Economica

Economica (2019)
doi:10.1111/ecca.12324

Unemployment and Effort at Work

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Final version received 6 August 2019.

We measure the sensitivity of work effort to local labour market conditions using self-reported non-work at the workplace in the American Time Use Survey (ATUS) 2003–12. Non-work at work is quantitatively significant and varies positively with local unemployment, but in opposite directions at the extensive and intensive margins. The fraction of workers reporting positive values declines with unemployment, while time spent in non-work conditional on any such time rises with unemployment. The results speak to issues of labour hoarding, efficiency wages and the cyclicality of labour productivity. We also demonstrate a relationship between the incidence of non-work and unemployment benefits in state data linked to the ATUS. There are also pronounced occupational differences in the incidence and intensity of non-work.

Introduction

The relationship between labour market slack and worker effort is a hoary topic in macroeconomics and labour economics. The notion of labour hoarding—retaining workers during times of low product demand even though their labour input is reduced—goes back at least 50 years and has been adduced as an explanation for procyclical changes in labour productivity—productivity falling as unemployment rises (Biddle 2014). The notion that unemployment incentivizes workers to work harder to avoid layoff—the idea of efficiency wages—is described formally in the now-classic study by Shapiro and Stiglitz (1984), and goes back to writings of Kalecki (1943) and even to Marx's reserve army of the unemployed described in Chapter 23 of *Das Kapital* (Marx 1867).[1] It implies countercyclical changes—that labour productivity and effort rise as unemployment rises. Both of these strands in economic thought describe the relationship between unemployment, worker effort and labour productivity in a local labour market. Yet their implications are contradictory.

A large empirical literature has inferred from lags in employment adjustment to output shocks that labour hoarding is important (Hamermesh 1993, ch. 7). A much smaller literature has used the theory of efficiency wages to examine how wages respond to workers' opportunities (e.g. Cappelli and Chauvin 1991). No study to date has examined directly how effort at work responds to differences or changes in unemployment.[2] The reason is simple: until very recently, no large-scale dataset has been available detailing what workers do on the job and providing such information as unemployment varies over time. The American Time Use Survey (ATUS), which began in 2003, allows examination of this issue.

In this study we lay out the patterns of non-work on the job, and show how the amount of non-work and its incidence and conditional magnitude vary with labour market conditions, as measured by the unemployment rate. Having demonstrated that these variations are statistically significant and economically important, we then examine how they differ across occupations and sectors. We show that this heterogeneity is pervasive across different sectors and occupations, and extends to both the intensive and extensive margins of effort at the workplace. Finally, we consider how local differences in wages and unemployment benefits affect on-the-job effort.

I. Data and Descriptive Statistics

Since 2003, the ATUS has generated time diaries of large monthly samples of individuals showing what they are doing and where they are located. (See Hamermesh *et al*. (2005) for a description of these data, and Aguiar *et al*. (2013) for an examination of some cyclical aspects of time use.) It thus allows the first study of how workers spend time on the job and its variation with differences and changes in unemployment. Throughout this analysis we use various subsamples over the period 2003–2012 from the ATUS, which contains 136,960 monthly diaries of former Current Population Survey (CPS) respondents' activities on one particular day between two and five months after their final rotation month in the CPS.

Because we focus on activities while the respondent was at work, the only diaries included are those for days for which a respondent reported some time at the workplace. Since half of the diary days in the ATUS are on weekends when relatively few respondents are working, a much smaller sample of 41,111 usable diaries is available for analysis. Moreover, since our focus is on employee productivity, we initially exclude the self-employed (most of the remaining excluded observations) and those diaries without information on usual weekly hours of work, further reducing our sample to 35,548 usable observations. For a typical month in the sample period after 2003, we thus have around 250 observations on employees.[3]

The ATUS codes each moment of the respondent's diary day—the day before it is recorded—into over 400 distinct activities. Respondents also note where they were while performing each activity, with one of the possible locations being 'at the workplace'. We focus on primary activities performed at that location, defining total time at work as all time spent at the workplace. We then divide time at the workplace into time spent working and time spent not working.[4] The latter is divided into time spent eating, and time spent at leisure, exercising, cleaning, and in other non-work non-eating activities.[5]

In the ATUS, eating at work can be a primary activity or a secondary activity to working or a part of the job. Non-work time at work spent eating corresponds to a response of eating as a primary activity at the workplace. Non-work work time also includes activities that might be viewed as investment in future productivity but that are not currently productive, such as cleaning and perhaps exercising, as well as others such as gossiping, web-surfing and chatting that are less likely to be productive.[6] Non-work time at work does not include any time spent away from the workplace during the workday.

Table 1 presents sample means and their standard errors of the proportions of time spent at the workplace in these activities and in actual work, along with the time spent at work and other variables that are central to our analysis. All the statistics are calculated using the ATUS sampling weights, thus accounting for disproportionate sampling across days of the week, for standard CPS weighting and for differential non-response to the ATUS by the former CPS participants.[7] The first thing to note is that the typical day at work lasts about 8 hours and 20 minutes, a statistic that yields a five-day workweek of 41.74 hours, which is consistent with the mean usual weekly hours of 41.38 hours reported retrospectively by employees in the sample.[8]

Sample respondents report spending nearly 7% of time at the workplace in non-work primary activities, amounting to 34 minutes per day. Roughly half of this time is spent

TABLE 1
DESCRIPTIVE STATISTICS, ATUS EMPLOYEES' WORKDAYS, 2003–12: MEANS AND THEIR STANDARD ERRORS (AND RANGES FOR SEVERAL VARIABLES)

	Unconditional mean	Mean if any time in category
Diary daily hours at work	8.35 (0.014)	
	[0.02, 24]	
Proportion of time at work not working at work:	0.0688 (0.00062)	0.1003 (0.00084)
Of which:		
Eating	0.0372 (0.00028)	0.0682 (0.00041)
Non-work not eating	0.0316 (0.00057)	0.0869 (0.00145)
Of non-work not eating:		
Leisure and exercise	0.0221 (0.00038)	
Cleaning	0.0045 (0.00031)	
Other	0.0050 (0.00028)	
Usual weekly work hours	41.38 (0.063)	
	[1, 160]	
State unemployment rate (three-month average)	6.65 (0.012)	
	[2.1, 14.4]	

Notes
$N = 35{,}548$. Standard errors in parentheses, ranges in brackets.
Conditional on having some non-work time in the particular category.

eating; the other half is spent in leisure, exercise, cleaning and other non-work activities. These latter three activities are so rare that henceforth we concentrate on the twofold division between non-work eating and non-work non-eating time at work. While 34 minutes per day at the workplace not working seems low, most eating reported during the workday as a primary activity probably occurs away from the workplace and thus is not specifically assignable to the job in these data. To the extent that eating away from the workplace during work hours varies cyclically, it will be reflected in cyclical variations in the length of the day at the workplace, for which we adjust in the estimates produced in the next section.

