American Time Use Over the Business Cycle

Ryan D. Edwards*

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Abstract

Macroeconomic fluctuations clearly alter the time allocations of workers who enter or leave employment as a result. Working and job search move in opposite directions, as do working and leisure. The advent of detailed time use surveys has facilitated more detailed examination of time use following job loss, and researchers have recently uncovered many more subtle effects of being unemployed on time use and on well-being. In this paper, I explore the broader impacts of macroeconomic fluctuations on time use among all consumers using the 2003–2007 waves of the American Time Use Survey (ATUS). Business-cycle variation in the prices of time and assets should in theory affect the time use of all consumers whether they are employed or not, and I find evidence that it does. All consumers report less sleeplessness when unemployment is high, more time spent caring for the elderly, and more time talking on the telephone. Sleeping, socializing, and traveling also rise on average, but the channel through which aggregate unemployment exerts these effects appears to be individual-level job loss. These results shed new light on the channels through which macroeconomic fluctuations affect health and well-being.

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*PRELIMINARY. Please do not quote. Assistant Professor of Economics, Queens College and the Graduate Center, City University of New York, and NBER. Mailing Address: Powdermaker 300, 65-30 Kissena Blvd., Flushing, NY 11367. redwards@qc.cuny.edu.

1 Introduction

Macroeconomists are interested in the causes and consequences of business cycles according to a tradition dating back at least to Keynes (1936). But during the last few decades, the focus of academic research in macroeconomics has shifted toward growth and away from fluctuations (Mankiw, 2006) for a variety of reasons, one of them being the view attributable to Lucas (1987, 2003) that the cost of business cycles is low.

Recently, some of the most interesting contributions on the impacts of business cycles have originated in labor and health economics. Some of these studies track individual cohorts, who tend to exhibit lasting negative impacts of business-cycle downturns. Oreopoulos, von Wachter and Heisz (2006) reveal significant impacts on wages of entering the labor market during a recession that die out relatively slowly, especially for low-skill workers. Sullivan and von Wachter (2007) trace similarly persistent adverse impacts on mortality following mass layoffs.

A rich literature that examines the dynamics in population health finds exactly the opposite kind of effect, namely temporary benefits from economic downturns spread across many individuals as opposed to long-lasting costs concentrated among job-losers. Ruhm (2000, 2003, 2007, 2008), Neumayer (2004), Tapia Granados (2005, 2008), and others have revealed patterns of mortality trending downward along with economic activity, so that population health improves during recessions. The epidemiology of the phenomenon suggests a role for reduced job stress and the unhealthy behaviors induced by stress, as well as for reduced traffic fatalities and air pollution. The broad-based incidence of the phenomenon (Edwards, 2008*b*), in particular at ages when labor force participation is low, raises lingering questions about transmission channels.

Recent efforts have made available a wealth of new microdata that have the potential to shed much light on the impacts of business cycles on behavior and well-being, and potentially on the connection between business cycles and health in particular. A previously untapped resource in this regard is the broad-based American Time Use Survey (ATUS), a repeated cross section of individuals in U.S. households conducted every year since 2003. Although the ATUS currently covers a relatively short time period, there still appears to be much identifying variation in the dataset. Following the collapse of the first technology bubble and the events of 9/11, U.S. unemployment peaked in June 2003 and receded. There is also considerable geographic variation in unemployment across state of residence, which the ATUS data identifies.

To my knowledge, this study is the first to examine business-cycle fluctuations in time use as broadly measured by the ATUS. Ahn, Jimeno and Ugidos (2005) study the impacts of employment status on time use and consumption among Spanish households. Similarly, Krueger and Mueller (2008*b*) examine differences in time use by labor force status in a cross section of countries including the U.S., finding significant differences in the amount of sleep, in home production, caring for others, and in socializing. Krueger and Mueller (2008*a*) focus on job search intensity among the unemployed in the ATUS. Although similar to these earlier efforts, this study examines how time use across all individuals responds to business cycle fluctuations rather than to individual job loss per se. As I will show, the two concepts are related and overlap to some degree, but there are distinct effects of each.

My results indicate that all consumers, regardless of their labor force attachment, report less sleeplessness, more time spent caring for the elderly, and more time talking on the telephone when unemployment is high. There are similar effects of macroeconomic conditions on sleeping, socializing, and traveling, but the channel through which aggregate unemployment exerts these effects appears to be individual-level job loss. These results shed new light on the channels through which macroeconomic fluctuations affect health and well-being and suggest continued investigation will prove fruitful.

The paper is laid out as follows. Section 2 briefly discusses a theoretical framework for thinking about macroeconomic fluctuations and time use and proposes a testing framework. Section 3 introduces the ATUS and presents some sample averages. In section 4, I present results using Tobit estimation of minutes of daily time use in 31 functionally interesting categories. Section 5 discusses the implications of these results and offers concluding remarks.

2 Theory

Per Becker (1965), I begin with the assumption that individuals in households combine purchases of market goods, $\vec{x}$, with time allocations $\vec{y}$ to produce commodities $\vec{z}$ that produce utility when consumed. A reduced form equation for the optimal time spent on activity k by individual i is

$$y_i^k = f_i^k(w_i, A_i, \vec{p}_x, \vec{\theta}_i). \tag{1}$$

where w is the wage rate, A is the value of assets, $\vec{p}_x$ is a price vector of market goods, and $\vec{\theta}$ is a vector of preferences.

The signs of the partial derivatives of $f^k(\cdot)$ depend on the nature of the activity. When y^k is market work, there are well-known income effects associated with A and $\vec{p}_x$ and substitution and income effects associated with w. Activities that are complementary with market goods in commodities production, such as vacation travel, should increase with income; activities that substitute for market goods, like cleaning or maintenance, probably decrease with income. Effects of changes in the wage are somewhat more complicated to trace because they typically involve both income and substitution effects.

Individual unemployment is a corner solution where either the market wage w is so low as to reduce optimal work effort to zero, or where market imperfections prevent earning the market wage at all. In either case, a parsimonious representation of individual unemployment is a dummy variable $E_i = 0$ when the individual is unemployed and 1 otherwise, interacted with the wage:

$$y_i^k = f_i^k(E_i \cdot w_i, A_i, \vec{p}_x, \vec{\theta}_i). \tag{2}$$

Recessions can affect consumers in three possible ways: they can become unemployed, their wages can fall, and their assets can lose value. Recent work in macroeconomics suggests that real wages are indeed procyclical, especially when measured as annual compensation divided by annual hours (Swanson, 2007). One interpretation of this dynamic is that during a recession, additional work effort by salaried workers is not rewarded by bonuses, either ex ante or ex post. A challenge to confront in estimating the effects of the business cycle on time use is that a macroeconomic shock could easily operate through all three channels simultaneously, and the first two are closely related.

Although surveys measure wages at the state and individual level, observed wages are not equivalent to the w_i that enters equation (1) due to selection problems. As a result, economists traditionally view the unemployment rate as a better measure of labor market conditions, and I will use unemployment to proxy for w_i. A testable version of equation (2) is

$$y_{it}^k = \alpha_s + \gamma^k \cdot urate_{st} + \lambda \cdot E_{it} + \delta^k \cdot sp500_t + \vec{\beta}^k \cdot \vec{X}_{it} + \epsilon_{it}^k \tag{3}$$

where α_s is a fixed effect for individual i living in state s, $urate_{st}$ is the unemployment rate in s at time t, E_{it} is an indicator variable for being employed, $sp500_t$ is the detrended level of the S&P 500 index of stock prices, $\vec{X}_{it}$ is a vector of characteristics that proxy for preferences and wealth, and $\epsilon_{it}^k \sim N(0, \sigma^2)$ is a white noise error.[1] About half of American households hold stock either directly or indirectly (Bucks, Kennickell and Moore, 2006), making the S&P 500 index a reasonable although far from ideal indicator of assets. I discuss the time use dataset and its limitations at greater length in the next section.

