American Time Use Over the Business Cycle

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Abstract

By the end of 2009, the Great Recession that began in December 2007 had doubled the unemployment rate, reduced stock prices by 25 percent, and lowered housing prices by 10 percent. The advent of the monthly American Time Use Survey (ATUS) in 2003 facilitates a detailed examination of trends in time allocations following these large macroeconomic shocks to the prices of time and assets. Previous research has explored the effects of being unemployed on time use and well-being, while here I explore the broader impacts of macroeconomic fluctuations on time use by all consumers using the 2003–2009 waves of the ATUS. When unemployment is high, consumers report spending more time sleeping, preparing food and eating or drinking, socializing and relaxing, and using the telephone, while they spend less time working and traveling for work. High unemployment also increases time spent by some subgroups on caring for children and adults outside the household. These effects are largely independent of labor force status, suggesting they are broad-based and reflective of incremental changes in the price of time rather than large jumps associated with the onset of unemployment. Wealth effects associated with lower housing prices shift time use toward home production and away from leisure. These results shed new light on the channels through which macroeconomic fluctuations affect health and well-being.

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1 Introduction

The onset of the Great Recession in December 2007 brought rapid increases in unemployment across the United States and in other industrialized countries. Figure 1 shows monthly unemployment rates for the country as a whole and for individual states between January 2003 and December 2009, the time period currently spanned by the new American Time Use Survey (ATUS). The pattern of gradual decline following the recession of 2001 is punctuated by a spike when Hurricane Katrina hit the Gulf coast in August 2005, and then it is quickly reversed starting in 2008. As the figure reveals, there is considerable variation across states around the national average over the parts of two business cycles in the data. At the end of 2009, unemployment was only 4.4 percent in North Dakota but 14.6 percent in Michigan. Figure 2 plots national unemployment rates in three other advanced economies during the same period, revealing similar impacts of the global financial crisis and recession of 2008 but also some interesting differences in initial levels and severity. Household portfolios were also hard-hit by the financial crisis, as depicted by trends in U.S. housing and stock prices in Figure 3. By the end of 2009 the FHFA's housing price index had declined by about 10 percent and the S&P 500 about 25 percent from their peaks. In this paper I use the ATUS to explore patterns in U.S. time use across the business cycle that are identified by the considerable intertemporal and interstate variation in unemployment rates and asset prices during this period.

In a tradition dating back to Keynes, macroeconomists are interested in the causes and consequences of business cycles, and recent events have resulted in renewed focus. In addition, several interesting contributions about the impacts of business cycles have originated in labor and health economics. With the benefit of improved longitudinal data, several studies track individual cohorts over time to assess transitory and permanent effects of economic downturns. These papers tend to reveal relatively permanent negative impacts of recessions that result in unemployment. Oreopoulos, von Wachter and Heisz (2006) report significant reductions in wages of college-educated entrants to the labor market during a recession that die out relatively slowly, especially for workers at the lower end of the skill distribution. Similarly, Sullivan and von Wachter (2009*a*,*b*) find persistently adverse impacts on mortality following mass layoffs in the 1980s. This literature reveals long-lasting costs of downturns in terms of economic and physical well-being that are concentrated among job-losers.

But a rich literature that examines the dynamics in population or average health finds the opposite kind of effect: temporary health benefits spread across many individuals associated with economic downturns. Ruhm (2000, 2003, 2007, 2008), Neumayer (2004), Tapia Granados (2005, 2008), and others have revealed patterns of procyclical mortality trending downward along with economic activity, so that most components of population health improve during recessions. Even during the Great Depression, when perhaps a quarter of workers were unemployed, there is evidence that mortality actually fell (Tapia Granados and Diez Roux, 2009). Cutler, Miller and Norton (2007) report little evidence of any lingering adverse health effects even for those *in utero* during the Great Depression, in contrast to the implications of the fetal origins hypothesis (Barker, 1992). Two noteworthy exceptions to these patterns include suicide mortality, which tends to rise during recessions, and mental health, which appears to worsen when times are bad.

The epidemiology of the phenomenon, as indicated by causes of death, broadly suggests roles for reduced job stress and any unhealthy behaviors associated with stress, as well as for reduced traffic fatalities and air pollution. But the broad-based incidence of procyclical mortality (Edwards, 2008*b*), in particular at ages when labor force participation is low, raises lingering questions about transmission channels that remain relatively unresolved. Miller et al. (2009) argue that the patterns in causes of death suggest that work behavior per se is an unlikely culprit. Evidence of the importance of traffic accidents at working ages and of cardiovascular disease in retirement does not appear to support a strong role for job stress, for example. They are partial to the view that externalities like pollution and traffic accidents, influences that are more indirectly caused by individual choices than healthy behaviors, are more likely culprits.

But two recent studies provide new insights into the connections between economic fluctuations and health or mortality from the perspective of individual behavior. Based on patterns of within-month mortality, Evans and Moore (2011) argue that reduced liquidity during downturns may reduce unhealthy behavior and thus produce procyclical mortality. Miller and Urdinola (2010) report that negative shocks to coffee prices in Colombia reduce the price of time and thus also the price of health. This channel is especially important for children, who benefit from increased parental time inputs during economic bad times.

In this paper, I examine the response of time use to business cycles in the U.S. by exploring seven waves of the broad-based American Time Use Survey. The ATUS is a repeated cross section of individuals in U.S. households drawn from the Current Population Survey measured each month in every year since 2003. Although the ATUS currently covers only a relatively short time period, there still appears to be much identifying variation in the dataset, as is shown in Figure 1. To my knowledge, mine is the first study 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) 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 (2010) 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 will be distinct effects of each.

My results indicate that when unemployment rises, individuals report more sleeping, more time spent preparing food and eating or drinking, more time looking for work, more time socializing and relaxing, and more time using the telephone. Some subgroups also increase their time spent caring for children and adults outside the household. These increases are paid for by reductions in time spent either working, traveling for work, or volunteering. Controlling for labor force status attenuates these effects, but they typically retain significance. The exceptions are time spent either working, searching for work, or traveling for work, all of which are linked to labor force status in clear ways. These results suggest that reductions in the price of time are felt broadly during recessions and have significant effects on time use that appear to favor health-promoting activities. Whether they also result in health improvements in the ATUS samples unfortunately remains unclear. The only relevant data in the ATUS are self-reported health status and body mass index (BMI), both measured only in the 2006–2008 Eating & Health modules. Neither fluctuates significantly with unemployment in the data, probably because a significant component of self-reported health is associated with psychological well-being, and BMI seems unlikely to vary appreciably over the business cycle. Although the ATUS provides better measures of socioeconomic well-being by nature of its connection to the CPS, the fact it is a repeated cross section hampers analysis of long-term effects on such outcomes for individuals, which are thus not a focus of this study.

The paper is laid out as follows. In section 2, I discuss a simple theoretical framework for thinking about macroeconomic fluctuations and time use, and I propose a set of testable relationships for the empirical analysis. Section 3 describes the ATUS and presents some sample averages. In section 4, I present results using Tobit estimation of minutes of daily time use across 31 functionally interesting categories. Section 5 discusses the implications of these results and offers concluding remarks.

2 Labor, leisure, home production, and the economy

2.1 Individuals

Following the treatment by Becker (1965), I assume that individual i draws utility from purchases of market goods combined with time allocations y and faces a market wage w.

In Becker's formulation, individuals combine goods and time to produce consumable commodities that enter the utility function. The ATUS data do not include spending data, so to simplify I assume that total utility is additively separable over purchases of market goods, purchases of home production, and leisure. I consider a single period in which individuals spend their labor income and assets. Specifically, individuals split their time allocation between working ℓ, home production h, and leisure $1 - \ell - h$ to solve

$$\max_{\ell,h}\ u([w\ell + A]/p) + v(e \cdot h) + z(1 - \ell - h), \tag{1}$$

where $u(\cdot)$ is utility drawn from market goods purchased at price p with labor earnings and assets A; $v(\cdot)$ represents utility drawn from consumption of goods produced at home with time input h at efficiency e; and $z(\cdot)$ is utility from consuming leisure time. All goods are normal with positive marginal utilities.

The first-order conditions describing optimal time allocations in interior solutions are the familiar equalities between marginal rates of substitution and relative prices:

$$\frac{u'([w\ell + A]/p)}{z'(1 - \ell - h)} = \frac{1}{w/p}, \tag{2}$$

$$\frac{v'(e \cdot h)}{z'(1 - \ell - h)} = \frac{1}{e}. \tag{3}$$

These equations imply time allocation demand functions for activity y^k, either ℓ, h, or $1 - \ell - h$, that I write parsimoniously as:

$$y^k = f^k(w, A, p, e, \theta), \tag{4}$$

where θ captures preferences, the shapes of $u(\cdot)$, $v(\cdot)$, and $z(\cdot)$. For labor supply to be upward sloping, the substitution effect associated with a rise in w must outweigh the income effect, which will obtain if the concavity of $u(\cdot)$ is sufficiently mild so that u' falls more slowly than w rises. (Chetty, 2006). An increase in assets A exerts a pure income effect that should reduce work and raise leisure, by equation (2). According to equation (3), it should also increase time spent in home production. That result seems counterintuitive and derives from the complementarity restrictions inherent in the additively separable preferences I have specified for clarity. A more general model as in Becker (1965) would allow for different results such as substitution of market goods for home production when assets increase. For my purposes, a key dynamic is that when labor supply is upward sloping in the wage, a rise in w will also tend to reduce time allocations other than working. That is, $\partial f^k/\partial w < 0$ for home production and leisure. But here too, the rigid complementarity structure is driving this result, and in a richer model one could imagine leisure possibly rising if home production could be fully replaced with newly affordable market purchases.