As Figure 1 shows, there are a substantial number of zeros in the responses (33.7% of the sample), and much of our subsequent analysis focuses on this fact. The conditional mean amount of positive non-work time is slightly over 50 minutes per day. Beyond that, the distribution is skewed to the right, with a tiny fraction of respondents even reporting not working the entire time on the job.[9] Some 30.8% of the respondents reported eating at the workplace but no other non-work time, 14.6% reported other non-work but no eating on the job, and 20.9% reported both eating and other non-work time on the job.

An important question is what reported non-work actually represents. This is a measure of not working while at work and is what the respondent believes it to be, just as reported hours of work in the household surveys underlying the immense literature on labour supply represent what respondents believe their work time to be. Unlike recall about past weekly hours in those surveys, non-work time in the ATUS is specifically limited to and anchored by the time an individual spends at the workplace on the randomly selected diary day. These data are based on one-day recall, and errors should thus be fewer than those in the one-week recall of hours of work that are used in most

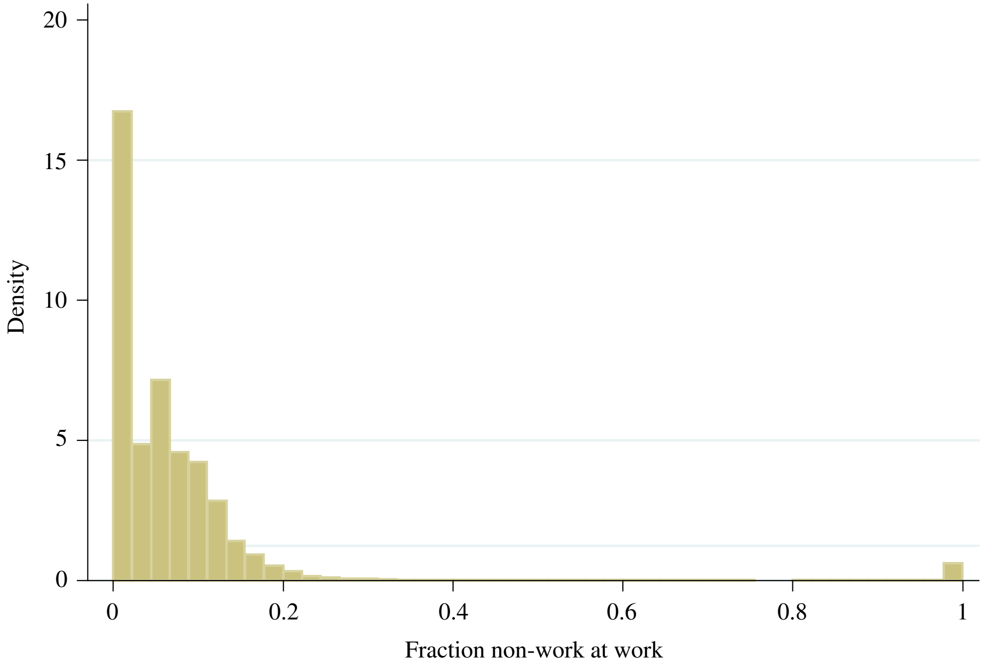

FIGURE 1. Distribution of the fraction of non-work time, ATUS 2003–12.

labour force surveys. Whether there are biases that are correlated with the forcing variables on which we focus is a more difficult question. If workers' willingness to report non-work varies with unemployment, then it might fall as unemployment rises, biasing the estimated impact of unemployment downwards towards zero. This effect would arise, however, only if people felt that their confidential time diaries were known to their employers, which does not seem likely.

Throughout this study, the central forcing variable is the local unemployment rate, measured as the jobless rate in the state where the worker resides.[10] The average unemployment rate in the sample is 6.6%, but it varies over a wide range—from barely 2% to over 14%. Partly because of the Great Recession, there is substantial variation in unemployment, which allows us to examine how non-work responds to changing local labour market conditions.

II. ON-THE-JOB NON-WORK AND ITS RELATIONSHIP WITH UNEMPLOYMENT

Economic theory is ambiguous about the sign of the relationship between non-work and business cycle conditions. This is because workers and their employers have different interests in non-work. If initiated by the worker, non-work might be interpreted as 'loafing', 'shirking' or 'goofing off on the job'. A raft of theories and motivations predicts a negative relationship between local labour market conditions and shirking.[11] High unemployment signals a lower value of utility in the state of unemployment, because either the incidence or the duration (or both) of joblessness is high. To avoid unemployment, employed workers exert higher effort to curry favour with their employers, to increase their productivity, or to reduce the probability of detection when they do shirk. Because effort is unobservable and monitoring is costly, firms accept this outcome passively, with few or no layoffs of shirkers occurring in equilibrium.

Alternatively, firms may find non-work by workers in some states of the world to be desirable. Firms face variable and imperfectly forecastable demand for their products, employing workers who represent substantial investments in human capital, search effort and other resources. In a temporary economic downturn, a layoff may be an inferior choice to maintaining employment, possibly even at standard hours. Labour hoarding by firms is often associated with the assignment of workers to ‘unproductive’ tasks such as cleaning, maintenance, painting, and so on, or even increased tolerance of worker-initiated non-work—that is, exactly what our data classify as on-the-job non-work time. The same result would arise from peer effects when the remaining employed workers seek to enjoy leisure like their unemployed fellows.

Central results

In Table 2 we present evidence on the cyclical behaviour of non-work in the USA based on the ATUS. This cyclical behaviour is measured by the response of non-work time at the workplace to variations in local labour market conditions. We assume that workers take those conditions as given, and we note that they vary across both time and space.[12] In the data, most of the variation in unemployment is across time: temporal movements account for two-thirds of the variance. Only 12% of the variance in unemployment rates is idiosyncratic at the state and month levels.

The initial least squares results shown in column (1) of Table 2 simply relate the proportion of non-work time at work to the state unemployment rate.[13] There is a highly significant positive association of unemployment with non-work time on the job. Over the entire range of unemployment observed in the data, the estimate suggests that the proportion of non-work time varies by 0.013 (on a mean of 0.069), variation large enough to alter assessments about the cyclical path of labour productivity.

The estimates in column (1) of Table 2 fail to account for the possible covariation of time spent in non-work with the amount of work performed. The equation underlying the estimates in column (2) includes quadratic terms in usual weekly hours and in time at work on the diary day. Also included but not reported are: indicators of race and ethnicity; a vector of indicators of educational attainment; a quadratic in potential experience (age − education − 6); indicators of gender and marital status and their interaction; and an indicator of metropolitan residence.