As shown by Ahn, Jimeno and Ugidos (2005) and Krueger and Mueller (2008*b*), the employment indicator E_{it} certainly explains much of the variation in time use. The problem for present purposes is that E_{it} is surely itself a function, here shown as a probit model, of the macro unemployment rate and other covariates:

$$Prob[E_{it} = 1] = \Phi\left[a + b \cdot urate_{st} + \vec{c} \cdot \vec{X}_{it}\right]. \tag{4}$$

Ignoring this problem could potentially lead to a type II error in testing $\gamma^k = 0$ in equation (3). If the macro shock were to change time use solely by changing employment status, one could easily fail to reject $\hat{\gamma}^k = 0$ while overlooking $\hat{b}$.

There are two ways of addressing this issue of the endogeneity of employment status in equation (3). One could run a two-step procedure in which equation (4) is estimated first, or one could simply drop employment status from equation (3). The two-step procedure is only identified if there are covariates the employment status equation that are excluded from the time use equation. Unfortunately, it is not obvious what variables belong in (4) but not in (3). Dropping employment status from equation (3) is certainly reasonable to the extent that *urate* is the truly exogenous treatment while E is endogenous. But omitted variable bias may arise if E actually contains other information missing from $\vec{X}$.

My strategy will be to compare results from estimating (3) with employment status dummies to estimates of my preferred equation without them:

$$y_{it}^k = \alpha_s + \gamma^k \cdot urate_{st} + \delta^k \cdot sp500_t + \vec{\beta}^k \cdot \vec{X}_{it} + \epsilon_{it}^k. \tag{5}$$

[1] I omit year fixed effects because including them washes out practically all impacts of the macroeconomic variables on time use. Identification presumably draws heavily on temporal variation over the single business cycle captured in the pooled dataset. Since the time use data are collected across all twelve months, I tested whether results changed significantly when I included month dummies to correct for seasonality. Results were not appreciably affected.

If the other regression coefficients besides γ^k do not change much when E is added as a covariate, I will infer that omitted variable bias is minimal. If γ^k becomes insignificant after including E, the natural interpretation is that the macroeconomic shock affects time use through individual employment.

As I discuss in the next section, time use data exhibits significant response pooling at zero minutes for many activities. I utilize the Tobit specification for regressions with truncated data, where y^k is given by equation (5) and the observed time use is

$$y^{k*} = \begin{cases} y^k & \text{if } y^k > 0, \\ 0 & \text{if } y^k = 0. \end{cases}$$

Although the behavioral coefficients in equation (5) are interesting, I will focus on the partial derivatives of $E[y^{k*}]$ and of the probability of y^k being uncensored. The former is the answer to the question of how much observed time use actually changes with a one percentage point rise in unemployment, while the latter is revealing of the intensive versus extensive margins of behavior (McDonald and Moffitt, 1980).

3 Data

3.1 The ATUS

The American Time Use Survey, conducted annually since 2003 by the Census Bureau, offers the broadest look at U.S. time allocation at high frequency. Respondents are drawn from outgoing rotations of the Current Population Survey and are reinterviewed for the ATUS 2–5 months later. ATUS datasets contain links to the CPS characteristics of the individual and the household, including labor force status, income, and state of residence.

Like the CPS, the ATUS is designed to be representative of the civilian noninstitutional population aged 15 and older. The Census Bureau provides sample weight designed to account for oversampling of certain subgroups and of weekend days, and for differential response rates. All reported statistics in this paper use the recommended sample weights for all waves in the analysis.

Time use data is collected via a telephone interview that follows notification by mail. The mailing includes a brochure explaining the nature of the questions. During the call, interviewers ask respondents to characterize their activities during a 24-hour period called the "diary" day starting at 4

AM the previous day and ending at 4 AM on the interview day. The unit of observation is the individual, although interviewers also ask about other participants in activities. Respondents are never asked to complete a written time diary; conversational interviewing techniques are employed to guide respondents in a nonleading way through memory loss and vague answers.

ATUS data is packaged into minutes of time spent during the diary day on particular activities. There are 17 major categories of activity, each of which has perhaps 5 subcategories further divided into specific examples. At the lowest level of disaggregation, the ATUS measures 400 distinct activities. A sign of the considerable influence wielded by the ATUS interviewers is the fact that no observations report more than the maximum 1440 minutes in daily time use. Only 12 percent of the records over the 5 sample years contain less than 1440 minutes.

Table 1 reports the average minutes reported spent on 31 functionally interesting activities tabulated by group characteristic. I have chosen activity classes that are likely to be interesting over the business cycle and omitted standard errors in Table 1 to enhance readability. The first column shows averages over all observations, the second and third explore average time use across males and females respectively, and the fourth through sixth columns present averages conditional on labor force status. The most interesting comparisons are between columns rather than within.

Table 1 about here

Sleeping is the longest single activity for all groups, with total sleep time averaging over 8 hours for each. But as remarked by Krueger and Mueller (2008*b*), the unemployed seem to enjoy significant increases in time spent sleeping. Sleeplessness is short on average, although the mean of only about 3 minutes obscures considerable variation in incidence across individuals as we will see later. The group most afflicted by sleeplessness in Table 1 is those who are out of the labor force, and not the unemployed, a pattern that can be explained by the positive correlation of sleeplessness with age.

Time spent on housework, food and drink preparation, and other household production activities are carried out in longer duration by females and those who are not employed. The same is true of time used in care for children and adults.

To little surprise, minutes of market work reveals the opposite pattern, while informal work and job search, though both rare, are longer among the unemployed. Minutes spent on education, which can include class time, extracurriculars other than sports, and homework, are relatively high even among the employed but are more numerous among the unemployed and those out of the labor force.

It is difficult to detect patterns across the columns in time spent on consumer research and purchases or using services of any variety, but some small differences exist. Use of medical services is significantly higher among those not in the labor force, again reflecting the effect of an older age distribution. Time spent using and performing government and services is significantly longer among the unemployed. This category includes using social services but also performing civic obligations like jury duty.

The most notable differences in the bottom cluster of activities are visible in the time spent on socializing, relaxing, and leisure. As reported by Ahn, Jimeno and Ugidos (2005) and Krueger and Mueller (2008*b*), the unemployed spend considerably more time on leisure activities, more than half again as much as the employed in Table 1. Those not in the labor force spend even more time on leisure, as retirement should entail. The unemployed also spend more time exercising, telephoning, and traveling. Travel related to work or job search is significantly more common among the employed.

To the extent that recessions make people unemployed, these cross-sectional results suggest that recessions should increase time spent on sleeping, household production, care arrangements, job search, education, socializing, exercise, and telephoning, while they decrease time spent working and traveling related to work. But Table 1 tells us nothing about the causal effect of macroeconomic shocks on time use, which could be very different depending on the strength of selection into unemployment. It also cannot inform us about any changes in behavior induced by macroeconomic shocks that are unrelated to changes in employment status. To examine further, I next turn to multivariate regression analysis.