Corner solutions could obtain where working, home production, or leisure is zero, or where two of the three are zero. The most common corner solutions we expect to see are when i is not employed and $\ell = 0$, or when i engages in no home production so that $h = 0$. In a model with fixed costs of participation or different complementarity assumptions, these scenarios could occur by choice if the wage w, assets A, or home efficiency e were sufficiently low or high. In the case of involuntary unemployment, the second first-order equation (3) governing leisure and home production must still hold. In a more realistic model with multiple periods and job search, current and expected future wages may still affect the time use of the unemployed.

2.2 Families and households

For individuals, market purchases substitute for inefficient or infeasible production. Households comprising heterogeneous individuals with different comparative advantages are likely to internalize at least some of these external transactions. In a traditional household, for example, one adult may specialize in providing the child care and meal preparation that the other, who specializes in market production, would otherwise purchase from the market.

A feasible and straightforward approach is to include individual characteristics and measures of household structure in the time demand functions $f^k(\cdot)$. But the f^k are best conceptualized as net or total household demands. A deeper question is how the shape of individual i's time demand f_i^k may differ systematically from that of the household's demand. This is relevant in the present context because a household's response to unemployment could be very different than that of an individual without a household. A newly unemployed husband may provide more housework in order to spell his wife, while an unemployed single man might not. The answer seems likely to hinge on what objectives households are optimizing and therefore smoothing in reaction to external shocks. The problem is that time use is both a means to a smoothable end, namely consumption, and an end in and of itself.

The answer may be more academic than practically interesting if we are concerned with individual outcomes like health, which arguably respond to individual time use. But we know that health is closely related to wealth, which is shared among household members. Given that one of the shortcomings of the ATUS is that it only measures the time use of a single member of each household, I am unable to shed much light on this question. My strategy will be instead to control for household composition and explore time use among discrete subgroups defined by age and sex.

2.3 Testable regression equations

Recessions can affect individuals 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 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 necessarily equivalent to the w that enters equations (1)–(4) 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 it to proxy for w. A testable version of equation (4) for individual i observed in month t suitable for estimation in repeated cross section without price data is

$$\begin{aligned} y_{it}^k &= \alpha + \beta_u^k \text{ urate}_{st} + \beta_S^k \log\left[\text{SP500}\right]_t + \beta_H^k \log\left[\text{HPI}\right]_t + X_{it}B^k \\ &\quad + \beta_p \text{ precip}_{st} + \beta_t \text{ temp}_{st} + Div_i + Y_t + M_t + D_t + \epsilon_{it}^k, \end{aligned} \tag{5}$$

where urate_{it} is the unemployment rate in state s at time t; SP500_t is the level of the S&P 500 index of stock prices; HPI_t is the Federal Housing Finance Agency's quarterly housing price index based on all transactions; X_{it} is a vector of characteristics that proxy for preferences and household structure; precip_{st} is inches of precipitation in state s at month t; temp_{st} is average temperature; Div_i is a vector of fixed effects for the 9 Census divisions; similarly, Y_t and M_T are year and month fixed effects, and D_t is a weekend fixed effect; and $\epsilon_{it}^k \sim N(0, \sigma^2)$ is a white noise error.

Some discussion of the fixed effect strategy is warranted. Changes in the ATUS survey instrument have occurred annually, and there may be seasonality in monthly observations, so year and month fixed effects are obvious choices. Time use differs considerably on weekends. State fixed effects are common in the literature when samples include a long time dimension. Here, with 7 years of monthly data, I find that state, year, and month fixed effects wash out an unacceptably high amount of variation in the data. With all three fixed effects, for example, hours spent working by all males of working age do not respond to the unemployment rate, a fairly clear indication that those fixed effects are obscuring meaningful relationships. Even with the considerable variation in the monthly state unemployment rate that is apparent in Figure 1, the R^2 in a model of the unemployment rate on state, year, and month dummies in the dataset is nearly 0.85, implying not much residual variation in the measure over a short panel. As a result, I use dummies for the 9 Census divisions instead and control for monthly state climatic conditions that might affect time use: the average temperature and total precipitation. In an earlier version of this paper without data from 2008 and 2009, I estimated models with state fixed effects only and recovered similar results.

The list of covariates I include in X_{it} is standard. I control for the sex, race, and ethnicity of the ATUS respondent; age and age-squared; a dummy for being married or coupled; the number of adults in the household; the number of children in the household; and the education of the respondent in years. I do not include earnings or household income because these are clearly endogenous to the labor supply decision, while education will pick up many influences of socioeconomic status and is much less endogenous.

I exclude labor force status from X_{it} initially and then add it in later. This is because I am interested in two types of marginal effects of the unemployment rate on time use. The first is the unconditional effect, which is a combination of an effect on time use through wages, or the price of time, and an effect through labor force status, which is likely to be very large among those affected. The second is the effect conditional on employment status, which should reflect only the influence felt through the price of time. If all of the effects of the unemployment rate on time use are channeled through the extensive margin of being employed or not, then I should see no effect on time use once I control for labor force status. As shown by Ahn, Jimeno and Ugidos (2005) and Krueger and Mueller (2008), labor force status explains much variation in time use in the cross section. Less clear is the extent to which it explains fluctuations in time use across the business cycle.

As I show in the next section, time use data exhibits significant response pooling at zero minutes for many activities, much like consumer expenditure data, the object of interest in Tobin's (1958) original research. 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*} where

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

Although the behavioral β coefficients in equation (5) are interesting, they are most directly relevant only for the untruncated variable y^k. Of greater interest are the partial derivatives of $E[y^{k*}]$, the expected value of the observed minutes of time use and of the probability of y^k being uncensored. For the Tobit, these are

$$\frac{\partial E[y^{k*}]}{\partial x_j} = \hat{\beta}_j \cdot \Phi[\hat{\bar{Z}}^k] \tag{6}$$

$$\frac{\partial \Phi[\hat{\bar{Z}}^k]}{\partial x_j} = \frac{\hat{\beta}_j \cdot \phi[\hat{\bar{Z}}^k]}{\hat{\sigma}} \tag{7}$$

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. The former is the answer to the question of how much observed time use actually changes with a one percentage point rise in unemployment, and the latter is revealing of the intensive versus extensive margins of behavior (McDonald and Moffitt, 1980). In particular, the part of $\partial E[y^{k*}]/\partial x_j$ that is attributable to participation equals $\partial\Phi[\hat{\bar{Z}}^{k*}]/\partial x_j$ times the average uncensored time use.

3 The American Time Use Survey

3.1 The structure of the data

The American Time Use Survey has been conducted each year since 2003 by the Census Bureau. The ATUS offers the broadest look at U.S. time allocation at high frequency. Respondents are drawn from outgoing rotations of the monthly Current Population Survey and are reinterviewed for the ATUS 2–5 months afterward. 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 about 12 percent of the records over the 5 sample years contain less than 1440 minutes, and the average record contains 1430 or 99 percent of daily minutes.

3.2 Trends in average time use, 2003–2009

The first column in Table 1 reports sample-weighted averages across all individuals in all years of minutes reported spent on 31 activities alongside their standard errors. These statistics are also graphically in Figure 4. Sleeping consumes the most time on average, 512.7 minutes or roughly 8.5 hours. Socializing and relaxing, activities that are clear examples of leisure, is next largest at 275.3 minutes or 4.5 hours. Working time averages the third largest total, 201.4 minutes or about 3.4 hours. There are many categories of home production, ranging from housework and food preparation at home to care of children and adults within and outside the household. The total average time spent in these categories (not shown) is 147.3 minutes.

A crude but informative cut of the data is revealed by the next three columns in Table 1. There I first report average time use in 2006, when the unemployment rate was at its lowest, averaging 4.7 percent as shown in the bottom row. Then in the next column I report time use in 2009, when unemployment averaged 9.2 percent, or roughly two times higher. Differences between these averages and their standard errors, shown in the final column, implicitly provides an admittedly rough estimate of how average time use changes with the unemployment rate. Several of these differences between 2006 and 2009 are statistically significant. As expected, time working falls while job search rises, while several other categories fluctuate. Time spent socializing and relaxing rises, as do religious and volunteer activities. But most categories of household production, including care and assistance, do not appear to respond at all.

Dividing each of the net changes in time allocations shown in the last column by the change in the unemployment rate shown at the bottom produces an estimate of the total derivative of the unemployment rate that is comparable to a regression coefficient. These data are shown by the dark bars in Figure 5. For comparison, the lighter bars in Figure 5 are the marginal effects of the state unemployment rate from the baseline Tobit model of individual time use presented in section 4. Some of the qualitative findings from this simple first pass appear to hold up in the regression analysis, but there are also important differences that emerge.

3.3 Time use by labor force status

Based on earlier findings in the time use literature (Ahn, Jimeno and Ugidos, 2005; Krueger and Mueller, 2008), we expect at least some of these rudimentary patterns to be driven by changes in average labor force status. The rise in the national unemployment rate not only represents a doubling of the prevalence of unemployed, who use time very differently, it may also have pushed discouraged workers out of the labor force altogether, which would also affect average time use. Working against this are negative shocks to asset prices, pure income effects that would likely have reduced retirement and thus changed average time use.

A first look at the decomposition is in Table 2, which lists average time use by labor force status and their standard errors across all years. As remarked by Krueger and Mueller (2008), the unemployed enjoy significant increases in time spent sleeping. 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 seems to be explained by the positive correlations of sleeplessness and retirement with age. The difference in sleeplessness between the employed and the unemployed is 0.8 minute but statistically insignificant. Time spent on housework, food and drink preparation, and other household production activities is considerably larger for those who are not employed. The same is somewhat true of time used in care for children and adults. As would be expected, minutes of market work reveals the opposite pattern, while informal work and job search are larger allocations 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 much more common among the unemployed and also those out of the labor force, a group that includes students. Time spent eating and drinking is lowest for the unemployed and highest for those out of the labor force. Time spent socializing and relaxing, exercising, and telephoning is higher for the unemployed and those not in the labor force. Total time spent traveling and in transit, which includes job-related travel, is much higher for the employed at 82 minutes per day.