A longer usual workweek significantly increases the fraction of work time not working up to 43 usual weekly hours, with decreases thereafter. Conditional on usual hours, however, spending more time at work in a day decreases the proportion of time spent in non-work activities, but only up to 5.9 hours of work time per day. Beyond that, and thus for 85% of the sample, additional time on the job increases the share of time spent not working. Whether because of boredom, fatigue or something else, the marginal effect of additional work time on non-work activities is increasing for most employees as the workday lengthens.[14]

While the estimated impact of unemployment does change with the addition of these covariates, their unsurprisingly very weak correlation with state unemployment rates guarantees that their inclusion does not qualitatively alter the estimated effect of unemployment on non-work time.[15] The inference may understate the magnitude of this effect: as unemployment rises, even holding demographic characteristics constant, workers who retain their jobs may be those who report less non-work at work, creating a

TABLE 2
BASE ESTIMATES OF THE FRACTION OF TIME AT WORK NOT WORKING, ATUS 2003–12: PARAMETER ESTIMATES AND THEIR STANDARD ERRORS

Dependent variable:	Non-work			Eating at work		Other non-work	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent variable							
State unemployment rate (3-month average)	0.00104 (0.00037)	0.00084 (0.00036)	0.00056 (0.00041)	0.00024 (0.00022)	0.00001 (0.00022)	0.00060 (0.00030)	0.00056 (0.00035)
Usual weekly hours		0.0029 (0.0004)	0.0027 (0.0004)	0.0007 (0.0002)	×	0.0022 (0.0003)	×
(Usual weekly hours)^2/100		−0.0034 (0.0004)	−0.0031 (0.0004)	−0.0010 (0.0002)	×	−0.0024 (0.0003)	×
Hours at work		−0.0368 (0.0028)	−0.0377 (0.0028)	0.0046 (0.0013)	×	−0.0414 (0.0026)	×
(Hours at work)^2/100		0.0032 (0.0002)	0.0032 (0.0002)	−0.0002 (0.00009)	×	−0.0034 (0.0003)	×
Demographic variables		×	×	×	×	×	×
Occupation fixed effects (22)			×		×		×
Industry fixed effects (51)			×		×		×
State fixed effects (51)			×		×		×
Month fixed effects			×		×		×
Adjusted R^2	0.0004	0.074	0.084	0.029	0.044	0.112	0.115

Notes
$N = 35{,}548$. Standard errors in parentheses.
× indicates that the variable or vector is also included. The demographic variables included here and in Tables 3 and 4 are indicators for being African-American, Asian-American or Hispanic; gender, marital status and their interaction; a quadratic in potential experience; and an indicator of metropolitan status. Other non-work includes all non-eating non-work activities at the workplace, including socializing, leisure, cleaning up and others.

compositional effect that negatively biases the estimated impact of unemployment on non-work time.

In column (3) of Table 2 we add vectors of fixed effects for occupation, industry, state and month to the estimating equation in column (2). Each of the four vectors of indicators is jointly statistically significant: there are substantial differences across occupations, industries and states in the proportion of time at work spent not working. Even with these additions, however, over half of the estimated positive effect of unemployment on time not worked remains, although it is not quite statistically significantly positive.[16]

These estimates have aggregated all non-work time at work; yet one might expect different responses to changing unemployment of eating at work, which is a partly biological activity, and the broader category of other non-work time on the job. We thus re-estimate the basic model, first using the proportion of time at work spent eating as the dependent variable, then using the proportion of time at work spent in other non-work time on the job. In each case, in columns (4) and (6) of Table 2, we first include the vectors of work time and demographic measures that were added to produce the estimates shown in column (2). We then add the same four vectors of fixed effects included in the estimates shown in column (3), results shown in columns (5) and (7). The results are clear: most of unemployment's impact on non-work time at work operates through other non-work time—that is, on leisure on the job.[17] Eating at the workplace is much less affected by variations in unemployment.[18]

As Table 1 and Figure 1 showed, there are many zeros in these data. Yet estimating these models using the Tobit estimator is problematic, because there is no presumption that the impacts of unemployment (or of any other regressors in Table 2) on the probability of non-work and on its conditional mean have the same sign. That difficulty suggests estimating both incidence and intensity of non-work if positive in a single model using a more free-form technique, perhaps the all-in-one approach suggested by Cragg (1971). But that approach yields coefficient estimates that are difficult to interpret. Instead, and as an equivalent, we use Heckman's two-step procedure (Heckman 1976), estimating a probit on the incidence of non-work and a conditional regression on the amount of non-zero non-work.[19] We are not selecting the sample based on the value of the dependent variable; we are simply estimating the determinants of whether someone records any non-work time and the determinants of the amount of such time if there is any.

Table 3 presents the probit derivatives of the variables' impacts on the probability of non-work on the job—the incidence of non-work—and regression coefficients describing their effects on the amount of non-work for the two-thirds of the sample respondents who report positive non-work—its conditional intensity. The independent variables are the same as those included in the regressions in columns (2) and (3) of Table 2. The differences between these results and those in columns (2) and (3) of Table 2, based on the unconditional regressions, are remarkable. While higher unemployment is positively associated with the proportion of time at work reported non-working, it significantly reduces the probability that a worker spends any time not working. This reduction is more than offset by the significant increase in the proportion of time not working as the unemployment rate rises by those who state that they spent some time not working at work.[20]

Unlike in the unconditional regressions, the negative impact on the probability of not working and the positive impact on the conditional mean are robust to the inclusion of all the vectors of fixed effects, as comparisons of the estimates between columns (1) and (2), and between columns (3) and (4), show. Moreover, the effects are economically important: moving from the lowest to highest unemployment rate in the sample, the probability of any non-work time falls by 0.061 on a mean of 0.663, while the fraction of time spent not working by those who report positive non-work time at work rises by 0.020 on a conditional mean of 0.100. It was difficult to construct a convincing scenario why errors in reported non-work would be correlated with unemployment. It seems even more implausible that errors could produce a negative bias in the estimated impact of unemployment on the incidence of non-work, but a positive bias on its estimated impact on the conditional intensity.