3.2 Unemployment and stock prices

The Bureau of Labor Statistics collects and distributes unemployment rates by state and month, which I match to the ATUS data through the CPS link to state of residence combined with the month of the time use interview. I experimented with seasonally versus not seasonally adjusted unemployment rates and found there to be no difference in regression results.

For a rough indicator of the level of assets, I examine the S&P 500 stock index, which is reported at the monthly frequency in the annual *Economic Report of the President*. Unlike the unemployment rate, the S&P 500 is highly nonstationary, while time use does not appear to be. I detrended the monthly S&P 500 using the popular filter proposed by Hodrick and Prescott (1997) with the smoothing parameter set to 129,600 as recommended by Ravn and Uhlig (2002). Results using the monthly percent change in the index were similar but less precise. In theory, behavior should respond to unexpected changes in the level of wealth, or exactly what a detrended series will capture.

4 Time use Tobit regressions

4.1 All individuals

Using pooled observations from all five years of the ATUS, I first estimate equation (5) separately for each category of time use listed in Table 1. The state unemployment rate and the level of the detrended S&P 500 are both exogenous to the individual, so they should reveal the causal effects of macroeconomic shocks on average time use behavior conditional on the other covariates. The latter include sex, race, ethnicity, age, age-squared, marital status, log family income, education, whether the diary day is a weekday, and state fixed effects. As I discussed earlier, I do not control for employment status in my initial specification because it is causally linked to the unemployment rate and will dilute its estimated effect. All regressions are run using survey weights and clustering at the state level.

4.1.1 Unemployment rate effects

The leftmost panel of Table 2 displays two types of marginal effects of the unemployment rate on time use. The left column shows the estimate, standard error, and significance level of the marginal effect on observed minutes of time use, while the right column shows the marginal effect on the probability of positive (uncensored) time use.[2] The middle panel of Table 2 depicts the same marginal effects for the S&P 500. The third panel lists mean time

[2] These are not the Tobit coefficients $\hat{\beta}_j$ on the latent variable that we assume determines observed time use. The latent variable, which could easily be and frequently is negative, and the marginal effect of a covariate on it are typically not of direct interest. The two

use conditional on positive time use and also the probability of positive time use. These are interesting in their own right and are useful for decomposing the marginal effects on observed time use into intensive and extensive effects per McDonald and Moffitt (1980). The next panel presents the share of the marginal effect on time use that is attributable to participation. The last panel shows estimates of the regression error σ and its standard error. Each regression has a sample size of 63,392.

Table 2 about here

Seventeen of the 31 coefficients in the first panel of Table 2 are statistically significant at the 10% or lower level. Of these the most interesting are the coefficients on sleep, adult care, socializing, telephoning, and traveling. An rise of one percentage point in the unemployment rate is estimated to increase daily sleep by 2.06 minutes and reduce sleeplessness by 1.16 minutes. It also raises the time spent caring for adults by 0.47 + 1.20 = 1.67 minutes, expands time spent socializing by 3.68 minutes, raises telephone time by 0.45 minutes, and increases time spent traveling by 0.83 minutes. We also see significant decreases in time spent working or traveling to or from work when unemployment rises, as well as an increase in job search. Miscellaneous household activities, such as caring for pets and maintaining appliances or vehicles, fall 0.83 minutes with a one-point increase in unemployment.

The second column of coefficients in the first panel reveals marginal effects on the probability of nonzero time use participation, which could also simply reflect reporting. A one percentage point rise in the unemployment rate reduces the probability of reporting any sleeplessness by 1.3 percentage points, which is large relative to the total sample probability of 4 percent. Effects on the probability of engaging in adult care are also large, between 0.8 and 1.4 depending on their physical relationship to the household compared with total probabilities of 5.8 and 9.2 percent. Marginal changes in probability for other activities are generally smaller in an absolute sense, except

marginal effects I report are transformations of $\hat{\beta}_j$:

$$\begin{aligned} \partial E[y^{k*}]/\partial x_j &= \hat{\beta}_j \cdot \Phi[\hat{\bar{z}}^k] \\ \partial \Phi[\hat{\bar{z}}^k]/\partial x_j &= \hat{\beta}_j \phi[\hat{\bar{z}}^k]/\hat{\sigma} \end{aligned}$$

where Φ is the standard normal cdf, ϕ is its pdf, and where $\hat{\bar{z}} = \hat{\beta} \cdot \bar{X}/\hat{\sigma}$, the transformed fitted value at the mean.

for the effect on working, and they are also smaller relative to the activities' overall frequencies.

Per McDonald and Moffitt (1980), the portion of the marginal effect on observed time use attributable to changes in participation or reporting is the marginal change in the probability of nonzero time use times the mean time use conditional on being nonzero. As a share of the total effect, this is naturally quite low in the case of extremely common activities like time spent sleeping, where the share is only 0.1 percent, as shown in the fourth panel. But for sleeplessness, a rare activity found in only 4 percent of the pooled observation, changes in participation represents almost 90 percent of the total effect. That is, rises in unemployment lower average sleeplessness primarily by eliminating it entirely.

Participation accounts for about two thirds of the effect on adult care, which is also relatively uncommon, and 80 percent of the effect on telephoning, which only 15.4 percent of the sample reports doing. To little surprise, participation accounts for practically the entire responses for both working, which is of course quite common, and job search, which is not. Socializing and traveling are interesting because they are both relatively common but they are also both significantly affected by increased participation. A quarter of the effect on socializing comes through the extensive margin, while about 40 percent of the effect on traveling does.

These results suggest that for the average consumer, a rise in the unemployment rate does not appreciably increase home production except the care of adults inside and outside the household. Rather, unemployment improves the amount and quality of sleep, increases time spent socializing both in person and over the phone, and increases travel. Decomposition analysis suggests much of the effects of higher unemployment come through new participation: a lack of sleeplessness, and time spent caring for adults when before there was none.

4.1.2 Wealth effects

The second panel in Table 2 displays marginal effects of the detrended S&P 500 on time use. I divided the detrended index level by 100, which is roughly equal to a standard deviation, in order to bring coefficient magnitudes in line with the unemployment results. To the extent that both unemployment and stock prices may be perfectly negatively correlated indicators of the business cycle,[3] we might expect to find similar coefficients simply with reversed sign. In fact, we find substantially different results in the second panel compared to the first.

Sleeping increases significantly when the S&P is above trend, by 4.55 minutes for every 100 points. Time spent on exterior maintenance declines by 2.41 minutes, and time spent working declines by 6.27 minutes. Use of professional services rises a little, while socializing rises a lot, 4.19 minutes. Watching sports actually declines slightly while religious activities and volunteering rise by less than a minute each, all primarily due to participation effects.[4] Finally, traveling related to work declines in tandem with time spent working.

These results are generally consistent with an interpretation of the S&P 500 as distinctly representing wealth as opposed to the wage rate. Time spent sleeping or socializing rises, which is consistent with a pure income effect raising expenditures on leisure. One major form of home production, exterior maintenance, falls when the S&P rises, as does time allocated to market work. Religious activities may be like socializing, or they may be similar to time bequests like volunteering; both rise with increased wealth.

4.1.3 Employment status

In Table 3, I rerun the regressions in Table 2 after inserting dummy variables for labor force status on the right-hand side. Comparing the two tables should indicate the extent to which variation in average time use attributable to the macroeconomic unemployment rate operates through changes in individual-

[3]Detrended stock prices and the unemployment rate are basically uncorrelated in the dataset (Pearson coefficient = 0.01), and display only weakly negative correlation (-0.18) in annual data since 1949.