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 2 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.

4 Effects of macroeconomic conditions on time use

4.1 National conditions, placebo tests, and identification

Because the unemployment rate is a macroeconomic variable, the estimation of equation (5) using individual-level data should be uncontaminated by endogeneity. But do macroeconomic variables really affect individual choice, or are they instead just proxying for general trends? Such concerns may be allayed somewhat by the use of year and month fixed effects, but with a large enough sample, even the most convoluted relationships might emerge with apparent statistical significance. How important is longitudinal versus cross-sectional variation for identifying responses in time use? My goals in this subsection are threefold: to test the relationship between the U.S. national average monthly unemployment rate and monthly average time use, to conduct placebo tests of whether other macroeconomic variables that should not affect U.S. time use in fact do, and to draw partial conclusions about sources of statistical identification.

Table 3 reports the marginal effects on U.S. time use that are associated with 4 different national unemployment rate series. Each cell in the table reports the marginal effect from a separate Tobit estimation of equation (5) on monthly ATUS data with the full set of covariates as described in section 2.3. The first column reports estimates of the marginal effect of the U.S. national unemployment rate. The second column reports estimates using the Australian unemployment rate, which behaved very similarly prior to the start of the Great Recession and then rose less quickly, as depicted in Figure 2. The third and fourth column substitute national unemployment rates from Canada and the Euro Zone, two similar economies.

The patterns that emerge are qualitatively similar, which should give us pause. We would ideally like to find no significant relationships in the rightmost three columns, because foreign unemployment rates should have relatively little independent effect on U.S. economic conditions and thus on time use. Instead, all four columns register significant increases in minutes spent preparing food at home and spent eating and drinking, and reductions in working and in religious activities. Several other "false positives" are scattered throughout the rightmost columns. But the sizes of coefficients vary across the columns, a pattern that points toward an underlying explanation. As Figure 2 reveals, there is much correlation in national unemployment rates across these 4 regions. But unemployment in the U.S. rose much more rapidly following the onset of the Great Recession than it did elsewhere. Given the visible correlation, if these regressions are drawing identification off the Great Recession, one would expect the coefficients to be larger in regressions that use those national unemployment series that rise less dramatically.

These results cast doubt on the ability of variation in the national unemployment rate to explain variation in individual time use. They also speak to the importance of the Great Recession in providing whatever identifying temporal variation there is. Absent an oddly shaped labor supply curve, we know that average time spent working must have fallen with rising unemployment and falling real wages, so the similarity of that result across columns is not so distressing. But the uniformity of other responses in Table 3 is a cause for some concern. Based on Figure 1, state-level variation in the unemployment rate is likely to provide important additional leverage.

4.2 Tests with state-level unemployment rates

4.2.1 All respondents

The leftmost column of Table 4 displays marginal effects of the state unemployment rate on time use which are analogous to results in the first column in Table 3, where I used national data. Comparison of the two reveals some similarities but also several key differences. Here in Table 4 we see a highly significant impact of the unemployment rate on time spent sleeping, 1.776 minutes for each percentage point of unemployment. Time spent preparing food at home is significantly increased but by a smaller amount, 0.449 minute. Working time falls and now job search rises, and time spent eating and drinking, socializing and relaxing, and telephoning all increase significantly, with the largest increase registered for socializing and relaxing. Volunteering and travel for work both fall with unemployment.

As I mentioned in section 3.2, Figure 5 depicts these Tobit marginal effects in light gray alongside the rudimentary total derivatives of time use, the changes in time use between 2006 and 2009 scaled by the change in the unemployment rate and colored in dark gray.

The lack of any dynamics in the home production categories at the top of the table, outside of preparation of food at home, is surprising. It could reflect a true lack of response or it could reflect smoothing behavior and reallocation within households. If high unemployment motivates men to take over some household chores from women, leaving total chores unchanged, then the presence of men and women together in the sample could produce a null effect of unemployment on average time use. Rather than include interactions terms to test for this, I return to this issue later by examining time use among subgroups categorized by age and sex. 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.

The middle column presents marginal effects of the S&P 500 index, which are negligible.

The only result with much significance is an increase in time sleeping of 0.198 minute for each percentage point increase in stock prices. The 25 percent drop in the index by the end of 2009 translates into 5 fewer minutes of sleep daily. Much more interesting results are visible in the third column, which lists the marginal effects of a 1 percent drop in the FHFA's housing price index, a measure that varies by quarter and state. None of the point estimates are very large, but signs and significance are plausible and compelling. Rising housing wealth reduces sleeplessness and most types of home production, chief among them ironically interior and exterior work on the home but also care of children and adults. Housing prices also increase time spent eating and drinking and exercise, while they decrease volunteering and religious activities. An odd result is that housing wealth stimulates travel for work; this could reflect moves to the suburbs and thus longer commutes fueled by housing price appreciation.

The fourth column shows the probability of positive time use by category. Sleeping, personal care, eating and drinking, and socializing are without surprise engaged in by practically everyone on a daily basis. The fifth column lists the share of the marginal effect on observed time use that is attributable to changes in participation, based on the decomposition analysis suggested by McDonald and Moffitt (1980) and discussed in section 2.3. The last column shows estimates of the regression error σ, which is equivalent to the root mean squared error in an OLS regression.

Participation drives a large number of these itemized activities. The average share of the marginal effect due to participation across all 31 categories is 67.9 percent. But when weighted by total time, which places more emphasis on common behaviors like sleeping and eating, that average drops to 32.8 percent. And among the activities that seem to respond most to the unemployment rate, such as sleeping, working, and socializing, the intensive margin of behavior appears to be relatively more important. This is suggestive evidence that movements into and out of unemployment, which appear likely to have large participation effects on time allocations, may be a less important as channel for macroeconomic conditions than changes in activity intensity associated with the price of time.

4.2.2 Age and sex subgroups

The lack of any responsiveness of home production to the unemployment rate in the results thus far is odd and seems inconsistent with theory. But home production is highly correlated with the age and sex of the individual, as is revealed in Table 5, where I list means and their standard errors for males and females in three broad age categories. With a few exceptions, females perform more types of home production than males at all ages, while males spend more time working and socializing or relaxing. As I noted earlier, shocks to the market price of time faced by individuals may well redistribute tasks within households, even if they do not increase home production on net, and any such shifting could prove interesting for health and other outcomes.

Table 6 reports marginal effects of the state unemployment rate on each category of time use for the six age and sex subgroups shown in Table 5. Many new results emerge, suggesting that intra-household shifting is indeed important. The first result of interest is that increases in sleeping associated with the unemployment rate appear to be enjoyed mostly by men of working age. Younger males and females may also benefit but coefficients are insignificant, while working-age females do not see their sleeping increase during recessions. This contrasts with the pattern that all groups under 65 find their working time reduced, but it may reflect the larger average amount of sleep reported by women of working age in Table 5.

Fluctuations in home production over the business cycle also appear in Table 6. When unemployment is high, young males spend more time taking care of children in the household, while young women shift their time around and may decrease their home production on net, possibly in response to the actions of mothers and fathers. Men of working age increase their contribution to housework and their care of adults living outside the household, presumably nonresident grandparents. Women under 65 are responsible for increases in food preparation at home. Respondents over 65 shift their behavior relatively little at all, but men over 65 spend more time taking care of children in the household, while women over 65 spend more time taking care of household adults, probably their spouses. Although we do not find many clear examples of equal and opposite marginal effects across groups that cleanly offset one another, the picture that emerges is one of heterogeneous responses within households according to traditional gender and age roles.

Increases in time spent eating and drinking are concentrated among young males and females. Those groups also report spending the least amount of time engaged in those activities. Increases in socializing and relaxing appear to be enjoyed primarily by men, with smaller increases among women that are not statistically significant. Decreases in religious and volunteer activities associated with higher unemployment appear to be due to the behavior of those under 25. Time spent on the telephone reacts strongly to unemployment only for women over 25. Travel for work falls with unemployment for all groups except oddly for women over 65.

4.2.3 Conditional on labor force status

In Table 7, I present marginal effects of the state unemployment rate conditional on individual labor force status. Because these regressions allow for different average levels of time use across groups according to their labor force attachment, these marginal effects of the unemployment rate should capture the average impacts on time use of the price of time holding constant its impacts on individual employment. As we have seen in Table 2, the latter could be large, but the unemployed may also be a select group with different preferences or budgets for time.

The pattern that emerges is one of remarkable similarity with Table 6, suggesting that for much of time use, only a small part of the effect of the macroeconomic unemployment rate is attributable to changes in individual employment. The coefficients that change markedly are those on time spent working, with the interesting exception of males under 25, and travel for work. Another change is the effect on socializing for working-age males, which evaporates after controlling for labor force status. But effects on sleeping, home production, eating and drinking, and telephoning are all largely unchanged. When unemployment is high, for example, more men become unemployed and thus sleep more, check on their elderly parents, work less, and socialize and relax; but even men who retain their jobs do most of these in similar albeit smaller time allocations.

4.2.4 Detailed results by age and sex

Most of these categories remain relatively broad, and the detail in the ATUS allows me to investigate behavior at a more granular level. In Table 8, I further decompose four of the more interesting categories of time use: care of children in the household, adults outside of the household, socializing and relaxing, and telephoning. I drop the dummies for labor force status, so these are the total marginal effects of the unemployment rate, inclusive of the impact on individual joblessness.

