.0007 ***	-.0002 **	-.0002 **	-.0002 **
Model 2	F=15.16 ***	F=28.29 ***	F=16.12 ***	F=14.07 ***	F=53.42 ***
Age	-.0332 ***	.0647 ***	.0179 *	.0380 ***	.0629 ***
Age squared	.0004 ***	-.0007 ***	-.0003 ***	-.0004 ***	-.0006 ***
Income	-.5305	.1288	1.3462 *	-.0141	.1116
Income squared	.0252	-.0070	-.0637 *	-.0041	-.0149
<i>Demographics^a</i>					
High education	-.0759	.1000	.0016	-.1044 *	-.1506 **
Disability	-.3897 ***	.4049 ***	.5763 ***	.4554 ***	1.2642 ***
Weekend	.2673 ***	-.4123 ***	-.1447 **	-.0532	.0392
Female	-.0822	-.1546 **	-.3733 ***	-.0494	-.1119 *
Married	.1868 ***	-.1073	.0682	-.0791	-.0191
Model 3	F=20.21 ***	F=29.05 ***	F=10.74 ***	F=11.20 ***	F=25.68 ***
Age	-.0273 ***	.0481 ***	.0154	.0368 ***	.0614 ***
Age squared	.0003 ***	-.0006 ***	-.0003 ***	-.0003 ***	-.0006 ***
Income	-.3799	-.0894	1.2582 *	-.0886	.0792
Income squared	.0189	.0010	-.0598 *	-.0001	-.0134
<i>Demographics^a</i>					
High education	-.0769	.0579	.0011	-.0986 *	-.1448 **

	Happy	Stress	Tired	Sad	Pain
Models for Age					
Disability	-.4116 ***	.5076 ***	.5633 ***	.4412 ***	1.2301 ***
Weekend	.1641 ***	-.1384 ***	-.0897	-.0281	.0473
Female	-.0696	-.2047 ***	-.3767 ***	-.0596	-.1079 *
Married	.1625 ***	-.0812	.0717	-.0564	-.0124
<i>Activities^b</i>					
Personal care	-.9346 **	-.1011	1.3981 ***	.6991 **	1.8052 ***
Household	.1343	-.10827 ***	-.0609	-.1472 *	.1047
Caring/Help HH	.9608 ***	-.12883 ***	-.1553	-.4063 ***	-.2553 ***
Caring/Help Non	.7926 ***	-.8167 **	-.1667	.0484	.1834
Education	-.3612	.0720	.0867	.1180	-.0325
Purchases	.2952 **	-.8355 ***	-.5211 ***	-.2493 **	-.1704
Prof Services	-.4145	-.1097	-.1301	.2076	.6372 *
Eating/Drinking	.6781 ***	-.13187 ***	-.4084 ***	-.2634 ***	-.1018
Social/Leisure	.4229 ***	-.13113 ***	-.1800 *	-.0643	-.0469
Sport/Recr	.6959 ***	-.14196 ***	-.2353	-.2951 ***	.3486 **
Religion	1.0826 ***	-.15585 ***	-.9540 ***	-.0175	-.3091 *
Volunteer	.6678 ***	-.9351 ***	-.5196 *	-.4053 **	-.1394
Telephone	.5526 ***	-.8099 ***	-.2453	.0942	.1860
Traveling	.3536 ***	-.9221 ***	-.1524 *	-.1351 **	-.1539 ***
Unable to code	.6252 ***	-.7836 ***	-.2208	-.0455	.1106
Income (log)					
Model 1	F=0.06	F=0.70	F=1.29	F=25.19 ***	F=62.02 ***
Income	-.1071	-.5761	.8389	.0037	.1180
Income squared	.0053	.0279	-.0404	-.0071	-.0196

Note: Unit of analysis is episode and BLS activity weights are applied. Standard errors are based on clustered estimates, vce(cluster ID).

Sample sizes for Age are between 12,222 and 12,240 and for Income between 11,703 and 11,721.

^d Demographic control variables (all 0–1 coded) were: education at the Associate degree level or above; age 60 years and older; presence of self-report disability; weekend day of reporting; and, being married.

^b Activities were dummy variables for 16 activities, including a category of “not coded” activities, based on the BLS Tier 1 coding of activities. “HH” means household members. “non” means non-household members. “Rec” means recreation. Reference activity category is “Work.”

* p<.05
** p<.010
*** p<.001