[4]The share of the effect on observed minutes attributable to participation is exactly the same as it was for unemployment. This seemingly odd result obtains because all marginal effects are evaluated at the same sample average, where the probability density normed by σ is the same. Mathematically, the share of the marginal effect attributable to participation reduces to

$$\frac{\partial\Phi[\hat{\bar{z}}^k]/\partial x_j \cdot \Phi[\hat{\bar{z}}^k]}{\partial E[y^{k*}]/\partial x_j} = \frac{\hat{\beta}_j \phi[\hat{\bar{z}}^k]/\hat{\sigma} \cdot \Phi[\hat{\bar{z}}^k]}{\hat{\beta}_j \cdot \Phi[\hat{\bar{z}}^k]} = \phi[\hat{\bar{z}}^k]/\hat{\sigma}.$$

Intuitively, any regressor changes both the latent variable and thus the probability of time use being nonzero by its own β_j, so β_j drops out of the ratio of the two marginal effects, which ultimately depends only on the probability density at the sample average and on $\hat{\sigma}$.

level employment status. If macroeconomic shocks do nothing but move people into and out of employment, there should be no independent effect of the unemployment rate on time use once I have controlled for labor force status. Stock prices could in theory affect employment too, but we have already seen how these influences are basically orthogonal in the data.

Table 3 about here

Compared to its counterpart in Table 2, the first panel of Table 3 reveals that several impacts of unemployment on time use derive solely from changing individual employment status. The coefficient on sleeping falls almost in half and becomes insignificant, as does the coefficient on socializing. Coefficients on working and job search fall virtually to zero; there are apparently no detectable changes in actual hours spent working or searching for a new job among those who remain employed during a recession, although work effort could certainly be different.

Coefficients on sleeplessness, adult care, and telephoning hardly change at all, nor do their high degrees of significance. These effects of unemployment appear to change time use for all consumers regardless of employment status. Several other coefficients continue to display statistical significance but remain economically small. Miscellaneous household activities still fall significantly during recessions, perhaps because reduced car travel entails less maintenance time.

As expected, the coefficients and standard errors in the second panel, which shows the marginal effects of stock prices, are essentially unaffected by the inclusion of controls for labor force status. The small attenuation of the coefficient on working fits easily within one of its standard errors.

4.2 Subgroups

4.2.1 By employment

To further explore the phenomenon, I ran separate Tobit models on subgroups defined by labor force status and then by sex.[5] Table 4 examines differences in the marginal effect of the unemployment rate on time use across

[5]As pointed out by Ai and Norton (2003), standard maximum likelihood estimates of interaction effects in nonlinear models like the logit, probit, and the Tobit are not necessarily equal to their true marginal effects. As of this writing, no convenient method for computing and testing interaction terms in a Tobit model is available, although it is theoretically feasible.

employment status, which is shown along the three columns, each of which is a separate Tobit regression. To be sure, the endogeneity of employment status means that we should interpret these estimates with much caution.

Evidence of the selection bias is apparent in the first row of coefficients on sleeping, which are volatile and highly imprecise. These patterns are consistent with earlier findings that suggest it is becoming unemployed that increases time sleeping. Coefficients on sleeplessness, by comparison, are precisely estimated across all three columns and reveal reductions for all groups during recessions that may be somewhat more concentrated among groups not in the labor force.

As in earlier results, home production activities seem to be relatively unaffected by the unemployment rate. What responses there may be seem to be concentrated among individuals not in the labor force. The sign on the largest and most significant effect, on miscellaneous household activities, is again inexplicably negative.

Increases in adult care with higher unemployment can be seen among all three groups, although they are insignificant among the small group of unemployed. Large standard errors on other coefficients hamper much further inference.

4.2.2 By sex

Table 5 examines differences in effects by sex, which is not an endogenous variable. Sample sizes are large and standard errors are more comparable to those in Tables 2 and 3. The left panel presents marginal effects of the unemployment rate on time use in separate Tobit regressions by sex, while the right panel shows marginal effects of stock prices by sex from the same Tobit regressions.

Sleeplessness rises with unemployment for both sexes, but sleeping rises significantly only among females. This is interesting in light of the earlier result suggesting a relationship between sleeping and becoming unemployed, but it does not appear to be the case that females are overrepresented among the unemployed. Sleeping increases rather strongly with stock prices among males but not females.

For that matter, barely any time uses among females respond significantly to stock prices. The exceptions are exterior maintenance, which declines; interior maintenance, which oddly rises; and traveling related to work, which declines. Men seem to be more impacted by the stock market than are women; men spend more time caring for adults, they work less, and they socialize more when stocks are above their trend.

There are some signs in the left panel that the unemployment rate may increase household production at least among females. This is consistent with theory, but varying signs preclude firm conclusions. Care of adults is strongly associated with the unemployment rate for both sexes, as is working and for men, job search. Large standard errors in the socializing regressions reduce significance, but coefficients are still positive and relatively large. Telephoning appears to be a recession activity carried out relatively more by females.

5 Discussion

Patterns of time use over the recent U.S. business cycle reveal interesting responses of behavior to the unemployment rate and to stock prices. Increases in aggregate unemployment put some consumers out of work, which drastically changes time use, but they also lower real wages and the price of time for the average consumer. Increases in stock prices raise wealth for the roughly half of households who own stock either directly or indirectly. Both types of effects should affect time use in theory, and indeed I find empirical evidence that they do.

5.1 Time use and the unemployment rate

Activities that are most significantly affected by a rising unemployment rate include increased sleeping, decreased sleeplessness, and increased care of adults, socializing, telephoning, and traveling. As we might expect, time spent working declines when unemployment rises, as does related travel, while job search rises. The effects on working and job search operate exclusively on the extensive margin; the macro-level unemployment rate only affects such time use through individual unemployment. Actual hours of work do not change appreciably for those who do not lose their jobs, although work effort may change.

Effects of the business cycle on sleeping are also channeled through individual unemployment, but the same is not true of sleeplessness. Everyone seems to sleep better, if not necessarily longer, when the unemployment rate is high. This seems counterintuitive to the extent that the unemployment rate signals macroeconomic malaise that could cause worry, stress, and sleeplessness. But it could also be the case that periods of high unemployment dampen economic activity and thus require less work effort, stress, and sleeplessness. That sleeplessness falls with unemployment even among the unemployed is suggestive that job stress is more important for sleeplessness than anxiety about the economy.

Except for adult care, traditional home production activities seem to be largely acyclical except possibly among women, which is somewhat surprising. The relative dissonance of these results with those of Ahn, Jimeno and Ugidos (2005), who study the unemployed in Spain, might be explained by the more temporary nature of U.S. unemployment shocks. American households may not significantly reorient their household production in response to short-lived shocks.

That adult care increases with unemployment is therefore remarkable and may reflect the similarity of adult care with socializing, another activity that rises with the unemployment rate. In the case of the latter, a large amount if not all of the increase is accounted for by the transition into unemployment, much as with sleeping. But adult care, telephoning, and travel all rise during periods of high unemployment regardless of labor force status, just like how sleeplessness falls for everyone. Increases in adult care and telephoning are primarily due to increases in participation. If it reduces job effort, a rising unemployment rate may increase individuals' feelings of having the energy to engage in adult care or using the telephone. Since the ATUS does not include expenditure data, it is unclear whether increased time spent on adult care may be substituting for market purchases of adult care, whose relative price rises as the wage falls.