The results displayed in Table 2 showed that the positive effect of higher unemployment on time spent not working was mainly on other non-work time, rather than on time spent eating at work. Table 4 presents estimates of effects on the probabilities of eating at work and engaging in other non-work, and on their conditional means. In all cases, we present only the specifications expanded to include all the vectors

TABLE 3
PROBIT DERIVATIVES AND CONDITIONAL REGRESSION ESTIMATES OF THE FRACTION OF TIME AT WORK NOT WORKING, ATUS 2003–12

	Incidence (Probit derivative)		Intensity (Conditional regression)	
Dependent variable:	(1)	(2)	(3)	(4)
Independent variable				
State unemployment rate (3-month average)	−0.00347 (0.00150)	−0.00507 (0.00172)	0.00159 (0.00042)	0.00162 (0.00048)
Demographic variables		×		×
Occupation fixed effects (22)		×		×
Industry fixed effects (51)		×		×
State fixed effects (51)		×		×
Month fixed effects		×		×
Pseudo or adjusted R^2	0.095	0.127	0.365	0.370
N	35,548	35,548	23,578	23,578

Notes
Standard errors in parentheses.
× indicates that the variable or vector is also included. Each equation also includes quadratics in usual weekly hours, time at the workplace, and potential experience; indicators of gender, marital status and their interaction; and metropolitan residence. The estimates in columns (3) and (4) are conditional on the sample respondent reporting positive non-work time at work.

of fixed effects. The negative impacts of unemployment on the probabilities of eating at work and engaging in other non-work are essentially identical. The difference in the responsiveness of eating and other non-work activities to higher unemployment that was shown in Table 2 results from the greater responsiveness of the latter among those workers who report some non-work time: the impact of changing unemployment on the intensity of other non-work time is three times larger than on time spent eating at work.

Robustness checks—alternative samples and specifications

Our central finding is that higher unemployment is associated with a greater fraction of time at work spent not working, with most of the effect coming from greater time at work in leisure, cleaning up, and so on. The net effect is the outcome of an important and surprising pair of subsidiary effects, namely that higher unemployment reduces the likelihood of non-work, while increasing the conditional amount of non-work sufficiently to generate a net positive relationship between unemployment and non-work on the job. In this subsection, we assess the sensitivity of our findings to alternative specifications of the estimating equations and underlying samples.

While we have controlled for a broad range of occupation (22) and industry (51) indicators, these might be insufficiently fine to account for differences in the structure of labour demand. The ATUS provides more detail on these measures, with 513 occupation and 259 industry categories. At the expense of many cells being very sparsely populated or empty, we re-estimate the equations in column (3) of Table 2 and columns (2) and (4) of Table 3 including these greatly expanded vectors of indicators. For this experiment and the others, Table 5 reports the parameter estimates of the effects of unemployment on the unconditional mean proportion of time spent not working at work, its incidence (probit derivatives) and its intensity (conditional regressions). This expansion of the

TABLE 4
PROBIT DERIVATIVES AND CONDITIONAL REGRESSION ESTIMATES OF THE FRACTION OF TIME EATING AT WORK AND OTHER NON-WORK, ATUS 2003–12

	Eating at work		Other non-work	
Dependent variable:	Probit derivative (1)	Conditional regression (2)	Probit derivative (3)	Conditional regression (4)
Independent variable				
State unemployment rate (3-month average)	−0.00579	0.00081	−0.00529	0.00231
	(0.00197)	(0.00032)	(0.00180)	(0.00072)
Occupation fixed effects (22)	×	×	×	×
Industry fixed effects (51)	×	×	×	×
State fixed effects (51)	×	×	×	×
Month fixed effects	×	×	×	×
Pseudo or adjusted R^2	0.153	0.143	0.058	0.498
N	35,548	18,401	35,548	12,612

Notes
Standard errors in parentheses.
× indicates that the variable or vector is also included. Each equation also includes quadratics in usual weekly hours. Time at the workplace, and potential experience; indicators of gender, marital status and their interaction, and metropolitan residence. The estimates in Columns (2) and (4) are conditional on the sample respondent reporting positive non-work time at work.

vector of controls generates a slight increase in the impact of higher unemployment on the conditional mean, but only negligible changes in its impacts on the incidence and intensity of non-work time.

With less cyclicality in demand and less exposure to the risk of job loss, we might expect public-sector employees' non-work time on the job to exhibit less cyclical sensitivity than that of private-sector workers. To examine this possibility, we delete the roughly one-sixth of the respondents who are public employees. As the results listed in the second row of Table 5 demonstrate, the expected change is exactly what we observe. Private-sector employees' non-work is more sensitive to variations in unemployment, but solely because its intensity is more variable; its incidence actually varies slightly less with unemployment than does that of all employees.

The Great Recession was a unique experience in postwar US history, and much of the variation in unemployment during our sample period arose because of this shock. To what extent are our results driven by responses to this unusual event? In the third experiment we delete observations from December 2007 to June 2009, the peak to trough of the NBER dating of this cycle. These deletions hardly alter the estimated impacts of unemployment on the three outcomes. Indeed, the effect on the unconditional mean is slightly larger than that estimated over the entire 120 months, because the impact on the intensity of non-work is greater when observations from the Great Recession are excluded.

While we included gender in the basic specification, we did not allow for different responses to unemployment by gender. In the fourth experiment, we estimate the three basic equations separately by gender, with the estimated impacts of unemployment shown in the fourth and fifth rows of Table 5. The average increase by men in time spent in non-work as unemployment rises exceeds women's, because men's probability of positive non-work is less sensitive than women's, while their conditional mean non-work time is more positively responsive to higher unemployment.[21]

It could be argued that the cyclical responsiveness of non-work differs by mode of compensation, even holding constant differences in demographics and occupational and industry attachment between hourly and salaried workers. In these data, hourly workers are more likely to report some non-work than are salaried workers. As the results in the sixth and seventh rows of Table 5 show, however, differences in the cyclical responsiveness of non-work on the job by payment method are small. The net impact is slightly greater among hourly workers, mainly because their conditional mean amount of non-work is more responsive to variations in unemployment. As with the central results, for both groups the incidence responds significantly negatively to increases in unemployment, while the conditional mean responds significantly positively.

The link between non-work and the demand for part-time workers might differ from that for workers more closely attached to the labour market. As shown in the eighth row of Table 5, the results do not change greatly when we limit the sample to full-time workers. While the net effect is smaller than in Table 2, both the incidence and intensity effects are statistically significant, of opposite sign, and differ very slightly from those shown in Table 3.

The ninth and tenth rows of Table 5 present estimates by union status of the effect of higher unemployment on the unconditional mean, the probability of not working and the conditional fraction of time not working at work by those who engage in any of it. In the union sector (which accounts for 14% of the sample), the decline in the fraction of employees reporting any non-work when unemployment rises is sharper than in non-union employment, all else equal. Because of this, and because the response of the