When unemployment is high, young males increase the time they spend playing with children in the household, as shown in the first column. If anything they decrease most other time allocations spent with children, especially time spent reading. There is little evidence they change their care of adults outside of the household. The increase in their socializing and relaxing comprises attending social events and watching television and movies. They appear to decrease the time they spend relaxing and thinking. Their telephone behavior appears to be unrelated to macroeconomic conditions. Among these activities, young females reallocate toward care of adults outside of the household, presumably grandparents or parents. The most significant increase takes the form of providing physical care.

Males of working age also take more care of adults outside the household, but they focus on helping, a category that includes housework, cooking, house and vehicle maintenance and other types of task management. They also spend some time with adults outside the household waiting for medical care. Men's increased relaxation time is accounted for by increased time spent watching television and movies, apparently a result common to males of all ages during economic hard times. Although their total time spent on the telephone does not change significantly, time spent talking on the telephone with friends appears to rise slightly. With the exception of telephoning, females of working age do not shift their behavior in these categories much at all when unemployment rises. There is some evidence they spend more time relaxing and thinking, but their primary response is via increased telephone contact with family, friends, and a small amount with salespeople.

Men over 65 are like men under 25 in the way they increase care of children in the household during economic bad times. But they tend to increase their provision of very different types of care: physical care and reading, rather than playing. Men over 65 spend more time relaxing and thinking when unemployment rises, they increase their tobacco and drug use slightly, and shift several other types of relaxation. They too may increase telephoning with friends when times are bad. Women over 65 change their behavior relatively little with the unemployment rate, except to increase their telephoning with friends.

5 Discussion

Patterns of time use over the recent U.S. business cycle reveal behavioral responses to the unemployment rate and to housing and stock prices. Changes in asset prices represent pure income effects that increase several types of leisure time like sleeping and socializing while they appear to decrease home production, implying that it may produce inferior goods. Increases in the aggregate unemployment rate puts some individuals out of work, which changes average time use in a mechanical way. But they also lower the price of time for the average individual and produce significant behavioral changes that are more clearly visible among distinct age and sex subgroups.

A rising unemployment rate increases sleeping, but gains are almost entirely enjoyed by men of working age. Given that they report the least amount of sleep on average, this is probably a most welcome change and may be efficient. Preparation of food at home also increases during periods of high unemployment, and this response is concentrated among females. Perhaps related to this are increases in time spent eating and drinking, which impact males and females under 25, who also spend the least amount of time on those activities. Whether social family dinners are increasing in quantity or duration or young people are simply taking more leisurely lunches is unclear, but the temptation is to view that development as being positive for their well-being.

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 very limited information on outcomes other than work and time use. The ATUS currently covers at most only parts of two business cycles, from the recovery following the trough in 2001 to the peak in December 2007 and the long trough since. Time use over the business cycle in general may be different than time use over the recent history covered by the ATUS.

A much larger 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) 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 the 2006–2008 waves, and the only health measures were self-reported health status on a Likert scale, height, weight, and thus BMI. Examining the link between the business cycle, time use, and health outcomes is simply not possible at the individual level in the ATUS data. With many more waves, it may ultimately be possible to examine a dataset of state-level averages either of health or mortality.

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. Increased participation in adult care when the unemployment rate rises is an example. As shown in Table 4, 9 percent of the ATUS sample reports caring for adults outside the household, while the total average time spent is 5 minutes, shown in Table 1. These figures imply an average of 55 minutes spent per day per respondent, which is a large time input for the elderly parents of the roughly 0.2 percent (not shown) who shift from non-participation when the unemployment rate rises 1 percent.

Increased sleepless 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, much of the effect of the business cycle on socializing and relaxing appears to show up as increased viewing of television and movies, hardly indicative of gains in healthy behavior. But care of children and adults and telephoning all seem to increase. 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 and increased social interaction in fostering the improvement in average health outcomes during recessions that we have seen reported in other literature (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.

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 of sleep appears to increase when unemployment rises, presumably because work effort slackens, reducing stress and worry. Care of children and the elderly seems to expand, possibly because individuals 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 results are suggestive of potential gains to be had by reassessing the character of our work-life arrangements. If it takes a recession to get us to sleep more and to interact with others, why are we working so hard? Although the current results are 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.

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Table 1: Average disposition of time use in the U.S., selected years

	Average 2003 to 2009		**2006**		**2009**		**Change 2009 − 2006**	
	Mean	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**
Sleeping	512.7	(1.7)	513.5	(2.9)	516.2	(2.4)	2.8	(3.8)
Sleepless	3.5	(0.2)	4.1	(0.4)	4.1	(0.3)	0.0	(0.5)
Personal care	45.9	(0.4)	46.1	(0.8)	45.6	(0.8)	-0.5	(1.1)
Housework	36.4	(0.4)	36.6	(1.2)	35.9	(1.0)	-0.6	(1.6)
Home food prep	31.4	(0.4)	31.7	(0.8)	32.3	(0.7)	0.6	(1.1)
Interior work	5.1	(0.2)	4.9	(0.4)	4.7	(0.5)	-0.1	(0.6)
Exterior work	15.5	(0.5)	15.0	(0.7)	15.2	(0.9)	0.2	(1.1)
Household misc.	19.4	(0.4)	19.4	(0.8)	19.5	(0.8)	0.1	(1.1)
Household finances	2.1	(0.1)	1.8	(0.1)	2.1	(0.2)	0.3	(0.2)
Care of HH kids	25.3	(0.5)	24.6	(0.6)	25.7	(0.6)	1.1	(0.8)
Care of HH adults	2.3	(0.1)	2.3	(0.3)	2.0	(0.2)	-0.3	(0.4)
Care of non-HH kids	4.7	(0.2)	4.5	(0.3)	4.3	(0.3)	-0.2	(0.5)
Care of non-HH adults	5.0	(0.2)	4.5	(0.4)	4.3	(0.4)	-0.2	(0.5)
Working & related	201.4	(2.2)	204.4	(3.6)	190.9	(3.9)	-13.5**	(5.3)
Informal work	1.7	(0.1)	1.4	(0.2)	1.8	(0.3)	0.4	(0.3)
Job search	1.6	(0.1)	1.4	(0.2)	2.6	(0.3)	1.2***	(0.3)
Education	25.8	(1.0)	27.4	(1.7)	26.1	(1.3)	-1.3	(2.2)
Consumer purchases	23.8	(0.2)	24.2	(0.5)	22.7	(0.6)	-1.6*	(0.8)
Professional services	2.2	(0.1)	2.2	(0.2)	1.9	(0.1)	-0.4*	(0.2)
Medical services	3.0	(0.1)	2.9	(0.2)	3.3	(0.2)	0.3	(0.3)
Household services	1.0	(0.1)	1.1	(0.2)	0.8	(0.1)	-0.3	(0.2)
Government services	0.4	(0.0)	0.6	(0.1)	0.4	(0.1)	-0.2*	(0.1)
Eating and drinking	66.6	(0.6)	66.8	(0.7)	66.5	(1.0)	-0.3	(1.2)
Socializing & relaxing	275.3	(2.6)	271.7	(3.2)	281.4	(3.8)	9.6*	(5.0)
Exercise	17.7	(0.4)	16.8	(0.7)	18.5	(0.8)	1.7*	(1.0)
Watching sports	2.0	(0.1)	2.2	(0.3)	1.5	(0.2)	-0.6*	(0.3)
Religious activities	8.1	(0.3)	7.2	(0.4)	8.7	(0.4)	1.5**	(0.6)
Volunteer activities	8.6	(0.2)	7.8	(0.4)	9.1	(0.5)	1.3**	(0.6)
Telephoning	7.0	(0.2)	7.1	(0.3)	6.8	(0.3)	-0.2	(0.4)
Travel & transit	57.3	(0.4)	57.0	(0.8)	55.4	(0.8)	-1.6	(1.1)
Travel for work	17.1	(0.4)	17.6	(0.7)	16.6	(0.7)	-1.0	(1.0)
Unemployment rate	5.9	(0.2)	4.7	(0.1)	9.2	(0.4)	4.6***	(0.4)
Observations	97,471		12,943		13,133			

Sources: American Time-Use Survey (ATUS) 2003–2009 waves, Bureau of Labor Statistics, and author's calculations. The average unemployment rate in the last row is the sample average of state-level unemployment rates, not the average rate of unemployment among ATUS respondents. Averages and standard errors are calculated using survey weights across all individuals and all days in the sample, both weekday and weekend, with clustering of standard errors are at the state level. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 2: Average disposition of time use in the U.S. by labor force status, 2003–2009