5.2 Time use and stock prices

We also expect time use to change with financial wealth, which fluctuates over the business cycle, and the ATUS reveals some dynamics along this dimension as well. The complete orthogonality in the current data between the detrended S&P 500 index and the unemployment rate is not historically uncommon, and it helps identify unique effects of both on time use.

Men sleep longer when the stock market is higher, and women appear to spend somewhat less time in home production. Time spent working declines strongly among men, as does their travel related to work, while their socializing increases. Oddly, time spent by men watching sports actually declines with stock prices; perhaps sports are best watched as a distraction from bad news. Religious activities and volunteering increase, which is consistent with magnanimity being positively influenced by wealth.

5.3 Questions and interpretations

Although revealing, the present study is limited by the nature of the ATUS dataset. Although ground-breaking in its focus, the ATUS is a relatively short repeated cross section with limited information on outcomes of interest other than work and time use.

The ATUS currently covers at most one business cycle, from the recovery following the trough in 2001 to the peak that will probably be dated to have occurred in 2007. The dataset also includes several observations in states struck by Hurricane Katrina, which caused very large spikes in unemployment, but I must naturally remain circumspect about the robustness of my conclusions here. Time use over the business cycle in general may be different than time use over this particular business cycle.

A second limitation is that we cannot tell from these data how fluctuations in time use associated with the business cycle may ultimately affect well-being. Krueger and Mueller (2008*b*) examine a sister dataset, the Princeton Affect and Time Survey, which asks about subjective well-being directly, but it was only conducted during one calendar year. Similarly, the ATUS included an eating and health module but only during one year, the 2006 wave. Establishing the link between the business cycle, time use, and outcomes awaits further study.

What we know from this study are the size of the effects on time use. At first glance, they seem neither extremely large nor microscopic. But when the extensive margin is important, small average effects on time may understate the phenomenon. If the impact on outcomes were a convex function of time use, small average effects on time use could be very meaningful for average outcomes. In the case of sleeplessness, the one minute decrease in average sleeplessness attributable to a one percentage point increase in the unemployment rate masks considerable heterogeneity. The 1.3 percent fewer Americans who experience an average of 79.3 minutes of sleeplessness seem likely to be considerably helped by it. Increased participation in adult care when the unemployment rate rises is a similar example. The 2.2 percent of dependent adults who newly receive between 40.2 and 56.3 minutes of care probably experience significantly improves outcomes.

Reduced sleeplessness and increased direct care of seniors appear to be two dimensions of direct relevance for outcomes, especially those involving health. An additional dimension of interest related to the latter seems to be that of expanded interactions with social networks when the unemployment rate is high. To be sure, the effect of the business cycle on socializing per se appears to be largely channeled through individual unemployment, which probably also extracts costs. But adult care and telephoning both increase for employed and unemployed alike. There has been much interest regarding the role of social networks in promoting good health (Seeman, 1996). Social networks improve mental health in fairly obvious ways, but they can also affect physical health through reducing stress or reinforcing healthy behavior.

The evidence presented here is certainly suggestive of a role for increased sleep, reduced sleeplessness, and increased social interaction in fostering the improvement in average health outcomes during recessions (Ruhm, 2000, 2003, 2007, 2008; Neumayer, 2004; Tapia Granados, 2005, 2008). An odd result is that exercise does not seem to rise with unemployment in the ATUS, while Ruhm (2000) found significant increases in exercise in data from the Behavioral Risk Factor Surveillance System. I have not examined the mode of travel in the ATUS, which could be active transport, but this is unlikely given U.S. travel modes (Edwards, 2008*a*).

The broader implications of this study seem to be that a rising unemployment rate, while certainly not costless especially to those who lose their jobs, appears to exert many neutral and even some beneficial influences on time allocation. There is relatively little evidence of large, wrenching shifts by consumers into home production. Quantity and quality of sleep appear to increase when unemployment rises, presumably because work effort slackens, reducing stress and worry. Elder care expands, possibly because consumers have more energy or are interested in greater social interaction. Socializing, either in person or over the telephone, increases.

While this is all certainly not to say that policymakers should intentionally steer the economy into recession, these provocative results suggest that we may gain by reassessing the character of our work-life arrangements. If it takes a recession to get us to sleep better and interact with others, why are we working so hard? Although the current results are loosely consistent with rational choice in time use, where market work yields to home production when the price of time declines, they are also consistent with a culture of putting work effort before social effort and health, which does not seem particularly time consistent.

References

Ahn, Namkee, Juan F. Jimeno and Arantza Ugidos. 2005. Mondays at the sun: Unemployment, Time Use, and Consumption Patterns in Spain. In *The Economics of Time Use*, ed. Daniel S. Hamermesh and Gerard A. Pfann. Boston: Elsevier chapter ?

Ai, Chunron and Edward C. Norton. 2003. "Interaction Terms in Logit and Probit Models." *Economics Letters* 80(?):123–129.

Becker, Gary S. 1965. "A Theory of the Allocation of Time." *The Economic Journal* 75(299):493–517.

Bucks, Brian K., Arthur B. Kennickell and Kevin B. Moore. 2006. "Recent Changes in U.S. Family Finances: Evidence from the 2001 and 2004 Survey of Consumer Finances." *Federal Reserve Bulletin* pp. A1–A38.

Edwards, Ryan D. 2008*a*. "Public Transit, Obesity, and Medical Costs: Assessing the Magnitudes." *Preventive Medicine* 46(1):14–21.

Edwards, Ryan D. 2008*b*. "Who Is Hurt by Procyclical Mortality?" Unpublished manuscript, February.

Hodrick, Robert J. and Edward C. Prescott. 1997. "Postwar U.S. Business Cycles: An Empirical Investigation." *Journal of Monetary, Credit and Banking* 29(1):1–16.

Keynes, John Maynard. 1936. *The General Theory of Employment, Interest and Money*. London: Macmillan.

Krueger, Alan B. and Andreas Mueller. 2008*a*. "Job Search and Unemployment Insurance: New Evidence from Time Use Data." Unpublished manuscript.

Krueger, Alan B. and Andreas Mueller. 2008*b*. "The Lot of the Unemployed: A Time Use Perspective." *IZA Working Paper* 3490.

Lucas, Robert E. 1987. *Models of Business Cycles*. New York: Blackwell.

Lucas, Robert E. 2003. "Macroeconomic Priorities." *American Economic Review* 93(1):1–14.

Mankiw, N. Gregory. 2006. “The Macroeconomist as Scientist and Engineer.” *Journal of Economic Perspectives* 20(4):29–46.

McDonald, John F. and Robert A. Moffitt. 1980. “The Uses of Tobit Analysis.” *Review of Economics and Statistics* 62(2):318–321.

Neumayer, Eric. 2004. “Recessions Lower (Some) Mortality Rates: Evidence from Germany.” *Social Science & Medicine* 58(6):1037–1047.

Oreopoulos, Philip, Till von Wachter and Andrew Heisz. 2006. “The Short- and Long-Term Career Effects of Graduating in a Recession: Hysteresis and Heterogeneity in the Market for College Graduates.” *NBER Working Paper* 12159.

Ravn, Morten O. and Harald Uhlig. 2002. “On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations.” *Review of Economics and Statistics* 84(2):371–376.

Ruhm, Christopher J. 2000. “Are Recessions Good for Your Health?” *Quarterly Journal of Economics* 115(2):617–650.

Ruhm, Christopher J. 2003. “Good Times Make You Sick.” *Journal of Health Economics* 22(3):637–658.

Ruhm, Christopher J. 2007. “A Healthy Economy Can Break Your Heart.” *Demography* 44(4):829–848.