TABLE 5
ROBUSTNESS CHECKS ON BASIC EQUATIONS DESCRIBING NON-WORK TIME: ESTIMATED IMPACTS OF UNEMPLOYMENT

Dependent variable:	Total (1)	Incidence (Probit derivative) (2)	Intensity (Conditional regression) (3)	*N* total (with positive non-work) (4)
Experiment:				
More occupation (513)	0.00067	−0.00506	0.00160	35,548
and industry (259) indicators	(0.00042)	(0.00202)	(0.00048)	23,578
Private sector only	0.00070	−0.00466	0.00177	29,292
	(0.00046)	(0.00191)	(0.00054)	19,402
Exclude Dec. 2007	0.00062	−0.00460	0.00201	30,204
to June 2009	(0.00046)	(0.00186)	(0.00054)	20,019
Men and women separately:				
Men	0.00085	−0.00437	0.00207	17,777
	(0.00057)	0.00270)	(0.00067)	11,808
Women	0.00026	−0.00701	0.00134	17,771
	(0.00058)	(0.00284)	(0.00067)	11,770
Workers separately by payment method:				
Hourly	0.00066	−0.00463	0.00173	20,541
	(0.00053)	(0.00214)	(0.00059)	14,644
Salaried	0.00050	−0.00490	0.00162	14,991
	(0.00064)	(0.00275)	(0.00082)	8932
Full-time (35+ weekly hours)	0.00032	−0.00511	0.00131	29,864
	(0.00040)	(0.00179)	(0.00047)	20,408
Non-union and union separately:				
Non-union	0.00067	−0.00456	0.00174	30,582
	(0.00045)	(0.00189)	(0.00053)	19,887
Union	−0.00053	−0.00798	0.00047	4966
	(0.00095)	(0.00362)	(0.00105)	3691
No 100% non-workers	0.00016	−0.00560	0.00089	35,059
	(0.00028)	(0.00177)	(0.00036)	23,089

Notes
Standard errors in parentheses.
Each equation also includes all the controls included in column (3) of Table 2.

conditional mean is much smaller, but still positive, in the union sector, the unconditional mean amount of non-work in unionized employment drops when unemployment rises. Because these equations hold industry and occupation constant, we can conclude that unionized workers appear more eager to avoid the risky behaviour of non-working when the labour market is slack, perhaps because their potential lost rents are greater than those of non-union employees.[22]

Finally, deleting those workers who report non-work for the entire workday (about 1% of the sample) means truncating the sample on the dependent variable, automatically biasing any estimation results. The last row of Table 5 shows that if we exclude these workers, the net impact of unemployment among the remaining group is nearly zero; but the incidence of non-work responds to higher unemployment even more negatively than in the entire sample, while the intensity of non-work responds significantly positively, as before, but less strongly than in the entire sample. The fundamental finding of significant opposite effects on incidence and intensity survives.

Overall, this array of alternative specifications with samples truncated temporally or by workers' characteristics supports the central conclusions that we draw from Tables 2 and 3. There is a small net positive effect of higher unemployment on the amount of non-work in the workplace, a net effect that is composed of a significant negative impact on the incidence of non-work and a more important significant positive impact on the amount of non-work by the roughly two-thirds of workers who report any non-work at all.

III. Incentives and Heterogeneity

Unemployment insurance and wages

While in Tables 2–5 we have held constant in large arrays of demographic variables and others that might be viewed as demand-side, we have not examined the impacts of the purely economic incentives that should affect effort at work. A higher wage rate should increase workers' incentives to supply effort and stimulate employers' interest in monitoring them more carefully. More generous unemployment insurance benefits reduce incentives to supply effort. We thus expand the models describing the unconditional mean, incidence and conditional mean of non-work time by adding measures that proxy these incentives. Rather than adding the wage rate itself, which would generate errors due to division bias, we add the usual weekly earnings that are reported in the ATUS. Since a quadratic in usual weekly hours is already included in the specifications, weekly earnings in this context become a proxy for the worker's hourly wage rate.

The relevant measure of unemployment insurance (UI) income for each worker depends on complicated formulae typically linking the most recent year's pattern of earnings and employment to state-specific regulations that are revised annually. The ATUS lacks worker-specific earnings histories, so we experimented with two measures of UI benefits that might represent the average benefit available to an unemployed worker. The first, the annual state-specific maximum weekly benefit amount (*maxWBA*), is set legislatively. Given the relatively low benefit ceilings that characterize most states' programmes, roughly half of UI recipients receive maximum benefits, so this measure could be a good proxy for the incentives facing workers. An alternative measure is the average weekly benefit amount (*averageWBA*) paid in each state each year.[23] We experiment with this too, although it is not as clean a measure as *maxWBA*, since it depends partly on state-specific variation in unemployment.

We re-estimate the models of column (3) of Table 2 and columns (2) and (4) of Table 3, adding each worker's usual weekly earnings and alternatively the *maxWBA* or *averageWBA* in the state in the particular year. For both *maxWBA* and *averageWBA* we present estimates of the determinants of the unconditional mean of the percentage of non-work time, the incidence of non-work (the extensive margin) and its conditional mean (the intensive margin). We measure UI benefits and weekly earnings in thousands of dollars for ease of presenting the parameter estimates, noting that their raw means are \$384, \$281 and \$858, respectively.

Even with all the demographic, industrial and occupational controls, however, conditional on hours of work, the estimates in columns (1) and (4) of Table 6 demonstrate that workers with higher weekly earnings (implicitly a higher wage rate) spend a smaller fraction of their time at the workplace in non-work, consistent with

TABLE 6
ESTIMATES OF THE EFFECTS OF EARNINGS AND UNEMPLOYMENT BENEFITS ON THE TOTAL AMOUNT, INCIDENCE AND INTENSITY OF NON-WORK, ATUS 2003–12

	Maximum benefit			Average weekly benefit		
Dependent variable:	Total (1)	Incidence (Probit derivative) (2)	Intensity (Conditional regression) (3)	Total (4)	Incidence (Probit derivative) (5)	Intensity (Conditional regression) (6)
Independent variable						
State unemployment rate (3-month average)	0.00049	−0.00640	0.00173	0.00058	−0.00635	0.00178
	(0.00045)	(0.00187)	(0.00052)	(0.00048)	(0.00197)	(0.00056)
Weekly earnings ($000)	−0.0035	−0.0266	−0.0020	−0.0035	−0.0261	−0.0019
	(0.0011)	(0.0054)	(0.0014)	(0.0011)	(0.0054)	(0.0014)
UI benefits ($000)	0.0180	0.2823	−0.0111	0.0048	0.3641	−0.0260
	(0.0231)	(0.1034)	(0.0259)	(0.0405)	(0.1861)	(0.0465)
Pseudo or adjusted R^2	0.085	0.129	0.370	0.085	0.129	0.370
N	35,548	35,548	23,578	35,548	35,548	23,578

Notes
Standard errors in parentheses.
Each equation also includes all the controls included in column (3) of Table 2.

incentives to supply effort. Controlling for education and other characteristics, workers with higher wage rates are less likely to engage in any non-work on the diary day in the ATUS (columns (2) and (5)). Finally, other things equal, including the large vectors of demographic, industry and occupational characteristics, the conditional fraction of non-work is lower among workers with higher hourly wages (columns (3) and (6)).