	Employed		**Unemployed**		**Not in LF**	
	Mean	**SE**	**Mean**	**SE**	**Mean**	**SE**
Sleeping	495.4	(1.6)	559.1	(3.3)	541.5	(1.7)
Sleepless	2.4	(0.1)	3.2	(0.4)	5.9	(0.3)
Personal care	45.5	(0.4)	42.3	(1.2)	47.6	(0.7)
Housework	28.5	(0.4)	43.0	(2.0)	52.1	(0.8)
Home food prep	25.1	(0.3)	34.1	(0.7)	44.6	(0.8)
Interior work	4.9	(0.2)	6.7	(1.0)	5.5	(0.4)
Exterior work	13.2	(0.5)	16.3	(1.5)	20.2	(0.7)
Household misc.	17.6	(0.4)	21.7	(1.1)	22.9	(0.5)
Household finances	1.8	(0.1)	2.0	(0.6)	2.8	(0.2)
Care of HH kids	24.8	(0.4)	31.1	(1.5)	25.3	(1.2)
Care of HH adults	1.6	(0.1)	2.1	(0.3)	3.9	(0.2)
Care of non-HH kids	3.5	(0.2)	7.0	(0.8)	7.0	(0.4)
Care of non-HH adults	4.5	(0.2)	8.3	(0.9)	5.4	(0.3)
Working & related	310.9	(2.0)	3.7	(0.7)	1.3	(0.2)
Informal work	1.3	(0.1)	4.4	(0.5)	1.9	(0.2)
Job search	0.5	(0.1)	21.4	(1.7)	0.3	(0.1)
Education	16.7	(0.5)	65.0	(2.8)	38.5	(2.9)
Consumer purchases	22.6	(0.3)	26.6	(1.0)	25.9	(0.4)
Professional services	2.2	(0.1)	1.8	(0.2)	2.3	(0.1)
Medical services	2.0	(0.1)	2.1	(0.3)	5.4	(0.2)
Household services	0.8	(0.1)	0.7	(0.1)	1.3	(0.1)
Government services	0.3	(0.0)	1.4	(0.3)	0.5	(0.0)
Eating and drinking	65.4	(0.7)	55.8	(1.2)	70.9	(0.7)
Socializing & relaxing	220.7	(1.5)	340.8	(4.5)	380.9	(5.2)
Exercise	16.5	(0.4)	22.7	(1.0)	19.6	(0.6)
Watching sports	2.1	(0.2)	2.5	(0.3)	1.6	(0.1)
Religious activities	6.8	(0.3)	7.6	(0.7)	10.9	(0.4)
Volunteer activities	7.4	(0.3)	9.1	(1.1)	11.3	(0.4)
Telephoning	5.2	(0.2)	12.7	(1.0)	9.7	(0.4)
Travel & transit	56.2	(0.5)	65.3	(1.7)	58.3	(0.5)
Travel for work	25.8	(0.6)	5.6	(0.7)	0.3	(0.0)
Unemployment rate	5.8	(0.2)	6.3	(0.2)	5.9	(0.2)
Observations	63,154		4,492		31,132	

Sources: American Time-Use Survey (ATUS) 2003–2009 waves, Bureau of Labor Statistics, and author's calculations. The average unemployment rate in the last row is the sample average of state-level unemployment rates, not the average rate of unemployment among ATUS respondents. Averages and standard errors are calculated using survey weights across all individuals and all days in the sample, both weekday and weekend, with clustering of standard errors are at the state level. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 3: Estimates of effects on U.S. time use associated with U.S. or foreign national unemployment rates

Dependent variable:	**Marginal effect of the national unemployment rate in:**			
U.S. time use in	**U.S.**	**AUS**	**CAN**	**Euro**
Sleeping	1.089	4.069	2.401	-1.187
Sleepless	-0.107	0.219	0.336	0.184
Personal care	0.311	0.876	1.039	0.931
Housework	-1.105	0.113	-1.552	-1.989*
Home food prep	1.409**	4.355**	2.047**	2.031**
Interior work	-0.025	-0.239	0.302	0.666
Exterior work	0.184	-1.138	-0.462	-0.275
Household misc.	-0.763	-0.576	-1.148	-0.859
Household finances	-0.035	0.317	-0.105	-0.118
Care of HH kids	0.656	2.497*	1.272	1.236
Care of HH adults	0.019	0.306	0.777**	0.292
Care of non-HH kids	-0.094	-0.045	0.247	0.158
Care of non-HH adults	-0.247	-0.133	-0.316	-0.632
Working & related	-7.100***	-17.473***	-9.079**	-8.931***
Informal work	-0.168	-0.436	0.154	-0.400
Job search	0.227	0.234	0.070	0.303
Education	0.743	-1.808	-0.071	0.418
Consumer purchases	0.017	1.411	0.534	0.604
Professional services	-0.130	-0.266	0.006	-0.160
Medical services	0.115	0.291	0.272	-0.192
Household services	0.057	-0.081	0.253	0.061
Government services	0.036	-0.163	-0.020	-0.003
Eating and drinking	1.333*	3.066**	1.640*	1.827*
Socializing & relaxing	0.532	3.809	1.889	2.304
Exercise	0.244	-0.745	-0.571	0.246
Watching sports	0.015	-0.358	-0.459	-0.313
Religious activities	-0.637***	-1.221*	-1.408***	-1.442***
Volunteer activities	0.094	0.133	0.423	0.730
Telephoning	0.284	0.352	0.290	-0.016
Travel & transit	0.598	1.464	1.322	0.747
Travel for work	-0.367	-0.748	-0.793	-0.410

Sources: American Time-Use Survey (ATUS) 2003–2009 waves, Bureau of Labor Statistics, OECD, and author's calculations. Each cell in the table is the marginal effect on the type of observed time use in the ATUS shown in that row that is associated with the national unemployment rate shown in that column, either the U.S., Australia (AUS), Canada (CAN), or the Euro Zone. A marginal effect of 1.0 means time use increases by 1 minute for each increase of 1 percentage point in unemployment. Each cell shows an estimate from a separate Tobit regression on pooled data observed at the monthly frequency. There are 97,471 observations in each regression. Models are estimated across all individuals and all days (weekday and weekend) in the sample using survey weights. Other covariates in each regression include the log of the S&P 500 index times 100, the log of the FHFA's quarterly Housing Price Index for all transactions times 100, indicator variables for the sex, race, and marital status of the respondent, age and age-squared, the number of coresident adults and children, years of education, indicators for MSA and weekday, monthly average temperature and precipitation, and dummies for the 9 Census divisions, year, and month of observation. Standard errors are clustered at the state level. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 4: Tobit marginal effects on time use, all ATUS respondents 2003–2009

Dependent variable: U.S. time use in	**Marginal effect of: State unemployment rate**	**Log stock prices (×100)**	**Log home prices (×100)**	**Prob. of use > 0**	**Share attrib. partic.**	σ
Sleeping	1.776***	0.198**	0.048	0.999	0.001	129.8
Sleepless	-0.073	-0.014	-0.014***	0.045	0.832	191.8
Personal care	-0.189	0.006	-0.025**	0.809	0.399	69.1
Housework	0.203	0.003	-0.020	0.365	0.640	147.2
Home food prep	0.449**	0.007	0.001	0.519	0.571	76.8
Interior work	-0.140	-0.001	-0.017**	0.036	0.835	356.7
Exterior work	-0.061	0.008	-0.048***	0.123	0.782	240.7
Household misc.	-0.241	0.007	-0.019*	0.363	0.570	99.7
Household finances	-0.045	-0.005	-0.004*	0.042	0.792	130.0
Care of HH kids	0.043	0.006	0.013	0.220	0.677	153.7
Care of HH adults	-0.053	-0.007	-0.007**	0.056	0.629	129.6
Care of non-HH kids	-0.036	-0.002	-0.011	0.056	0.772	216.9
Care of non-HH adults	0.176	0.000	-0.012*	0.090	0.640	156.5
Working & related	-5.798***	-0.211	-0.030	0.444	0.718	405.1
Informal work	-0.040	0.008	-0.004	0.010	0.875	480.2
Job search	0.165**	0.009	0.007	0.014	0.876	317.7
Education	0.127	0.009	-0.040	0.084	0.926	432.6
Consumer purchases	0.199	0.000	-0.005	0.410	0.603	93.1
Professional services	0.030	0.012*	0.002	0.058	0.783	94.8
Medical services	0.040	-0.001	-0.003	0.034	0.848	216.4
Household services	-0.016	0.006*	0.003*	0.022	0.763	136.7
Government services	-0.014	-0.004	0.002	0.007	0.862	189.9
Eating and drinking	0.499**	0.011	0.068***	0.956	0.267	49.9
Socializing & relaxing	2.874***	-0.007	0.001	0.953	0.267	190.2
Exercise	-0.093	0.028	0.039***	0.177	0.764	187.3
Watching sports	-0.098	0.001	-0.006	0.013	0.929	408.3
Religious activities	-0.075	0.016	-0.023***	0.083	0.857	190.2
Volunteer activities	-0.381**	0.017	-0.039***	0.068	0.822	292.3
Telephoning	0.311***	0.016	-0.007	0.156	0.726	90.5
Travel & transit	0.001	0.040	0.022	0.774	0.422	89.6
Travel for work	-0.428***	0.002	0.027***	0.386	0.611	62.3

Sources: See notes to Table 3. In this table, each row (rather than each cell) presents estimates from a separate Tobit regression of time use on the same list of covariates discussed in the notes. The unemployment rate is the monthly state average. There are 97,471 observations in each regression. The fifth column presents the share of the marginal effect on observed time use that is attributable to participation per McDonald and Moffitt (1980). It is the probability of positive time use, shown in the fourth column, times the marginal effect of x on the probability (not shown, available upon request) divided by the marginal effect of x on observed time use y^*. The last column reports σ, the estimated standard error of the regression, the equivalent of the root mean squared error in an OLS regression.