Ruhm, Christopher J. 2008. Macroeconomic Conditions, Health and Mortality. In *Making Americans Healthier: Social and Economic Policy as Health Policy*, ed. Robert F. Schoeni, James S. House, George A. Kaplan and Harold Pollack. New York: Russell Sage.

Seeman, Teresa E. 1996. “Social Ties and Health: The Benefits of Social Integration.” *Annals of Epidemiology* 6(5):442–451.

Sullivan, Daniel and Till von Wachter. 2007. “Mortality, Mass-Layoffs, and Career Outcomes: An Analysis using Administrative Data.” *NBER Working Paper* 13626.

Swanson, Eric T. 2007. “Real Wage Cyclicality in the Panel Study of Income Dynamics.” *Scottish Journal of Political Economy* 54(5):617–647.

Tapia Granados, José A. 2005. “Increasing Mortality During the Expansions of the US Economy, 1900–1996.” *International Journal of Epidemiology* 34(6):1194–1202.

Tapia Granados, José A. 2008. “Macroeconomic Fluctuations and Mortality in Postwar Japan.” *Demography* 45(2):323–343.

Table 1: Average minutes spent on activities during the ATUS diary day, 2003-2007, by group characteristic

Activity	All	Males	Females	Employed	Unemployed	Not in labor force
Sleeping	512.0	508.2	515.5	494.7	562.6	541.2
Sleeplessness	3.3	2.7	3.9	2.1	3.3	5.9
Personal care	45.9	38.1	53.2	45.4	43.6	47.3
Housework	36.8	14.6	57.5	28.5	43.7	53.5
Food & drink preparation	31.3	16.2	45.4	24.7	34.1	45.1
Interior maintenance	5.5	7.2	3.8	5.2	7.0	5.9
Exterior maintenance	15.7	22.0	9.8	13.6	16.9	20.1
Miscellaneous household activities	19.4	20.1	18.8	17.5	21.6	23.2
Household finances	2.1	2.0	2.2	1.8	1.7	2.8
Care of household children	25.3	14.9	34.9	24.6	29.5	26.0
Care of household adults	2.4	2.0	2.8	1.6	2.0	4.1
Care of non-household children	4.7	3.2	6.2	3.5	8.0	6.9
Care of non-household adults	5.2	5.3	5.2	4.7	8.6	5.8
Working and work-related activity	203.2	244.4	164.6	311.7	4.4	1.2
Informal work	1.6	1.6	1.6	1.3	4.5	1.8
Job search	1.3	1.6	1.0	0.5	18.0	0.3
Education	25.6	24.9	26.3	16.5	63.5	39.2
Consumer purchasing and research	24.2	18.3	29.7	23.0	26.8	26.3
Using professional services	2.3	1.3	3.2	2.3	1.9	2.4
Using medical services	3.0	2.5	3.5	2.0	2.5	5.3
Using household services not done by self	1.0	1.1	0.9	0.9	0.8	1.4
Using and performing government services	0.4	0.4	0.4	0.3	1.9	0.4
Eating and drinking	66.6	68.5	64.8	65.5	53.9	71.0
Socializing, relaxing, and leisure	273.6	287.8	260.3	220.3	340.3	377.5
Exercise through sports or recreation	17.6	23.5	12.1	16.3	22.1	19.7
Watching sports	2.1	2.3	1.8	2.2	2.5	1.7
Religious activities	7.9	6.5	9.1	6.7	7.4	10.4
Volunteering	8.5	7.8	9.2	7.1	9.6	11.4
Telephoning	6.9	3.9	9.7	5.3	12.6	9.4
Traveling	58.1	56.0	60.1	56.9	67.9	59.2
Traveling related to work or job search	17.3	22.0	12.9	26.0	6.2	0.3

Notes: All data are means within the subgroup indicated by the column of minutes of time spent on the activity shown in the row. The source is the 2003–2007 waves of the American Time Use Survey (ATUS). Survey weights are used to calculate means.

Table 2: Tobit estimates of the marginal effects of the unemployment rate and stock prices on time use, all ATUS respondents

	Marginal effects of the unemployment rate on:		Marginal effects of the detrended S&P 500 on:					
Time use, y	Observed time use	Probability of time use > 0	Observed time use	Probability of time use > 0	Mean of positive time use	Probability of positive time use	Share of effect on time use attributable to participation:	sigma
Sleeping	2.06 (0.97) **	0.000	4.55 (1.64) ***	0.000	512.7	0.999	0.001	129.3 (1.4)
Sleeplessness	-1.16 (0.17) ***	-0.013	-0.13 (0.18)	-0.001	79.3	0.040	0.882	197.8 (6.0)
Personal care	-0.30 (0.34)	-0.002	-0.91 (0.51) *	-0.006	56.3	0.813	0.398	68.5 (1.6)
Housework	-0.20 (0.35)	-0.001	0.94 (0.69)	0.007	99.4	0.367	0.743	145.9 (1.2)
Food & drink preparation	0.02 (0.34)	0.000	-0.27 (0.50)	-0.003	60.0	0.514	0.645	76.7 (1.0)
Interior maintenance	0.07 (0.25)	0.000	0.67 (0.35) *	0.004	144.3	0.038	0.883	365.4 (10.8)
Exterior maintenance	0.01 (0.27)	0.000	-2.41 (0.59) ***	-0.017	124.3	0.124	0.889	243.5 (4.0)
Miscellaneous household activities	-0.83 (0.31) ***	-0.009	0.25 (0.48)	0.003	54.2	0.358	0.592	102.2 (1.3)
Household finances	0.18 (0.10) *	0.003	0.19 (0.11) *	0.003	49.0	0.042	0.849	126.4 (4.0)
Care of household children	0.11 (0.19)	0.001	0.34 (0.31)	0.003	114.5	0.228	1.136	172.9 (2.1)
Care of household adults	0.47 (0.09) ***	0.008	0.21 (0.14)	0.003	40.2	0.058	0.657	125.9 (5.1)
Care of non-household children	0.12 (0.15)	0.001	0.37 (0.29)	0.004	81.4	0.057	0.789	211.9 (5.7)
Care of non-household adults	1.20 (0.13) ***	0.014	-0.50 (0.30)	-0.006	56.3	0.092	0.650	159.1 (4.5)
Working and work-related activity	-8.41 (1.39) ***	-0.018	-6.27 (1.92) ***	-0.013	454.7	0.453	0.957	400.7 (3.3)
Informal work	0.10 (0.09)	0.001	0.17 (0.13)	0.001	161.6	0.010	0.910	484.7 (26.6)
Job search	0.13 (0.04) ***	0.001	-0.02 (0.09)	0.000	105.3	0.012	1.002	293.4 (16.1)
Education	-0.23 (0.30)	-0.001	0.34 (0.57)	0.002	299.7	0.087	1.452	434.6 (6.0)
Consumer purchasing and research	0.03 (0.37)	0.000	-0.34 (0.49)	-0.004	59.0	0.414	0.616	94.7 (0.9)
Using professional services	0.13 (0.07) *	0.003	0.21 (0.11) **	0.005	38.4	0.060	0.808	96.7 (3.0)
Using medical services	0.14 (0.13)	0.002	0.07 (0.17)	0.001	88.9	0.033	0.967	216.8 (7.6)
Using household services not done by self	0.11 (0.04) **	0.002	0.00 (0.08)	0.000	45.0	0.022	0.809	136.7 (9.7)
Using and performing government services	-0.04 (0.02) **	-0.001	-0.02 (0.05)	0.000	62.2	0.007	0.934	194.8 (17.1)
Eating and drinking	-0.50 (0.28) *	-0.002	0.61 (0.58)	0.002	69.7	0.954	0.263	50.2 (0.5)
Socializing, relaxing, and leisure	3.68 (1.33) ***	0.003	4.19 (1.78) **	0.004	284.3	0.953	0.240	188.2 (1.2)
Exercise through sports or recreation	0.16 (0.31)	0.001	-0.78 (0.48)	-0.006	99.7	0.176	0.793	188.4 (4.1)
Watching sports	0.17 (0.09) *	0.001	-0.38 (0.18) **	-0.002	153.8	0.014	0.996	404.7 (9.9)
Religious activities	-0.12 (0.18)	-0.001	0.64 (0.26) **	0.007	97.8	0.077	1.018	190.7 (2.8)
Volunteering	-0.38 (0.29)	-0.003	0.83 (0.38) **	0.006	128.1	0.067	0.863	293.2 (5.5)
Telephoning	0.45 (0.14) ***	0.008	0.13 (0.25)	0.002	42.9	0.154	0.796	86.2 (1.6)
Traveling	0.83 (0.38) **	0.005	-0.11 (0.75)	-0.001	74.8	0.779	0.422	90.0 (1.5)
Traveling related to work or job search	-0.53 (0.22) **	-0.009	-0.87 (0.28) ***	-0.015	44.0	0.398	0.774	61.8 (2.2)