While the results are very similar for both measures of UI benefits, the explanatory power is slightly higher when we include *maxWBA*. We see in columns (1) and (4) of Table 6 that neither *maxWBA* nor *averageWBA* has a significant impact on the unconditional mean of non-work time. However, workers in states and at times where the maximum (average) UI benefit is higher conditional on their earnings and hours are more likely to spend at least part of their day at work in non-work. If they do, though, then the amount of time spent in non-work does not vary with UI benefits (columns (3) and (6)). In sum, monetary incentives affect the amount of non-work in the expected directions, although such reduced-form models cannot distinguish among the possible sources of causation that motivated our empirical work.

Heterogeneity of non-work—the self-employed

The estimates in Section II suggested substantial heterogeneity in non-work at the workplace. We explicitly excluded the self-employed from our empirical analysis because we wished to focus on how the employment relationship expresses differences and changes in non-work time at work. Yet the existence of self-employed individuals—who by definition are not subject to monitoring—suggests an additional examination: they should behave qualitatively and quantitatively differently from employees. To test this,

TABLE 7
EFFECTS OF UNEMPLOYMENT ON NON-WORK TIME AMONG THE SELF-EMPLOYED

Dependent variable:	Total (1)	Incidence (Probit derivative) (2)	Intensity (Conditional regression) (3)
Independent variable			
Unemployment	0.00275	−0.00360	0.00448
	(0.00149)	(0.00610)	(0.00223)
R^2 or pseudo R^2	0.087	0.137	0.518
N	3347	3347	1359

Notes
Standard errors in parentheses.
Each equation also includes all the controls included in column (3) of Table 2.

we estimate the same equations for self-employed ATUS respondents who reported time at the workplace on the diary day, of whom there are 3347 with complete information on workdays in the ATUS 2003–12.

The estimates of the same expanded models that appeared in column (3) of Table 2 and columns (2) and (4) of Table 3 are presented for self-employed workers in Table 7. Before noting the remarkable differences in the responses of the unconditional and conditional means of non-work, and its incidence, the difference in the fraction of self-employed workers who report any non-work from that among employees is striking. We saw that 66% of employees say that they engage in non-work at the workplace; but only 41% of the self-employed record any non-work at work in the time diaries. This much greater average incidence of what may be viewed as productive work does not arise from the self-employed being in occupations where the incentives for non-work are low, but more likely arises from a direct linkage between remuneration and productive labour.

The estimates of the unemployment rate on the probability of non-work, shown in column (2) of Table 7, are negative, as was that parameter among employees, although because of the small number of self-employed workers in the sample, it is not statistically different from zero. Both the unconditional mean and conditional intensity are, however, four to five times more responsive to increases in unemployment than is true among employees. It is reasonable to expect that when unemployment is high and demand is slack, the self-employed might spend less time working at work, instead waiting for work or for customers. These findings imply much more cyclicality of non-work time at work among the self-employed than among employees.

Heterogeneity of non-work—occupational differences

In the equations presented in Tables 2 and 3, the parameter estimates of the vector of occupational indicators were both statistically and economically significant. Figures 2, 3 and 4 present these estimates for the net impact, the extensive margin (incidence) and the intensive margin (intensity) of non-work time at work, respectively, with management as the excluded occupation (effect on non-work time is zero). (These are based on the estimates in column (3) of Table 2 and columns (2) and (4) of Table 3.) As the equations already hold constant a large vector of demographic characteristics as well as industrial attachment, the parameter estimates suggest an interesting pattern of heterogeneity that is independent of personal characteristics and even assumes implicitly that we are

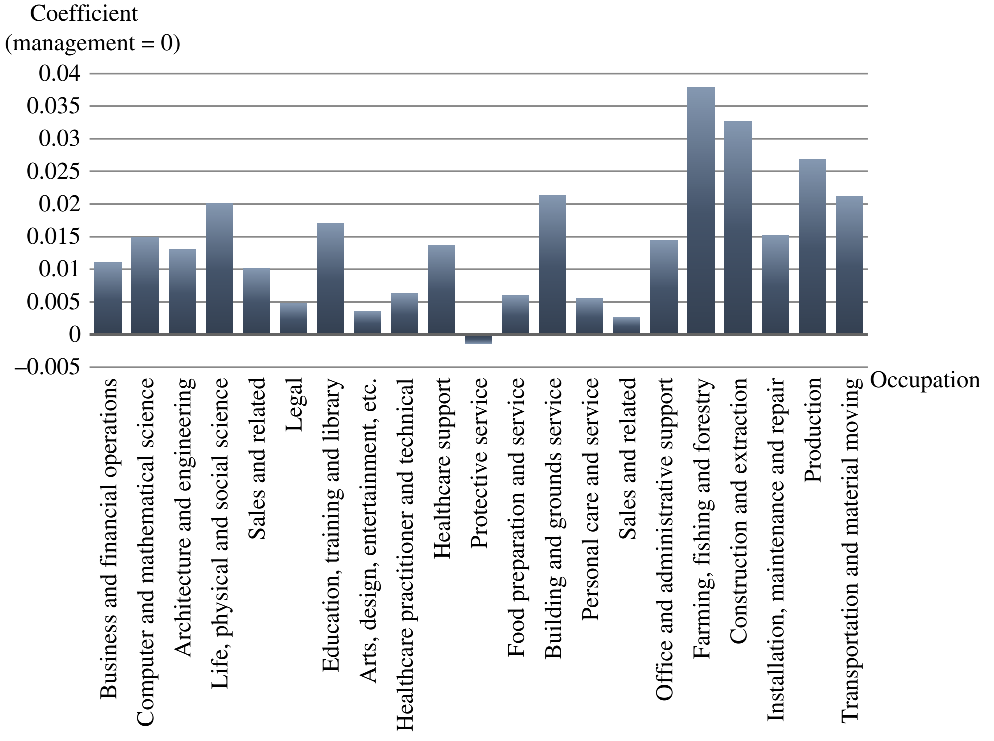

FIGURE 2. Coefficients on occupational indicators (management is the excluded category): net fixed effect on non-work (overall regression), based on column (3) of Table 2.

comparing differences by occupation within the same industry (presumably thus with similar characteristics of product demand). This pattern corresponds to expectations regarding the availability of down-time for work breaks and the potential for loafing behaviour, as well as the volatility of demand and delivery requirements associated with particular occupational tasks.

Consider Figure 2. Except for protective services, in which employees spend as small a proportion of their workday not working as do managers, workers in all other occupations experience more non-work on the job than do managers, other things equal. Examining which occupations exhibit the greatest fraction of time at work not working, the heterogeneity is correlated with being in manual or less-skilled occupations (those ten occupations depicted on the right-hand side of the figure). We cannot tell whether these occupational differences result from differences in preferences for using time or from the differing ability of managers to monitor workers, within the demographic categories already held constant (mostly supply-side effects) or within industries (presumably mostly demand-side effects). But the pattern is striking.