Table 5: Average disposition of time use across age and sex subgroups

	Males 15–24		**Females 15–24**		**Males 25–64**		**Females 25–64**		**Males 65+**		**Females 65+**	
	Mean	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**
Sleeping	550.2	(3.6)	551.3	(3.0)	494.3	(1.9)	503.7	(1.7)	528.9	(2.1)	526.4	(2.4)
Sleepless	2.2	(0.2)	2.0	(0.3)	2.5	(0.2)	3.6	(0.2)	5.2	(0.5)	8.3	(0.5)
Personal care	38.5	(0.8)	55.1	(0.8)	38.0	(0.5)	52.1	(0.7)	38.0	(0.8)	56.1	(0.9)
Housework	10.5	(0.7)	27.8	(1.8)	15.7	(0.5)	60.4	(0.9)	15.9	(0.7)	71.5	(1.7)
Home food prep	7.5	(0.4)	18.4	(0.9)	18.1	(0.3)	49.3	(1.1)	21.7	(0.7)	57.5	(1.2)
Interior work	2.8	(0.5)	2.2	(0.5)	7.5	(0.5)	4.1	(0.2)	8.3	(0.7)	3.2	(0.4)
Exterior work	6.9	(0.9)	2.0	(0.3)	22.1	(0.9)	9.9	(0.5)	41.4	(2.1)	16.3	(0.9)
Household misc.	15.3	(0.7)	16.0	(1.0)	19.7	(0.5)	18.7	(0.5)	26.5	(1.1)	24.0	(0.8)
Household finances	0.3	(0.1)	0.5	(0.1)	1.9	(0.1)	2.4	(0.1)	4.2	(0.3)	3.7	(0.2)
Care of HH kids	5.6	(0.5)	25.8	(1.4)	21.0	(0.5)	45.1	(1.0)	0.8	(0.2)	1.5	(0.3)
Care of HH adults	1.0	(0.1)	1.4	(0.2)	1.8	(0.1)	2.7	(0.2)	4.2	(0.7)	3.6	(0.4)
Care of non-HH kids	3.0	(0.5)	4.8	(0.4)	2.8	(0.3)	6.3	(0.4)	4.6	(0.5)	7.5	(0.6)
Care of non-HH adults	4.7	(0.6)	4.3	(0.4)	5.2	(0.2)	5.1	(0.2)	5.3	(0.4)	4.5	(0.4)
Working & related	161.1	(6.4)	132.6	(5.0)	301.2	(3.3)	205.4	(3.0)	56.1	(2.3)	28.8	(1.5)
Informal work	3.0	(0.3)	3.1	(0.4)	1.2	(0.1)	1.4	(0.1)	1.9	(0.6)	1.1	(0.2)
Job search	2.5	(0.3)	1.2	(0.3)	2.3	(0.2)	1.4	(0.1)	0.1	(0.0)	0.1	(0.0)
Education	108.2	(3.0)	119.9	(3.7)	6.1	(0.4)	8.8	(0.5)	1.2	(0.3)	2.1	(0.3)
Consumer purchases	14.6	(0.7)	27.1	(0.8)	18.3	(0.3)	30.8	(0.4)	21.2	(0.6)	25.1	(0.5)
Professional services	1.1	(0.1)	2.2	(0.2)	1.3	(0.1)	3.1	(0.1)	1.4	(0.2)	3.9	(0.3)
Medical services	1.3	(0.3)	1.9	(0.3)	2.1	(0.2)	3.5	(0.2)	5.5	(0.5)	5.5	(0.3)
Household services	0.3	(0.1)	0.4	(0.1)	0.9	(0.1)	1.0	(0.1)	2.6	(0.4)	1.2	(0.2)
Government services	0.3	(0.1)	0.5	(0.1)	0.4	(0.1)	0.5	(0.0)	0.5	(0.1)	0.3	(0.1)
Eating and drinking	54.7	(1.0)	56.4	(1.0)	68.8	(0.6)	63.5	(0.8)	86.4	(1.1)	78.3	(0.9)
Socializing & relaxing	287.8	(4.3)	246.0	(3.4)	260.6	(2.5)	233.4	(3.0)	436.0	(4.6)	393.0	(2.9)
Exercise	43.1	(1.2)	18.5	(0.9)	19.1	(0.6)	11.0	(0.4)	20.2	(0.9)	9.9	(0.7)
Watching sports	3.9	(0.3)	3.7	(0.6)	2.1	(0.2)	1.4	(0.1)	1.0	(0.2)	0.7	(0.2)
Religious activities	6.1	(0.5)	6.4	(0.5)	6.0	(0.3)	8.8	(0.4)	11.3	(0.7)	14.4	(0.5)
Volunteer activities	7.3	(0.6)	6.9	(0.7)	7.6	(0.4)	9.0	(0.4)	11.2	(0.9)	12.4	(0.7)
Telephoning	7.9	(0.5)	13.1	(0.8)	2.9	(0.1)	8.1	(0.3)	3.9	(0.2)	12.8	(0.5)
Travel & transit	62.5	(0.9)	68.1	(1.6)	53.1	(0.6)	59.9	(0.6)	54.1	(1.1)	48.4	(0.9)
Travel for work	15.5	(0.6)	10.5	(0.5)	26.9	(0.8)	15.9	(0.4)	4.7	(0.3)	2.1	(0.2)

Sources: See notes to Table 3.

Table 6: Tobit marginal effects of the unemployment rate on time use, ATUS respondents grouped by age and sex

	Marginal effect of the unemployment rate on the time use of:					
Dependent variable: U.S. time use in	**Males 15–24**	**Females 15–24**	**Males 25–64**	**Females 25–64**	**Males 65+**	**Females 65+**
Sleeping	3.019	3.216	2.699***	0.830	1.131	-0.182
Sleepless	0.015	0.114	-0.033	-0.154	-0.297	-0.092
Personal care	-0.557	-0.319	-0.439	0.000	0.527	0.024
Housework	0.132	-1.845*	0.654**	-0.039	-0.590	1.028
Home food prep	0.294	0.745**	0.088	0.808**	0.394	0.509
Interior work	-0.488	-0.760**	-0.080	0.319*	-1.105*	-0.135
Exterior work	0.427	0.258	0.306	-0.349*	-1.833	-0.307
Household misc.	-0.346	-0.991**	0.321	-0.375	-1.204	-0.188
Household finances	-0.072	-0.048	-0.018	-0.015	-0.223	-0.060
Care of HH kids	0.492**	-0.475	-0.136	0.001	0.224***	-0.206
Care of HH adults	0.045	-0.248	-0.077	-0.137	0.241	0.572*
Care of non-HH kids	-0.107	-0.220	-0.027	-0.061	0.329	0.172
Care of non-HH adults	0.043	0.682*	0.427**	-0.202	0.143	0.472
Working & related	-8.941**	-7.929**	-7.680***	-4.330***	-3.989	0.452
Informal work	-0.338	-0.483	0.112	0.037	-0.786*	-0.082
Job search	0.136	0.097	0.293*	0.185**		
Education	-1.290	0.087	0.201	0.191	0.405**	-0.475**
Consumer purchases	0.203	0.440	0.132	0.229	-0.091	0.449
Professional services	-0.035	-0.033	-0.007	0.089	0.139	-0.070
Medical services	0.015	-0.369	0.142	0.141	0.029	-0.089
Household services	-0.014	-0.230**	0.082	-0.050	0.042	-0.028
Government services	-0.077	-0.076	0.031	-0.052		0.052
Eating and drinking	2.015***	1.494**	-0.173	0.457	0.410	0.435
Socializing & relaxing	6.387**	4.453	3.615***	1.476	4.909*	-1.414
Exercise	-1.149	-0.689	-0.102	0.009	1.249*	0.032
Watching sports	-0.320	-0.392	-0.142	0.027	0.048	0.016
Religious activities	-0.930*	-0.628**	-0.050	0.126	-0.268	0.193
Volunteer activities	-0.929*	-0.226	-0.377	-0.302	-0.468	-0.481
Telephoning	0.313	-0.244	0.097	0.391**	0.247	0.930***
Travel & transit	0.702	0.583	-0.334	0.206	-0.785	0.177
Travel for work	-0.941*	-0.632**	-0.550**	-0.234*	-0.366	0.184**

Sources: See notes to Table 5. Each cell shows an estimate of the marginal effect of the state unemployment rate from a separate Tobit regression of the time use shown in that row among the age/sex subgroup shown in that column. Blanks show models that did not converge because of insufficient variation in time use.

Table 7: Tobit marginal effects of the unemployment rate on time use, after conditioning on labor force status, ATUS respondents grouped by age and sex

	Controlling for labor force status, the marginal effect of the unemployment rate on the time use of:					
Dependent variable: U.S. time use in	**Males 15–24**	**Females 15–24**	**Males 25–64**	**Females 25–64**	**Males 65+**	**Females 65+**
Sleeping	2.459	2.468	1.840**	0.368	1.177	-0.338
Sleepless	0.031	0.078	-0.069	-0.179	-0.291	-0.144
Personal care	-0.551	-0.102	-0.346	0.095	0.526	0.039
Housework	0.021	-2.099**	0.469*	-0.402	-0.556	0.864
Home food prep	0.248	0.573	-0.093	0.568*	0.390	0.423
Interior work	-0.433	-0.744**	-0.138	0.306*	-1.129*	-0.155
Exterior work	0.310	0.224	0.108	-0.420**	-1.753	-0.322
Household misc.	-0.202	-1.131**	0.209	-0.453	-1.221	-0.194
Household finances	-0.075	-0.046	-0.031	-0.022	-0.218	-0.055
Care of HH kids	0.406*	-0.647	-0.243	-0.182	0.216***	-0.202
Care of HH adults	0.040	-0.267	-0.102	-0.154	0.238	0.543*
Care of non-HH kids	-0.110	-0.223	-0.047	-0.108	0.326	0.170
Care of non-HH adults	0.063	0.686*	0.377**	-0.228*	0.148	0.446
Working & related	-6.580**	-2.622	-0.447	0.251	-2.879*	1.297
Informal work	-0.342	-0.542	0.102	0.027	-0.797*	-0.144
Job search	-0.045	0.010	0.043	0.149**		
Education	-1.649	-0.578	0.054	0.080	0.397**	-0.473**
Consumer purchases	0.232	0.389	0.086	0.151	-0.085	0.422
Professional services	-0.022	0.023	-0.009	0.093	0.139	-0.069
Medical services	0.021	-0.400	0.106	0.124	0.057	-0.120
Household services	0.008	-0.227**	0.079	-0.055	0.034	-0.029
Government services	-0.076	-0.085	0.015	-0.060*		0.051
Eating and drinking	2.121***	1.476**	-0.163	0.428	0.463	0.419
Socializing & relaxing	5.374*	2.844	1.267	0.174	4.488	-2.136
Exercise	-1.189	-0.711	-0.165	-0.023	1.301**	0.024
Watching sports	-0.314	-0.407	-0.136	0.030	0.048	0.017
Religious activities	-0.911*	-0.636**	-0.051	0.108	-0.293	0.188
Volunteer activities	-0.944*	-0.287	-0.398	-0.338	-0.457	-0.467
Telephoning	0.365	-0.315	0.054	0.333**	0.251	0.908***
Travel & transit	0.827	0.576	-0.555	0.121	-0.747	0.133
Travel for work	-0.705	-0.205	0.005	0.148	-0.250	0.312***