Notes: Statistical significance is indicated by one (10%), two (5%), or three (1%) asterisks. Each row shows coefficients and standard errors (in parentheses) from a separate Tobit regression of the indicated type of time use on the state unemployment rate during the month of the ATUS interview, the detrended level of the S&P 500 in 100s during the month of the ATUS interview, individual covariates, and state fixed effects. All tobit regressions are estimated using survey weights with clustering at the state level. The sample size in each regression is 63,392. Dichotomous covariates include indicators for sex, whether African American, Hispanic ethnicity, whether married, whether completed high school, whether completed college, and whether the time diary day was a weekday; continuous covariates include age and age squared, log of family income, and educational attainment. The data source is the American Time Use Survey (ATUS) waves 2003–2007. Unemployment rates by state and month are provided by the Bureau of Labor Statistics. The monthly average S&P 500 is taken from the Economic Report of the President and detrended using the Hodrick-Prescott filter.

Table 3: Tobit estimates of the marginal effects of the unemployment rate and stock prices on time use, all ATUS respondents, controlling for employment status

Time use, y	Marginal effects of the unemployment rate on:		Marginal effects of the detrended S&P 500 on:		sigma
	Observed time use	Probability of time use > 0	Observed time use	Probability of time use > 0	
Sleeping	1.25 (1.01)	0.000	4.57 (1.62) ***	0.000	128.2 (1.4)
Sleeplessness	-1.17 (0.17) ***	-0.013	-0.12 (0.17)	-0.001	196.8 (5.9)
Personal care	-0.20 (0.34)	-0.001	-0.91 (0.50) *	-0.006	68.5 (1.6)
Housework	-0.53 (0.36)	-0.004	0.99 (0.67)	0.008	144.0 (1.2)
Food & drink preparation	-0.25 (0.33)	-0.003	-0.23 (0.51)	-0.003	75.6 (1.0)
Interior maintenance	0.02 (0.24)	0.000	0.66 (0.35) *	0.004	363.6 (10.7)
Exterior maintenance	-0.11 (0.27)	-0.001	-2.41 (0.58) ***	-0.017	242.4 (4.1)
Miscellaneous household activities	-0.90 (0.31) ***	-0.010	0.26 (0.47)	0.003	101.8 (1.3)
Household finances	0.18 (0.10) *	0.003	0.19 (0.11) *	0.003	126.4 (4.0)
Care of household children	0.01 (0.19)	0.000	0.39 (0.31)	0.004	169.2 (2.1)
Care of household adults	0.44 (0.09) ***	0.007	0.21 (0.14)	0.003	125.4 (5.1)
Care of non-household children	0.07 (0.15)	0.001	0.36 (0.28)	0.004	210.2 (5.6)
Care of non-household adults	1.18 (0.13) ***	0.014	-0.49 (0.30)	-0.006	158.9 (4.4)
Working and work-related activity	-0.69 (0.88)	-0.003	-4.85 (1.36) ***	-0.018	294.3 (2.4)
Informal work	0.08 (0.09)	0.000	0.16 (0.13)	0.001	483.2 (26.1)
Job search	0.02 (0.02)	0.000	-0.02 (0.04)	0.000	230.8 (12.0)
Education	-0.28 (0.29)	-0.001	0.32 (0.53)	0.002	423.9 (5.7)
Consumer purchasing and research	-0.05 (0.37)	-0.001	-0.32 (0.49)	-0.003	94.6 (0.9)
Using professional services	0.14 (0.07) *	0.003	0.22 (0.11) **	0.005	96.7 (3.0)
Using medical services	0.10 (0.12)	0.001	0.05 (0.17)	0.001	214.5 (7.6)
Using household services not done by self	0.10 (0.04) **	0.002	0.00 (0.08)	0.000	136.7 (9.6)
Using and performing government services	-0.04 (0.02) **	-0.001	-0.02 (0.04)	0.000	190.6 (15.6)
Eating and drinking	-0.50 (0.28) *	-0.002	0.61 (0.56)	0.002	50.2 (0.5)
Socializing, relaxing, and leisure	1.72 (1.33)	0.001	4.23 (1.85) **	0.003	181.5 (1.2)
Exercise through sports or recreation	0.09 (0.31)	0.001	-0.77 (0.47)	-0.006	187.7 (4.1)
Watching sports	0.16 (0.09) *	0.001	-0.38 (0.18) **	-0.002	404.5 (9.8)
Religious activities	-0.12 (0.18)	-0.001	0.64 (0.26) **	0.007	190.7 (2.8)
Volunteering	-0.43 (0.28)	-0.003	0.81 (0.37) **	0.005	292.1 (5.4)
Telephoning	0.39 (0.14) ***	0.007	0.12 (0.25)	0.002	85.7 (1.6)
Traveling	0.64 (0.38)	0.004	-0.08 (0.75)	0.000	89.6 (1.5)
Traveling related to work or job search	0.02 (0.18)	0.000	-0.59 (0.21) ***	-0.014	55.7 (2.0)

Notes: See notes to Table 2. The Tobit regressions in this table also include dummy variables for labor force status.