Among five of these manual occupations, this occupational difference in the net amount of non-work from that in other occupations arises from both the greater incidence of non-work (Figure 3) and its greater intensity (Figure 4). In the other five manual-type occupations (food preparation to office and administrative support), the difference results almost entirely from differences in intensity. In these occupations, the incidence of non-work is even less than among managers, controlling for demographics, hours of work and industry.

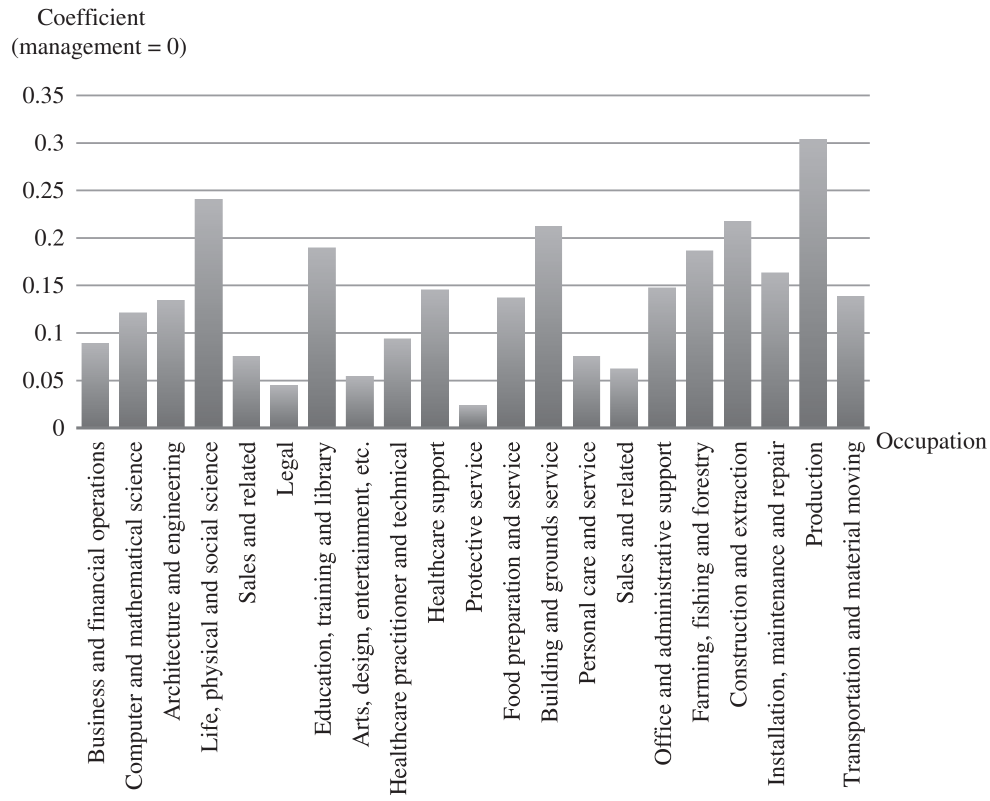

FIGURE 3. Coefficients on occupational indicators (management is the excluded category): extensive margin (from probit model), based on column (2) of Table 3.

Ignoring the apparent difference between what are mostly manual occupations and others, the heterogeneity of occupational differences in non-work time at work is due more to differences in incidence rather than in intensity. The coefficient of variation in Figure 3 is 0.60, while that in Figure 4 is only 0.41.[24] This differs from the pattern that we saw in comparing cyclical variations in non-work: as Table 3 showed, these are mostly due to cyclicality in intensity, not in incidence, rather than substantially due to both, as here. Whether the pattern of occupational differences in non-work time at work results from greater differences in monitoring technology at the intensive margin or from the role of differences in preferences of employees by occupation (all within demographic and industry groups) cannot be inferred from these essentially reduced-form estimates. Yet another possibility is that the pattern is due to differences in the incentives to hoard labour, although this seems inconsistent with the greater unconditional amount of non-work in manual occupations. Suffice it to say that any one of these potential causes operates at both the intensive and extensive margins.[25]

IV. CONCLUDING REMARKS

We have focused on measuring changes in effort exerted by workers as slack in the labour market decreases or increases. This would appear to be a simple

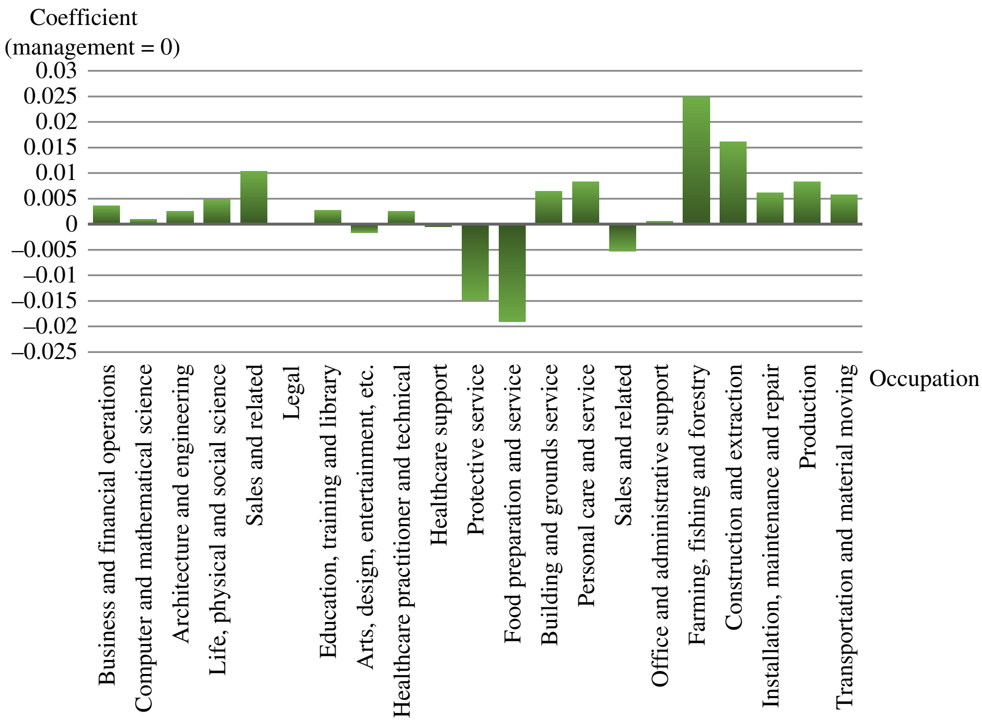

FIGURE 4. Coefficients on occupational indicators (management is the excluded category): intensive margin (from conditional regression), based on column (4) of Table 3.

measurement issue, one that would have been reflected in official aggregate data for many years; yet this has not been the case. The American Time Use Survey provides information on time use on the job since 2003. These new data allow us to provide the first measures of the cyclical variability of time not working while at the workplace.