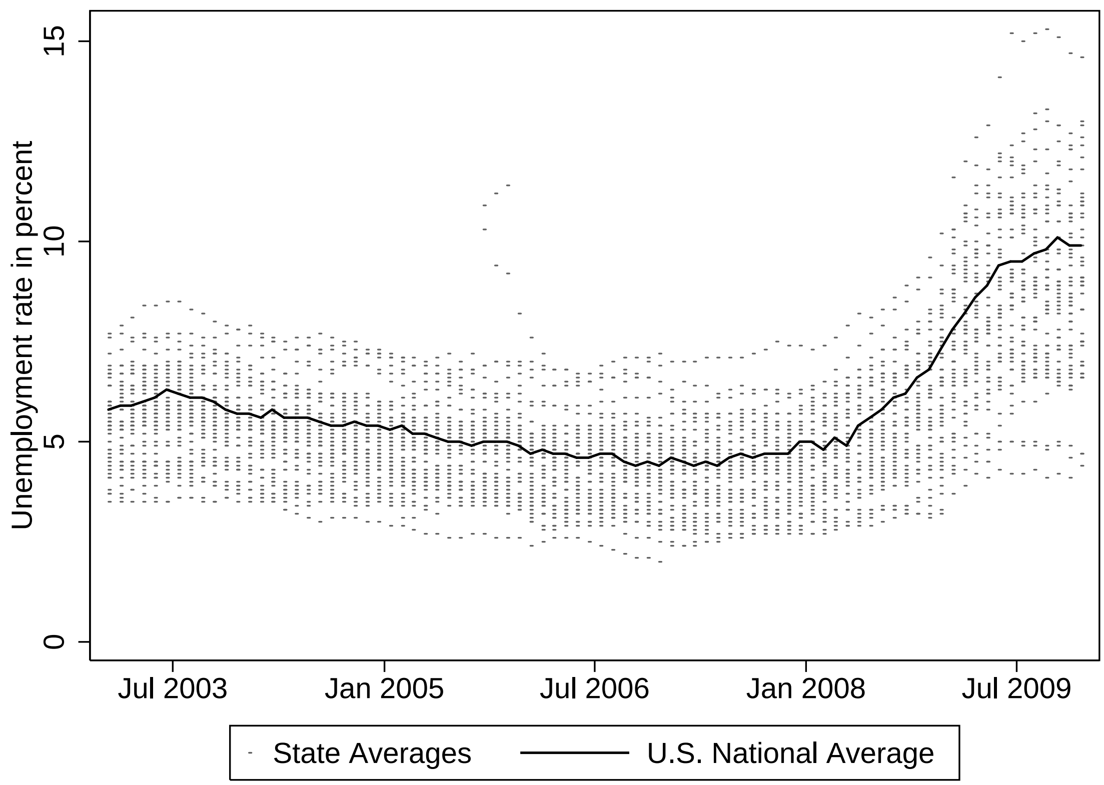
Sources: See notes to Table 6. Each cell shows an estimate of the marginal effect of the state unemployment rate from a separate Tobit regression of the time use shown in that row among the age/sex subgroup shown in that column. Blanks show models that did not converge because of insufficient variation in time use. All regressions in this table also control for labor force status. Thus these estimates can be interpreted as the marginal effects of an economic slowdown on time use independent of whether it pushes individuals into unemployment.

Table 8: Tobit marginal effects of the unemployment rate on fine categories of time use, ATUS respondents grouped by age and sex

	Marginal effect of the unemployment rate on the time use of:					
Dependent variable: U.S. time use in	**Males 15–24**	**Females 15–24**	**Males 25–64**	**Females 25–64**	**Males 65+**	**Females 65+**
Care of HH kids	0.492**	-0.475	-0.136	0.001	0.224***	-0.206
Physical care	-0.092	0.196	-0.008	-0.060	0.076**	-0.040
Reading to/with	-0.051***	0.042	-0.009	-0.054	0.168**	
Playing with	0.273*	0.384	-0.174	-0.069		-0.049
Arts & crafts			-0.005	0.002		
Playing sports with	-0.005		0.005	0.013		
Talking & listening	-0.019	-0.017	0.033	0.084	0.020	-0.061**
Planning events		-0.009	0.010	-0.044*		
Looking after	0.002	0.217	-0.069	-0.044		0.037
Attending events		0.065	-0.014	-0.192**		
Waiting for/with	-0.001	0.010	0.012	0.018		
Pick up & drop off	0.018	-0.042	-0.005	0.012	0.000	-0.012*
Kids' education		0.028	-0.005	0.074		
Kids' health	-0.003	-0.153	0.017	0.104		
Care of non-HH adults	0.043	0.682*	0.427**	-0.202	0.143	0.472
Physical care		0.224**	0.003	0.032		0.031
Looking after			0.018	0.027*		
Providing medical care			0.007	0.031		
Obtaining medical care				0.020		
Waiting for medical care			0.048*	-0.015		
Helping	0.040	0.248	0.336*	-0.217*	0.340	0.272
Socializing & relaxing	6.387**	4.453	3.615***	1.476	4.909	-1.414
Communicating	0.106	1.545	0.045	-0.161	-1.037	-0.238
Social events	0.823**	0.146	-0.280	-0.216	-0.217	0.366
Relaxing & thinking	-1.048*	-0.068	0.163	0.561**	2.919*	0.045
Tobacco & drugs	-0.035	0.024	-0.059	-0.017	0.081**	0.039
TV & movies	3.102*	0.888	3.150***	1.627	2.170	0.795
Religious TV			0.014	-0.053**		0.001
Radio	0.088	0.076	-0.018	0.002	-0.568	-0.424
Other music	0.443	-0.065	0.130	0.067	-0.378***	0.061
Games	1.973	0.540	-0.254	0.058	0.262	-0.904
Other computer	0.683	0.849	0.204	0.259*	1.098**	-0.558**
Arts & crafts	-0.078	-0.105	-0.101	-0.056	-0.838**	-0.579**
Collecting			0.044***			
Other hobbies			-0.073	-0.060*	-0.046	
Reading	-0.274	-0.555	-0.522	-0.379	-0.526	0.162
Writing		0.055	-0.013	-0.073*	-0.135	0.035
Arts & entertainment	0.314	-0.302	0.016	-0.308	0.179	0.047
Telephoning	0.313	-0.244	0.097	0.391**	0.247	0.930
Family	0.054	0.096	0.020	0.179**	0.158	0.277
Friends	-0.020	-1.092*	0.059**	0.121*	0.132*	0.294**
Education providers				0.003		
Salespeople			0.009	0.013**	-0.028	-0.023
Professional services		-0.066**	0.019	0.017	-0.005	0.021
Household services		0.008	0.002	-0.005		-0.011
Care providers				-0.003		
Government			0.005**	0.009	-0.006	

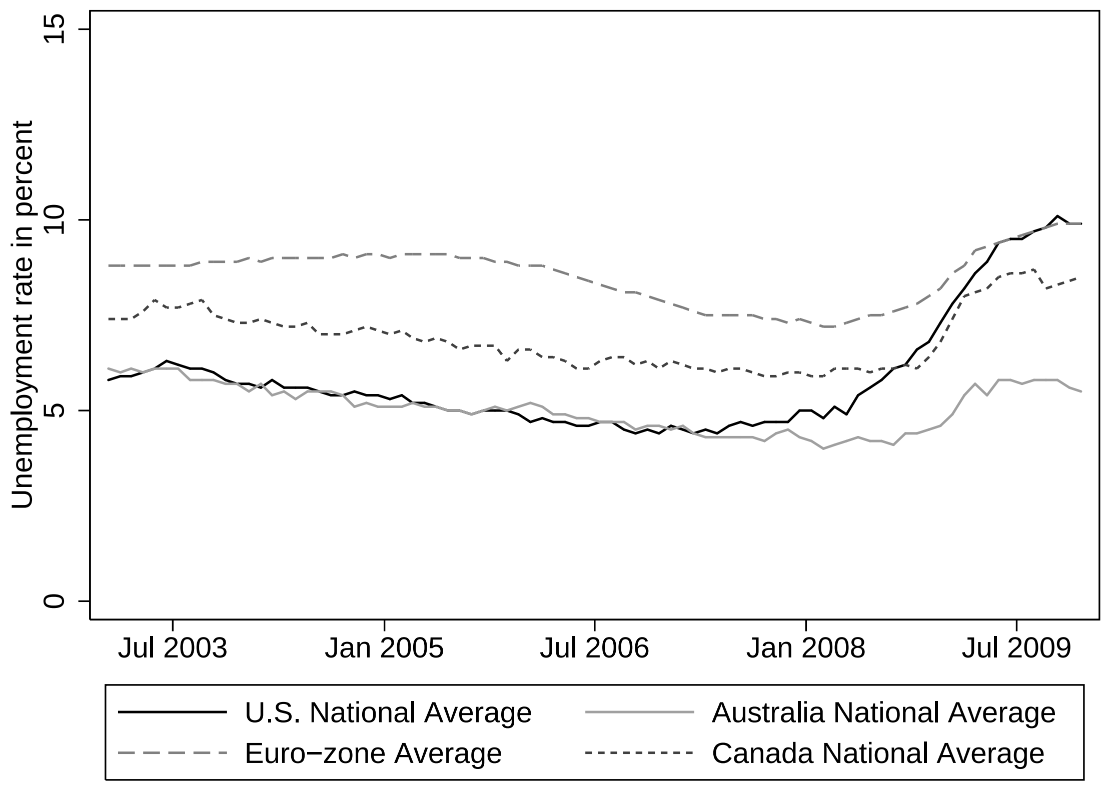
Sources: See notes to Table 6.