Table 4: Tobit estimates of the marginal effect of a 1 percentage point rise in the unemployment rate on time use by labor force status

	Marginal effects of the unemployment rate on: Observed time spent by:		
Time use, y	**Employed**	**Unemployed**	**Not in labor force**
Sleeping	0.92 (1.16)	-1.64 (5.29)	1.80 (1.46)
Sleeplessness	-0.89 (0.14) ***	-0.56 (0.22) **	-1.59 (0.33) ***
Personal care	-0.30 (0.40)	-0.39 (2.26)	-0.07 (0.73)
Housework	-0.53 (0.54)	-3.53 (2.34)	-0.14 (0.99)
Food & drink preparation	-0.40 (0.35)	1.37 (2.17)	0.04 (0.65)
Interior maintenance	-0.25 (0.28)	0.52 (0.47)	0.72 (0.36) **
Exterior maintenance	0.05 (0.41)	1.38 (2.26)	-0.54 (0.53)
Miscellaneous household activities	-0.58 (0.33) *	0.11 (1.92)	-1.69 (0.59) ***
Household finances	0.16 (0.14)	0.02 (0.01) *	0.14 (0.08) *
Care of household children	0.09 (0.11)	-0.83 (0.53)	-0.26 (0.57)
Care of household adults	0.36 (0.09) ***	0.30 (0.19)	0.67 (0.22) ***
Care of non-household children	0.13 (0.21)	-0.73 (0.81)	0.29 (0.35)
Care of non-household adults	1.15 (0.17) ***	1.25 (0.84)	1.28 (0.31) ***
Working and work-related activity	-4.36 (2.19) *	0.01 (0.01) *	0.54 (0.14) ***
Informal work	0.11 (0.12)	0.03 (0.10)	-0.05 (0.20)
Job search	0.05 (0.03) *	-0.23 (0.92)	0.00 (0.05)
Education	-0.18 (0.54)	-0.06 (1.35)	-0.78 (0.82)
Consumer purchasing and research	-0.12 (0.44)	0.24 (1.97)	0.07 (0.54)
Using professional services	0.12 (0.09)	-0.06 (0.30)	0.31 (0.11) ***
Using medical services	0.05 (0.10)	-0.15 (0.27)	0.27 (0.27)
Using household services not done by self	0.08 (0.04) *	0.36 (0.16) **	0.08 (0.08)
Using and performing government services	-0.01 (0.02)	-0.36 (0.17) **	0.00 (0.01)
Eating and drinking	-0.16 (0.42)	-4.36 (1.93) **	-0.30 (0.57)
Socializing, relaxing, and leisure	2.79 (1.41) *	3.63 (8.77)	-3.15 (2.46)
Exercise through sports or recreation	0.41 (0.39)	-1.24 (1.31)	-0.15 (0.71)
Watching sports	0.13 (0.13)	0.03 (0.23)	0.22 (0.10) **
Religious activities	0.04 (0.22)	-0.09 (1.00)	-0.36 (0.31)
Volunteering	-0.55 (0.38)	0.67 (0.92)	0.10 (0.49)
Telephoning	0.46 (0.19) **	3.80 (2.94)	0.35 (0.22)
Traveling	0.74 (0.65)	-0.15 (0.34)	0.35 (0.84)
Traveling related to work or job search	-0.05 (0.43)	1.80 (1.46)	0.09 (0.04) **
N in each regression	20,079	1,181	6,279

Notes: See notes to Table 2. Each cell in each panel represents an estimate from a separate Tobit regression. Regressions of Job search for the employed are estimated with Census division fixed effects because state fixed effects perfectly predict censoring. The same is true for regressions of Using professional, medical, household, and government services, and Watching sports for the unemployed; and for regressions of Household finances, Working, Informal work, Job search, Using household services, and Traveling related to work for those not in the labor force. All other regressions use state fixed effects.

Table 5: Tobit estimates of the marginal effects of the unemployment rate and stock prices on time use by sex

Time use, y	Marginal effects of the unemployment rate on: Observed time spent by: Males			Females			Marginal effects of the detrended S&P 500 on: Observed time spent by: Males			Females		
Sleeping	0.78	(1.41)		3.29	(0.94)	***	6.01	(2.01)	***	3.05	(2.10)	
Sleeplessness	-1.00	(0.22)	***	-1.28	(0.21)	***	-0.07	(0.26)		-0.17	(0.28)	
Personal care	0.24	(0.45)		-0.91	(0.51)	*	-0.99	(0.70)		-0.73	(0.72)	
Housework	-0.40	(0.46)		0.13	(0.73)		1.34	(0.70)	*	0.34	(1.29)	
Food & drink preparation	-0.78	(0.41)	*	1.21	(0.57)	**	0.06	(0.53)		-0.64	(0.88)	
Interior maintenance	0.20	(0.49)		0.00	(0.19)		0.52	(0.57)		0.75	(0.31)	**
Exterior maintenance	-0.36	(0.51)		0.24	(0.24)		-2.27	(1.32)	*	-2.26	(0.38)	***
Miscellaneous household activities	-0.69	(0.44)		-0.88	(0.37)	**	0.48	(0.83)		0.06	(0.75)	
Household finances	0.13	(0.14)		0.20	(0.09)	**	0.16	(0.17)		0.21	(0.18)	
Care of household children	-0.16	(0.14)		0.32	(0.38)		0.23	(0.23)		0.43	(0.73)	
Care of household adults	0.35	(0.13)	***	0.57	(0.13)	***	0.53	(0.23)	**	-0.15	(0.18)	
Care of non-household children	-0.02	(0.15)		0.32	(0.20)		0.46	(0.34)		0.24	(0.47)	
Care of non-household adults	1.33	(0.19)	***	1.08	(0.20)	***	-0.35	(0.45)		-0.59	(0.32)	*
Working and work-related activity	-9.66	(3.09)	***	-7.44	(2.11)	***	-12.69	(3.38)	***	-1.07	(2.48)	
Informal work	0.19	(0.12)		0.07	(0.10)		0.12	(0.17)		0.16	(0.18)	
Job search	0.17	(0.04)	***	0.04	(0.05)		-0.01	(0.13)		-0.05	(0.09)	
Education	0.18	(0.43)		-0.64	(0.40)		0.23	(0.75)		0.42	(0.81)	
Consumer purchasing and research	-0.08	(0.46)		0.13	(0.50)		0.03	(0.59)		-0.78	(0.95)	
Using professional services	0.16	(0.08)	*	0.10	(0.13)		0.32	(0.15)	**	0.03	(0.19)	
Using medical services	0.08	(0.08)		0.05	(0.20)		0.20	(0.30)		-0.04	(0.21)	
Using household services not done by self	0.06	(0.05)		0.11	(0.06)		0.00	(0.19)		0.01	(0.07)	
Using and performing government services	-0.05	(0.01)	***	0.02	(0.02)		-0.03	(0.03)		0.03	(0.04)	
Eating and drinking	-0.17	(0.52)		-0.81	(0.56)		1.33	(0.82)		-0.10	(0.67)	
Socializing, relaxing, and leisure	4.49	(2.51)	*	3.43	(1.84)	*	6.83	(2.57)	**	1.69	(2.19)	
Exercise through sports or recreation	-0.03	(0.59)		0.33	(0.31)		-2.11	(1.07)	*	0.19	(0.49)	
Watching sports	0.12	(0.15)		0.18	(0.14)		-0.64	(0.21)	***	-0.10	(0.23)	
Religious activities	0.03	(0.20)		-0.26	(0.30)		0.77	(0.30)	**	0.49	(0.40)	
Volunteering	-0.36	(0.32)		-0.36	(0.46)		0.97	(0.53)	*	0.65	(0.52)	
Telephoning	0.29	(0.16)	*	0.67	(0.20)	***	0.37	(0.25)		-0.16	(0.41)	
Traveling	1.10	(0.80)		0.54	(0.74)		0.15	(1.28)		-0.46	(1.05)	
Traveling related to work or job search	-0.56	(0.41)		-0.50	(0.23)	**	-1.25	(0.56)	**	-0.55	(0.26)	**
N in each regression	27,539			35,853			27,539			35,853		

Notes: See notes to Table 2. Each cell in each panel represents an estimate from a separate Tobit regression, but corresponding elements across panels are from the same regression. Regressions of Using medical services and Using household services for males are estimated with Census division fixed effects because state fixed effects perfectly predict censoring. Regressions of informal work and job search for women use Census division fixed effects for the same reason. All other regressions use state fixed effects.