While non-work time at work is countercyclical, this net result is the outcome of highly significant but opposite-signed impacts of higher unemployment at the intensive and extensive margins. The potential role of shirking or labour slack is strongly reflected in the procyclical variation in the incidence of non-work time; but among those who shirk at all, the intensity of their non-work is strongly countercyclical. We find that, in general, higher unemployment benefits lead to slightly more non-work on the job, but this effect is due entirely to their inducing employees to be more likely to report at least some non-work time at work. Estimates of occupation fixed effects of both extensive and intensive margins are consistent with our knowledge about those occupations, in particular the importance of the distinction between manual and other labour that is likely to be more skill-intensive.

There are undoubtedly many other applications in this new approach to measuring effort on the job. For example, the cyclical changes might be used to generate refined series of labour productivity, similar to other refinements in, for example, Burda *et al.* (2013). More generally, rationalizing these results within a consistent micro-based macroeconomic model would be a useful contribution. We leave this large set of potential extensions and applications to future work.

ACKNOWLEDGMENTS

We thank Dan Black, Peter Egger, Albrecht Glitz, Mathias Hoffmann, Christian Merkl, Richard Murphy, Silvia Sonderegger, Jeff Woods and participants in several seminars, as well as Matthew Notowidigdo for providing the files on states' unemployment insurance programmes.

Hamermesh thanks the Humboldt Foundation for financial support. The Collaborative Research Center 649 of the German Science Foundation also funded this research.

NOTES

1. A recent sociological study, Paulsen (2015), presents cases illustrating the role and reasons for people loafing on the job. Brodsky and Amabile (2018) study the effects of downtime. Lazear *et al*. (2016) and Pencavel (2015) analyse changes in effort and productivity in single firms.
2. Hamermesh (1990) examines cross-sectional differences in the allocation of time on the job.
3. The ATUS collected more diaries in its first year, generating about 450 usable diaries each month in 2003.
4. Time spent working includes time spent in 'Work Related Activities' or ATUS codes 50000–50299. Work-related activities include socializing and eating as a part of the job.
5. In the original data, non-work time on the job is divided into the following broad primary activities: personal care; household production; care-giving; educational activities; shopping; services; eating, leisure, exercising and sport; and volunteering and religious activities. Several of these are observed so infrequently as to prevent them from being analysed separately, so that we combine them into the fifth (other) category of non-work time on the job. Household production is not considered an act at work.
6. The ATUS does not collect information on secondary activities of this nature, so we cannot measure time spent in non-work while also working, such as reading the news while the employee's primary activity is working on a conference call. Likewise, the measure of non-work time that we study may not capture very short increments of non-work time, such as checking social media websites for a few minutes, because respondents are less likely to remember short events compared to long events even though the ATUS survey collectors ask about activities at every minute of the previous day.
7. Evidence in Abraham *et al*. (2006) suggests that while non-response in the ATUS is substantial, it is nearly random and does not alter generalizations based on those individuals who do respond.
8. This near equality differs from the result in the literature that recall weekly hours exceed diary hours (Juster and Stafford 1991; Frazis and Stewart 2004). The difference may arise because we restrict the workday to the time that respondents spend at the workplace in any activity.
9. We cannot tell if these respondents simply do not understand how to complete the diaries, or whether they are in fact cleaning up or enjoying leisure during their entire workday. Suffice it to say that their number is so few that deleting them from all the subsequent analyses produces only minute changes in the estimates.
10. Experiments with the one-month unemployment rate consistently yielded weaker fits, so we limit the reported results to those based on the three-month average. Replacing the most recent three-month average unemployment rate with a lagged three-month average yielded similarly weaker fits (but no qualitative change in the estimates), and similarly for non-linear transformations of the unemployment rate.
11. The most prominent of these are Calvo (1979), Akerlof (1982), Shapiro and Stiglitz (1984), and Bowles (1985).
12. We cannot rule out that workers might self-select via migration, effectively choosing regions in which unemployment is lower and thus affecting the conditions under which they work. The same argument applies to employers and capital mobility. Either possibility would bias estimated sensitivity to unemployment towards zero.
13. All the results in this section remain qualitatively identical if we use minutes of the various types of non-work time rather than their proportions of the workday as the dependent variables. Similarly, using more flexible representations of usual weekly hours and time spent at work does not alter the results, nor does deleting the quadratic in time at work from the estimates in columns (2) and (3) change the central conclusions.
14. This finding is consistent with older evidence from the scientific management literature charting workers' productivity over the workday (Florence 1958).
15. The covariates included in column (2) of Table 2 describe 0.92% of the variation in state unemployment rates over time.
16. Almost the entire drop in the estimate arises from the inclusion of state fixed effects. Re-estimating the model excluding state effects, the estimated impact of unemployment is essentially unchanged from that in column (2) of Table 2.
17. One might be concerned that employees change the amount of non-work multi-tasking that they do as unemployment changes. The ATUS does not provide information on secondary activities in most months; but for 2006 and 2007, as part of the Eating and Health Module, it collected information on secondary eating, including at work. Of the employees in our sample in those years, 41% report some secondary eating and/or drinking at work. Among those who do report this, the average amount of time spent in these

secondary activities is almost exactly 2 hours per day. Although this activity is important, re-estimates of the models in Table 2 show that variations in secondary eating are independent of differences in unemployment rates across states and over these two years.

18. Nor is it the case that eating time outside of work varies cyclically. In regressions specified as in column (5) of Table 2, but with total eating time away from the workplace as the dependent variable, the impact of unemployment is not statistically significantly non-zero ($t = 0.24$). The size of the impact of unemployment on eating away from work is tiny, only one-third that of the very small effect on time spent eating at work.
19. This procedure is usually applied when one believes that there is sample selectivity, but it applies equally well to the case where the dependent variable is truncated. It is used frequently in this manner (e.g. recently, Jiménez *et al*. 2014).
20. Commuting time might affect the amount of non-work while being correlated with the local unemployment rate. Although this measure is obviously endogenous, which is why we have excluded it, experimenting with adding it to the equations presented in column (3) of Table 2 and columns (2) and (4) of Table 3 increases the absolute values and statistical significance of the coefficient estimates on the unemployment rate.
21. The presence of young (age 13 or less) children significantly reduces men's unconditional mean non-work while not affecting women's. This result seems consistent with income effects on married men's efforts in households with young children where the male is the major earner.
22. One should note, however, that the average amount of non-work is greater in the union sector, conditional on all the covariates included in Table 2.
23. These data represent an extension of the sample used by Kroft and Notowidigdo (2016).
24. In calculating these statistics, we re-based the estimated coefficients so that no negative coefficients entered the calculations.
25. Vectors of interactions of the occupational indicators with the unemployment rate were not statistically significant in the equations underlying any of these figures.

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