Figure 1: Monthly unemployment rates in the U.S., 2003–2009



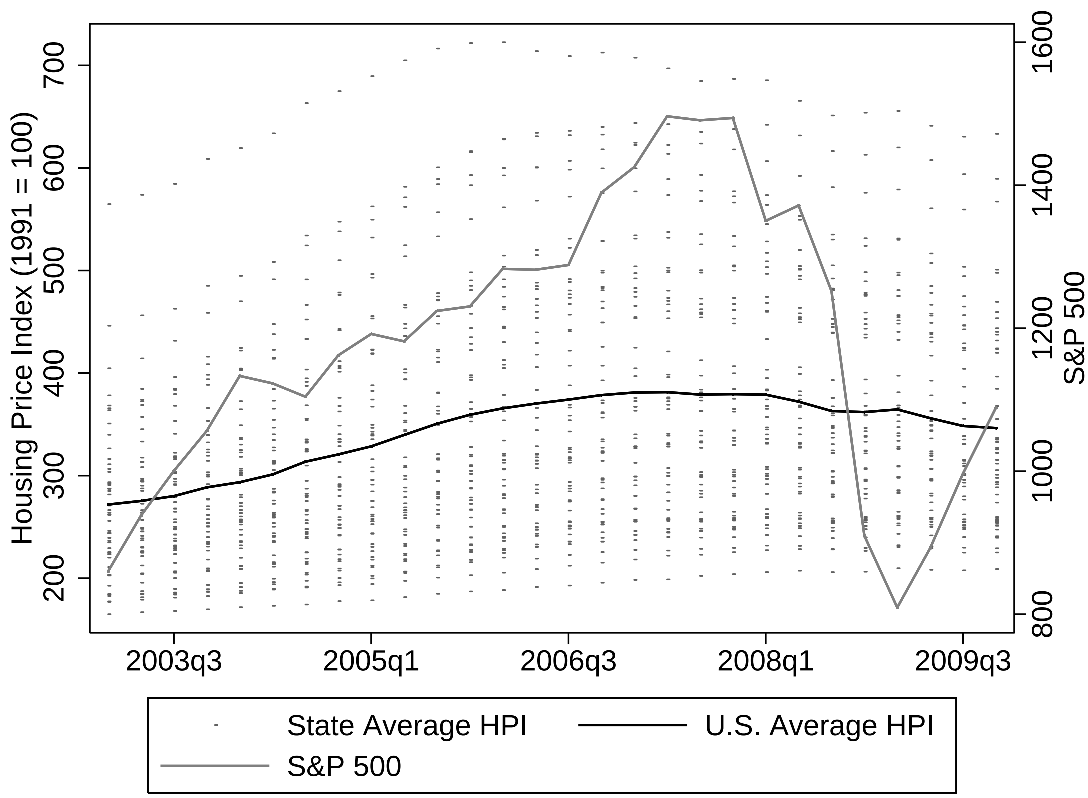
Source: Bureau of Labor Statistics. Data are seasonally adjusted state or national averages.

Figure 2: Monthly unemployment rates in several industrialized regions, 2003–2009



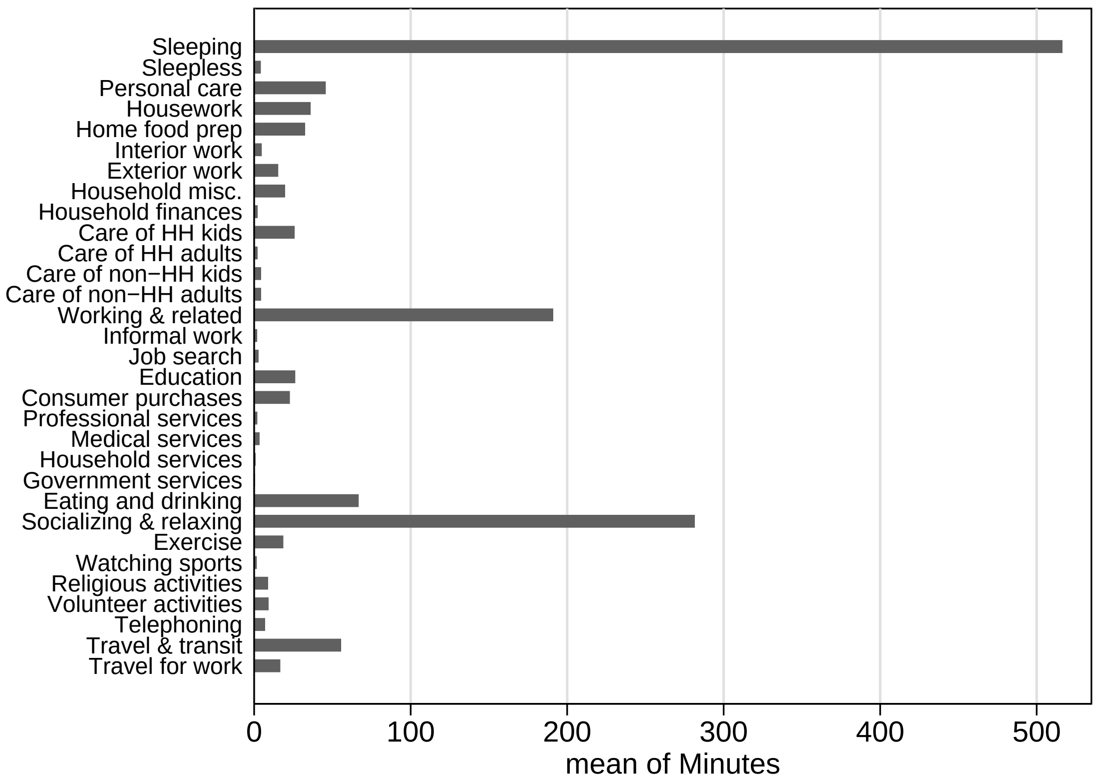
Sources: Bureau of Labor Statistics and OECD. Data are seasonally adjusted national averages.

Figure 3: Quarterly stock and housing prices in the U.S., 2003–2009



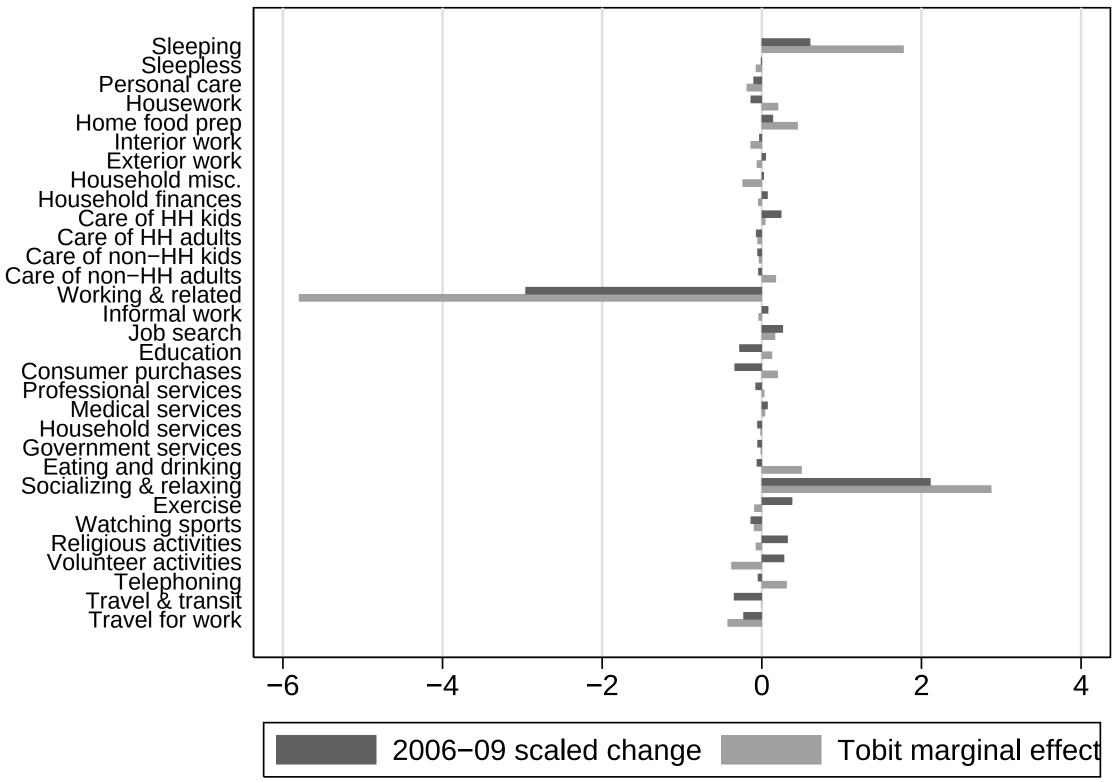
Sources: HPI all-transactions, Federal Housing Finance Agency; S&P 500, *Economic Report of the President*, various years. All data are quarterly averages. The regressions in the paper use the monthly S&P 500 index but the quarterly (not interpolated) HPI by state.

Figure 4: Average disposition of time use in the U.S., 2003–2009



Source: American Time-Use Survey (ATUS) 2003–2009 waves and author's calculations. Averages are calculated using survey weights across all individuals and all days, weekday and weekend, in the samples.

Figure 5: Effects of a one percent increase in unemployment on U.S. time use



Source: American Time-Use Survey (ATUS) 2003–2009 waves and author's calculations. The 2006-09 scaled change is the change in average time use by category between 2006 and 2009 divided by the change in the average unemployment rate between 2006 and 2009. The Tobit marginal effect is the Tobit regression coefficient rescaled by the probability of nonzero time use to show the estimated average effect of a one percent change in unemployment on time use by category.